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Statistical Modeling of Spring discharge at Apopka and Bugg Springs in Lake County, Florida

ST. JOHNS RIVER

SJR

WATER MANAGEMENT DISTRICT

Statistical Modeling of Spring Discharge at Apopka and Bugg Springs in Lake County, Florida

FINAL REPORT

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EXECUTIVE SUMMARY

Currently, the St. Johns River Water Management District (District) is engaged in hydrologic modeling and data analysis in support of the ongoing Minimum Flows and Levels (MFLs) and Water Supply Development projects. MFLs define the frequency and duration of high, average, and low water events necessary to prevent significant ecological harm to aquatic habitats and wetlands from permitted water withdrawals. An integral component of the District's MFL program is the development of long-term daily discharge predictions at various streams in the District. This report describes the development of statistical models for predicting daily spring discharge time series for Apopka and Bugg springs from an assortment of auxiliary data such as: (a) previously recorded spring discharge rates at the spring of interest and at adjacent springs, (b) groundwater level measurements from adjacent monitoring wells, (c) lake level measurements from nearby lake gages and (d) rainfall data from nearby gauging stations.

The presented regression models are based on the statistical correlation between the explanatory and response variables. For example, spring discharge is correlated with aquifer water levels, perhaps with a lead time. This correlation explains some of the variability in the observed spring discharge rates. Further, the correlation is improved using the average water level values rather than the individual measurements which are known to display higher variances.

Data screening indicates that most measurements of spring discharge and groundwater level are at a frequency of ~30 days or greater – necessitating the generation of moving averages with commensurate lags to be used as independent variables for predicting spring daily discharge. Also, Bugg Spring discharge values have an average data frequency of 14 days. Hence, independent variables generated by moving averages of Bugg Spring discharge have been utilized to help estimate discharge for Apopka Spring. Analysis of data overlap is helpful in determining how to partition the period of record into sub-periods where a common set of variables can be defined.

Stepwise regression analysis is used to build multivariate linear input-output models between the response variable (spring discharge) and the independent variables (moving averages of spring discharge, water level measurements, lake levels and precipitation) at the springs of interest. Typically, two regression models of spring discharge are needed: (a) one for the period when spring discharge, groundwater levels, lake levels and rainfall data are available, and (b) one for the period when rainfall data are supplemented with lake levels and perhaps groundwater levels from one or two long-term monitoring wells.

The following regression models are developed for Apopka Spring:

- Apopka discharge as a function of water level measurements from Floridian aquifer well (FAW) L-0199 (2- and 6-week moving average) and L-0062 (52-week moving average), 3-, 8-, 24-, and 48-week moving averages of Lake Apopka water level, 48-week moving average of Bugg discharge and 2-, 3-, 24- and 48-week moving averages of rainfall at Clermont 9 S (R^2=0.7934). This model is used to predict post-1990 daily spring discharge for Apopka Spring.

- Apopka discharge as a function of 3-, 4-, 48- and 52-week moving averages of Lake Apopka water level and 48-week moving average of rainfall at Clermont 9 S (R^2=0.6152). This model is used to predict pre-1990 daily spring discharge for Apopka Spring when no measurements are available at the spring.

For Bugg Spring, the regression models developed are as follows:

- Bugg discharge as a function of water level measurements from Floridian aquifer well (FAW) L-0096 (3-, 4-, and 24-week moving average), L-0703 (8-, 12-, 24-, and 48-week moving average) and L-0062 (52-week moving average), 3-, 8-, 24- and 48-week moving averages of Lake Apopka water level, 6-, 8-, and 12-week moving averages of Bugg discharge and 6- and 52-week moving averages of rainfall at Bushnell 2 E (R^2=0.7128). This model is used to predict post-1990 daily spring discharge for Bugg Spring.

- Bugg discharge as a function of water level measurements from Floridian aquifer well (FAW) L-0054 (24- and 52-week moving average) and 3-, 4-, 12-, 24- and 48-week moving averages of rainfall at Bushnell 2 E (R^2=0.5651). This model is used to predict pre-1990 daily spring discharge for Bugg Spring when no measurements are available at the spring.

Using these models, daily discharge predictions are made for Apopka and Bugg springs as far as 1949 and 1973 respectively, with reasonable accuracy. Flow duration curves are also generated for the two springs along with high- and low-frequency analyses for set durations (1-, 2-, 3-, 4-, 6-, and 12-months) from the simulated daily spring discharge.

This report incorporates comments provided by peer review of the first report in this Statistical Modeling of Spring Discharge series. The peer review comments and their resolution as they apply to this report are in Appendix B.

1.0 INTRODUCTION

The Minimum Flows and Levels (MFLs) Program of the St. Johns River Water Management District (District), mandated by state water policy (section 373.042, *F.S.*), establishes MFLs for lakes, streams and rivers, wetlands, and groundwater aquifers. MFLs define the frequency and duration of high, average, and low water events necessary to prevent significant ecological harm to aquatic habitats and wetlands from permitted water withdrawals. The MFLs Program is subject to chapter 40C-8, *F.A.C.* and provides technical support to the District's regional water supply planning process and the consumptive use-permitting (CUP) program.

MFLs designate hydrologic conditions that prevent significant harm and above which water is available for reasonable beneficial use. The determinations of MFLs consider the protection of non-consumptive uses of water, including navigation, recreation, fish and wildlife habitat, and other natural resources. MFLs take into account the ability of wetlands and aquatic communities to adjust to changes in hydrologic conditions. Therefore, MFLs allow for an acceptable level of change to occur relative to the existing hydrologic conditions. However, when use of water resources shifts the hydrologic conditions below those defined by the MFLs, significant ecological harm occurs. As it applies to wetland and aquatic communities, significant harm is a function of changes in the frequencies and durations of water level and/or flow events, causing impairment or destruction of ecological structures and functions.

Currently, the District is engaged in hydrologic modeling and hydrologic data analysis in support of the ongoing MFLs and Water Supply Development projects. An integral component of the District's MFL program is the development of long-term daily discharge models at various streams in the District. MFLs for two springs in Lake County, Florida, namely, Apopka and Bugg springs, are currently needed. As discussed in the following sections, while the Bugg Spring has more data than Apopka Spring, each of these springs has limited spring flow measurements (Osburn et al., 2002). This study evaluates the application of statistical models to generate long-term daily discharge simulations for each of these two springs.

2.0 OBJECTIVE

The objective of this study is the development of daily spring discharge time series for Apopka and Bugg springs from an assortment of auxiliary data such as: (a) previously recorded spring discharge rates at the spring of interest and at adjacent springs, (b) groundwater level measurements from adjacent monitoring wells, (c) lake levels from nearby lake level gages and (c) rainfall data from nearby gauging stations. The study investigates and tests the applicability of the correlation structure between various data types, and test the applicability of simple multivariate linear models to generate daily discharge records based on these other variables for the common period of record.

This report presents the results of data screening and preliminary statistical analysis for rainfall, groundwater and lake water level and spring discharge data for Apopka and Bugg springs. It also explores the use of empirical models to provide estimates of daily discharge at these springs. These statistical models will take advantage of all available data to try to provide the most accurate estimates. In general, early time records are sparse and often not available for a number of locations. This will require the use of different models ranging in sophistication from simple correlation based models to multivariate regression models which can only be constructed when enough supporting data (e.g., rainfall and groundwater levels) are available at a sufficient number of nearby locations. These models will be used to run a continuous simulation model covering the period of record referenced by the constituent data. From the results of statistical modeling, standard flow-duration analysis for the system (discharge versus percent exceedance for the long-term simulation) will be conducted and standard high- and low-flow frequency analyses for the system (frequency of spring discharge for set durations) will be carried out.

This report is organized as follows. Data screening and preliminary statistical analysis is described in Section 3. Section 4 contains the regression modeling methodology and the regression models developed for Apopka and Bugg springs. In section 5, daily discharge predictions are presented along with flow duration curves and frequency analyses for each of these springs. Section 6 contains conclusions and recommendations from this study.

3.0 DATA SCREENING AND PRELIMINARY ANALYSIS

This section summarizes the available data and shows the results of data screening and preliminary statistical analyses conducted for the available time series. The objective of these analyses is to identify the correlation structure between the spring discharge at the three springs of interest and the other time series. Results from these analyses will be used to guide the construction of explanatory models which will predict daily discharge values at each spring.

3.1 Data Sources

Figure 1 shows a map of the study area and highlights the location of various data sources. Although the map shows numerous groundwater wells and lake gages around the springs of interest, very few wells and lake gages have data records with consistent frequency and a long enough period of record to be considered for statistical modeling. The selected groundwater wells and lake gages with a reasonable data frequency and period of record have been highlighted in the map. Also, one long term NOAA rainfall gage has been selected for each spring of interest, since the rainfall gages around the springs do not show significant difference in daily rainfall values. The following are the various data sources to be used with each spring:

- Spring discharge measurements at Apopka and Bugg springs.
- Groundwater level measurements at monitoring wells:
    - L-0199 and L-0062 for Apopka Spring
    - L-0054, L-0703, and L-0096 for Bugg Spring
- Lake level measurements at lake level gages
    - Lake Apopka at Oakland WL gage for Apopka Spring
- Precipitation measurements at rain gages:
    - Clermont 9 S for Apopka Spring
    - Bushnell 2 E for Bugg Spring

In order to conduct exploratory data analysis, a database was compiled of spring discharge (response variable), groundwater levels (explanatory variable), lake levels (explanatory variable) and precipitation (explanatory variable) with a common time basis.

Table 1 shows summary statistics (i.e., minimum, maximum, average and standard deviation) for these various data types at Apopka and Bugg springs.

The frequency of observation for each data type was subsequently calculated. This is useful for determining appropriate lag and moving average windows. Moving averages were calculated for recorded groundwater and lake levels, precipitation and spring discharge at the spring of interest as well as at adjacent springs at selected lag times such as 1, 2, 3, 4, 6, 8, 12, 24, 48 and 52 weeks. These moving averages act as independent variables and carry useful information regarding the physical state of the system prior to the time of interest.

Table 1 Basic statistics for various data types at Apopka and Bugg springs.

Data Type	Range	Min	Max	Average	Std Dev	Variable Type
Apopka Spring	5/14/1997 - 9/26/2005	9.58	36.49	26.41	4.88	Discharge (cfs)
L-0199	1/26/1990 - 1/30/2006	67.51	76.03	73.03	2.16	Water-level (ft)
L-0062	5/6/1976 - 10/7/2005	93.91	102.31	99.78	1.42	Water-level (ft)
Lake Apopka	9/1/1942 - 12/31/2005	62.59	69.09	66.66	0.87	Lake-level (ft)
CLERMONT 9 S	7/1/1948 - 12/31/2005	0.00	7.29	0.14	0.41	Rainfall (in)
Bugg Spring	3/11/1990 - 10/18/2005	3.80	19.80	11.47	2.31	Discharge (cfs)
Bugg Spring	3/11/1990 - 10/18/2005	3.80	19.80	11.47	2.31	Discharge (cfs)
L-0096	8/22/1989 - 1/30/2006	74.93	87.15	81.72	2.46	Water-level (ft)
L-0703	4/27/1999 - 1/30/2006	53.67	60.49	57.64	1.56	Water-level (ft)
L-0054	10/25/1973 - 10/5/2005	56.70	68.97	64.14	2.20	Water-level (ft)
BUSHNELL 2 E	10/11/1936 - 11/30/2005	0.00	9.08	0.14	0.41	Rainfall (in)

3.2 Frequency of Observation

Table 2 shows the mean and standard deviation of frequency of observation for each data type for Apopka and Bugg springs. For Apopka Spring, the spring discharge had a period of record dating back to May 1997 at an average frequency of 75 days – although a few isolated observations extend back to May 1971. All the Apopka discharge data recorded prior to 7/18/1997 were collected by the USGS. It was found that including the USGS Apopka discharge data in the model did not yield a good statistical model for Apopka Spring. This is primarily due to the large measurement errors in USGS data as pointed out in German (2004). Hence, all the Apopka discharge data prior to 7/18/1997 were ignored for the purpose of statistical modeling of Apopka Spring. At well L-0199, groundwater levels are available daily from January 1990. At well L-0062, groundwater levels are available from May 1976 at a frequency of 32 days. For Lake Apopka lake level gage, daily water level observations are available from September 1942. For the Clermont 9 S rain gage, daily precipitation observations are available from July 1948. Finally, the moving averages of discharge for Bugg Spring are included as explanatory variables for Apopka Spring. For Bugg Spring, discharge values are available from March 1990 at an average frequency of 14 days – although a few isolated observations extend back to 1943.

Table 2 Frequency of observation of various data types at Apopka and Bugg springs.

Data Type	Range	Mean obs freq	Std Dev	Outlier Data Points
Apopka Spring	5/14/1997 - 9/26/2005	75	75	5/4/1971 - 12/8/1992
L-0199	1/26/1990 - 1/30/2006	Daily	8	N/A
L-0062	5/6/1976 - 10/7/2005	32	36	N/A
Lake Apopka	9/1/1942 - 12/31/2005	Daily	1	N/A
CLERMONT 9 S	7/1/1948 - 12/31/2005	Daily	N/A	N/A
Bugg Spring	3/11/1990 - 10/18/2005	16	14	3/16/1943 - 2/7/1985
Bugg Spring	3/11/1990 - 10/18/2005	16	14	3/16/1943 - 2/7/1985
L-0096	8/22/1989 - 1/30/2006	Daily	3	N/A
L-0703	4/27/1999 - 1/30/2006	Daily	15	N/A
L-0054	10/25/1973 - 10/5/2005	59	97	N/A
BUSHNELL 2 E	10/11/1936 - 11/30/2005	Daily	11	4/1/1918 - 9/30/1918

As described earlier, for Bugg Spring, discharge values are available from March 1990 at an average frequency of 14 days – although a few isolated observations extend back to 1943. At well L-0096, groundwater levels are available daily from August 1989. At well L-0703, groundwater levels are available daily from April 1999. Since, L-0703 has data only starting in April 1999, it is essential to backfill L-0703 data using linear regression with another adjacent well having a good period of record, for moving average variables of L-0703 to be useful in statistical modeling of Apopka Spring. A linear regression between L-0703 and L-0096 results in an R^2 of 0.9027. Figure 2 shows the regression plot and the equation used to backfill L-0703 till August 1989. This new backfilled L-0703 variable will be further addressed as L-0703R in this report. At well L-0054, groundwater levels are available from October 1973 at an average frequency of 59 days. Investigating further on the data frequencies for this well, it is found that L-0054 has no water level data from August 2000 to October 2003. For that reason, it is essential to fill this data gap using linear regression with another adjacent well having a good period of record, for moving average variables of L-0054 to be useful in statistical modeling of Apopka Spring. A linear regression between L-0054 and L-0096 results in an R^2 of 0.8319.

Figure 3 shows the regression plot and the equation used to fill L-0054 between August 2000 and October 2003. This new regressed L-0054 variable will be further addressed as L-0054R in this report. For the Bushnell 2 E rain gage, daily precipitation observations are available from October 1936 - although a few isolated observations are present in the year 1918.

3.3 Analysis of Overlap

Periods of overlap between different data types were analyzed for each of the springs of interest. This is useful for determining how the period of record can be split up into sub-periods with common sets of explanatory variables. The frequency of observation for each data type was subsequently calculated. This is useful for determining appropriate lag and moving average windows. Moving averages were calculated for recorded water levels, precipitation and spring discharge at adjacent springs at selected lag times such as 1, 2, 3, 4, 6, 8, 12, 24, 48, and 52 weeks. The moving averages act as independent variables and carry useful information regarding the physical state of the system prior to the time of interest.

Figure 4 shows the overlap between various data types for the Apopka Spring. Shown here are the periods of record for (a) Apopka and Bugg springs discharge, (b) groundwater levels at monitoring wells L-0199 and L-0062, (c) Water level measurements at Lake Apopka gage and (d) precipitation measurement at Clermont 9 S. Also indicated therein is the average frequency of observation for each data type (as was discussed in detail in the previous section). From 1990, several time series are available which could be used to estimate daily discharge at Apopka Spring. Prior to that, lake levels for Lake Apopka gage, precipitation and groundwater level data at well L-0062 are available. L-0062 has an average data frequency of 32 days but it also has huge data gaps between years 2001 and 2003. For that reason, it is likely that a moving average window of 48 weeks or greater will be used to take advantage of this water level measurement. Also, moving average window of 1 week or greater, 6 weeks or greater, and 2 weeks or greater will be used for Clermont 9 S, Bugg Spring and L-0199 respectively, due to the presence of data gaps. Choosing the right moving average variables becomes particularly important for Apopka Spring since it has only 39 good discharge measurements starting from 7/18/1997. All the 39 measurement dates need to have corresponding values for the explanatory variables which in turn restricts selection of smaller moving average variables due to data gaps.

Based on the above discussion of overlap analysis for Apopka Spring, the following two datasets are used for Partial Correlation Coefficient and Stepwise Analysis to build a regression model:

- Dataset for Apopka regression model to predict pre-1990 Apopka discharge values:
    - Dependent variable: Apopka Spring (39 discharge values from 7/18/1997)

    - Independent variables:
        - Lake Apopka and 1-, 2-, 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Lake Apopka
        - 1-, 2-, 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Clermont 9 S
        - 48- and 52-week moving averages of L-0062

- Dataset for Apopka regression model to predict post-1990 Apopka discharge values:
    - Dependent variable: Apopka Spring (39 discharge values from 7/18/1997)
    - Independent variables:
        - Lake Apopka and 1-, 2-, 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Lake Apopka
        - 1-, 2-, 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Clermont 9 S
        - 48- and 52-week moving averages of L-0062
        - 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Bugg Spring
        - 2-, 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of L-0199

Figure 5 shows the overlap between various data types for Bugg Spring. Shown here are the periods of record for (a) Bugg Spring discharge, (b) groundwater levels at monitoring wells L-0096, L-0703 and L-0054, and (c) precipitation measurement at Bushnell 2 E. Also indicated therein is the average frequency of observation for each data type (as was discussed in detail in the previous section). From 1990, several time series are available which could be used to estimate daily discharge at Apopka Spring. L-0703 is available from April 1999 and hence is backfilled using linear regression with L-0199 as described earlier. The new backfilled time series is L-0703R which goes back till 1989. Prior to 1990, groundwater level data at well L-0054 and precipitation at Bushnell 2 E are available. As described earlier, L-0054 has a data gap between 2000 and 2003 and this data gap is filled using linear regression with L-0096. The new variable is L-0054R which now has an average frequency of 9 days as compared to 59 days for L-0054.

Based on the above discussion of overlap analysis for Bugg Spring, the following two datasets are used for Partial Correlation Coefficient and Stepwise Analysis to build a regression model:

- Dataset for Bugg regression model to predict pre-1990 Bugg discharge values:
  - Dependent variable: Bugg Spring (337 discharge values from 4/7/1990)
  - Independent variables:
    - 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Bushnell 2 E
    - 12-, 24-, 48-, and 52-week moving averages of L-0054R
- Dataset for Bugg regression model to predict post-1990 Bugg discharge values:
  - Dependent variable: Bugg Spring (337 discharge values from 4/7/1990)
  - Independent variables:
    - 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Bushnell 2 E
    - 12-, 24-, 48-, and 52-week moving averages of L-0054R
    - 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of Bugg Spring
    - 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of L-0096
    - 3-, 4-, 6-, 8-, 12-, 24-, 48-, and 52-week moving averages of L-0703R

3.4 Partial Correlation Coefficient (PCC) and Stepwise Analysis

Partial Correlation Coefficient (PCC) is the degree of correlation between any two variables, all others being kept constant. PCCs can be used to find which variables are responsible for multicollinearity. Thus, PCCs can be used to drop the explanatory variable(s) which causes multicollinearity. Another option is to include all the variables in the stepwise regression analysis, where variables are added or removed one at a time until no additional variables can be found that improve the goodness-of-fit of the input-output model. Stepwise procedures select the most correlated independent variable first, remove the variance in the dependent, then select the second independent which most correlates with the remaining variance in the dependent, and so on until selection of an additional independent does not increase the

R-squared by a significant amount (significance = .05). In other words, stepwise regression chooses the variables with the highest partial correlations and includes variables until the partial correlation of all remaining excluded variables with the dependent variable is below some limit. This selection process in a way ensures that no variables with high multicollinearity are picked in the regression model using stepwise regression.

Table 3 shows the PCCs and the variables selected in stepwise regression for the Apopka Spring dataset for predicting pre-1990 discharge values. The variables with p-value<0.1 are highlighted in red, indicating a significant partial correlation for that variable. 3-, 4-, 48-, and 52-week moving averages for Lake Apopka and 48-week moving average for Clermont 9 S are selected in stepwise regression.

Table 3 PCCs and variables selected in stepwise regression for the Apopka dataset for predicting pre-1990 discharge values.

Apopka Spring	PCC	p-value
LakeApopka	-0.15	0.57
LakeApopka-1-week	-0.20	0.45
LakeApopka-2-week	0.39	0.13
LakeApopka-3-week	-0.49	0.05
LakeApopka-4-week	0.34	0.20
LakeApopka-6-week	-0.14	0.61
LakeApopka-8-week	-0.01	0.97
LakeApopka-12-week	0.01	0.96
LakeApopka-24-week	0.11	0.67
LakeApopka-48-week	-0.38	0.15
LakeApopka-52-week	0.43	0.10
CLERMONT 9 S-1-week	0.39	0.14
CLERMONT 9 S-2-week	-0.18	0.51
CLERMONT 9 S-3-week	-0.17	0.54
CLERMONT 9 S-4-week	0.14	0.61
CLERMONT 9 S-6-week	0.08	0.77
CLERMONT 9 S-8-week	-0.18	0.51
CLERMONT 9 S-12-week	0.23	0.40
CLERMONT 9 S-24-week	0.34	0.19
CLERMONT 9 S-48-week	0.34	0.20
CLERMONT 9 S-52-week	-0.30	0.26
L-0062-48-week	0.29	0.28
L-0062-52-week	-0.24	0.37

Apopka-pre1990 Selected variables-stepwise
LakeApopka.3.week
LakeApopka.4.week
LakeApopka.48.week
LakeApopka.52.week
CLERMONT.9.S.48.week

Table 4 shows the PCCs for the Apopka Spring dataset for predicting post-1990 discharge values. The variables with p-value<0.1 are highlighted in red, indicating a significant partial correlation for that variable. The variables were prescreened using PCCs since the dataset had only 39 data points and including all the variables for stepwise regression led to an over-parameterization of the final regression model. Three-, 4-, and 8-week moving averages for L-0199, 1-, 2-, 4-, 6- 12-, and 52-week moving averages for Lake Apopka, 8-, 12-, and 52-week moving averages for Bugg Spring and 48-week moving average for L-0062 are not included in stepwise regression analysis from the variable list.

Table 4 PCCs and variables selected in stepwise regression for the Apopka dataset for predicting post-1990 discharge values.

Apopka Spring	PCC	p-value
L-0199-2-week	0.98	0.02
L-0199-3-week	-0.97	0.03
L-0199-4-week	0.89	0.12
L-0199-6-week	0.26	0.74
L-0199-8-week	-0.44	0.56
L-0199-12-week	0.97	0.03
LakeApopka	-0.92	0.08
LakeApopka-1-week	-0.73	0.27
LakeApopka-2-week	-0.98	0.02
LakeApopka-3-week	0.97	0.03
LakeApopka-4-week	-0.95	0.05
LakeApopka-6-week	0.81	0.19
LakeApopka-8-week	0.78	0.22
LakeApopka-12-week	0.48	0.52
LakeApopka-24-week	-0.98	0.02
LakeApopka-48-week	0.96	0.04
LakeApopka-52-week	-0.95	0.05
CLERMONT 9 S-1-week	0.96	0.04
CLERMONT 9 S-2-week	0.95	0.05
CLERMONT 9 S-3-week	-0.98	0.02
CLERMONT 9 S-4-week	-0.51	0.49
CLERMONT 9 S-6-week	0.96	0.04
CLERMONT 9 S-8-week	-0.85	0.15
CLERMONT 9 S-12-week	0.96	0.04
CLERMONT 9 S-24-week	-0.98	0.02
CLERMONT 9 S-48-week	-0.91	0.09
CLERMONT 9 S-52-week	0.94	0.06
Bugg Spring-6-week	0.37	0.63
Bugg Spring-8-week	-0.23	0.77
Bugg Spring-12-week	-0.02	0.99
Bugg Spring-24-week	0.76	0.24
Bugg Spring-48-week	-0.97	0.04
Bugg Spring-52-week	0.96	0.04
L-0062-48-week	-0.71	0.29
L-0062-52-week	-0.73	0.27

Apopka-post1990 Selected variables-stepwise
L.0199.2.week
L.0199.6.week
LakeApopka
LakeApopka.3.week
LakeApopka.8.week
LakeApopka.24.week
LakeApopka.48.week
CLERMONT.9.S.2.week
CLERMONT.9.S.3.week
CLERMONT.9.S.24.week
CLERMONT.9.S.48.week
Bugg.Spring.48.week
L.0062.52.week

Table 5 shows the PCCs and the variables selected in stepwise regression for the Bugg Spring dataset for predicting pre-1990 discharge values. The variables with p-value<0.1 are highlighted in red, indicating a significant partial correlation for that variable. Three-, 4-, 12-, 24-, and 48-week moving averages for Bushnell 2 E and 24- and 52-week moving averages for L-0054R are selected in stepwise regression.

Table 5 PCCs and variables selected in stepwise regression for the Bugg dataset for predicting pre-1990 discharge values.

Bugg Spring	PCC	p-value
BUSHNELL 2 E-3-week	-0.07	0.23
BUSHNELL 2 E-4-week	0.08	0.15
BUSHNELL 2 E-6-week	0.03	0.53
BUSHNELL 2 E-8-week	-0.02	0.73
BUSHNELL 2 E-12-week	0.13	0.02
BUSHNELL 2 E-24-week	0.11	0.05
BUSHNELL 2 E-48-week	0.11	0.05
BUSHNELL 2 E-52-week	0.05	0.32
L-0054R-12-week	-0.04	0.44
L-0054R-24-week	0.27	0.00
L-0054R-48-week	-0.01	0.91
L-0054R-52-week	-0.07	0.23

Bugg-pre1990 Selected variables-stepwise
BUSHNELL.2.E.3.week
BUSHNELL.2.E.4.week
BUSHNELL.2.E.12.week
BUSHNELL.2.E.24.week
BUSHNELL.2.E.48.week
L.0054R.24.week
L.0054R.52.week

Table 6 shows the PCCs and the variables selected in stepwise regression for the Bugg Spring dataset for predicting post-1990 discharge values. The variables with p-value<0.1 are highlighted in red, indicating a significant partial correlation for that variable. Six-, 8-, and 12-week moving averages for Bugg Spring, 3-, 4-, and 24-week moving averages for L-0096, 6-, and 52-week moving averages for Bushnell 2 E , 8-, 12-, 24-, and 48-week moving averages for L-0703R and 24- and 52-week moving averages for L-0054R are selected in stepwise regression.

Table 6 **PCCs and variables selected in stepwise regression for the Bugg dataset for predicting post-1990 discharge values.**

Bugg Spring	PCC	p-value
Bugg Spring-6-week	0.12	0.04
Bugg Spring-8-week	-0.08	0.19
Bugg Spring-12-week	0.10	0.07
Bugg Spring-24-week	-0.02	0.70
Bugg Spring-48-week	-0.01	0.85
Bugg Spring-52-week	0.19	0.74
L-0096-3-week	0.05	0.34
L-0096-4-week	-0.05	0.34
L-0096-6-week	-0.02	0.70
L-0096-8-week	0.04	0.53
L-0096-12-week	0.00	0.99
L-0096-24-week	0.11	0.05
L-0096-48-week	-0.07	0.24
L-0096-52-week	0.07	0.23
BUSHNELL 2 E-3-week	-0.03	0.63
BUSHNELL 2 E-4-week	0.00	0.95
BUSHNELL 2 E-6-week	0.08	0.19
BUSHNELL 2 E-8-week	0.03	0.66
BUSHNELL 2 E-12-week	-0.03	0.64
BUSHNELL 2 E-24-week	0.01	0.84
BUSHNELL 2 E-48-week	-0.03	0.56
BUSHNELL 2 E-52-week	0.09	0.13
L-0703R-3-week	0.03	0.64
L-0703R-4-week	0.01	0.90
L-0703R-6-week	-0.04	0.53
L-0703R-8-week	0.07	0.20
L-0703R-12-week	-0.06	0.30
L-0703R-24-week	-0.18	0.00
L-0703R-48-week	0.08	0.17
L-0703R-52-week	-0.07	0.20
L-0054R-12-week	-0.04	0.54
L-0054R-24-week	0.18	0.00
L-0054R-48-week	-0.02	0.69
L-0054R-52-week	-0.03	0.60

Bugg-post1990
Selected variables-stepwise
Bugg.Spring.6.week
Bugg.Spring.8.week
Bugg.Spring.12.week
L.0096.3.week
L.0096.4.week
L.0096.24.week
BUSHNELL.2.E.6.week
BUSHNELL.2.E.52.week
L.0703R.8.week
L.0703R.12.week
L.0703R.24.week
L.0703R.48.week
L.0054R.24.week
L.0054R.52.week

4.0 REGRESSION MODELING

4.1 Methodology

The objective of regression modeling is to build a multivariate linear input-output model between the response variable (spring discharge) and the surrogate predictor variables (moving averages of spring discharge, groundwater and lake water level measurements, and precipitation) at the spring of interest. Such a relationship can be expressed by:

$$q_t = a_0 + a_1 q_{t-i} + \ldots + a_2 h_{t-j} + a_3 p_{t-k} + a_4 r_{t-l} + \varepsilon \qquad (1)$$

where q is spring discharge; h is groundwater level; p is the lake level; r is precipitation; ε is a random error term; $a0$, $a1$, $a2$, $a3$ and $a4$ are regression coefficients; t is time, and i, j, k and l denote lags that maximize the correlation between the response and predictor variable pair of interest. Here, the use of surrogate predictors is necessitated by the fact that most predictor variables are not measured on a daily basis. Generation of daily discharge thus requires the use of predictor variables for which daily values can be generated, e.g., on the basis of averaging over some moving time window.

Eq. (1) can be symbolically re-stated as follows, where MA denotes moving average:

$$\begin{gathered}[\text{Spring discharge}] = \boldsymbol{f}\ \{\ [\text{same spring MA}] + [\text{groundwater level MA}] + \\ [\text{lake water level MA}] + [\text{precipitation MA}] + \\ [\text{adjacent spring MA}]\ \}\end{gathered} \qquad (2)$$

Depending on the information available for the spring of interest, the regression model can contain all five terms in Eq. (2). This is especially true for the recent period since 1990s, when detailed measurements of groundwater levels are available. For Apopka Spring, good discharge measurements are not available prior to 1997. Thus, for Apopka Spring regression models, the variables comprising the first term in Eq. (2); i.e., Apopka Spring moving averages, are not included. For Bugg Spring, discharge measurements start from 1990. Thus, Bugg regression model for discharge predictions prior to 1990 will have to rely on rainfall, discharge at adjacent springs, lake levels and, water levels from monitoring wells and Bugg regression model for discharge predictions post-1990 can include all the five terms in Eq. (2).

As described earlier, the model building process can be carried out using stepwise regression, where variables are added or removed one at a time until no additional variables can be found that improve the goodness-of-fit of the input-output model. At each successive step in the regression modeling process, the variable that explains the largest fraction of unexplained variance is included. This is the variable with the largest absolute value of the partial correlation coefficient (*PCC*), which measures the correlation between the output and the selected input variable after the linear influence of the other variables have been eliminated.

The model generated at every step is tested to ensure that the each of the regression coefficients is significantly different from zero. A partial **F**-test, or, an equivalent **t**-test, is used to reject the hypothesis that a regression coefficient is zero, at a 100(1 - α) % confidence level. The stepwise regression process continues until the input-output model contains all of the input variables that explain statistically significant amounts of variance in the output, i.e., no more variables can be found with a statistically significant regression coefficient.

Note that the number of potential explanatory variables can be quite high, given that moving averages from multiple lags are considered for each of the terms in Eq. (1). It is therefore necessary to ensure that the regression model includes only those independent variables that have the highest correlation with the response variable, while taking into account any variable-variable correlations. However, the selection of the most relevant independent variables is carried out automatically as part of the stepwise regression process – thus, eliminating this onerous pre-processing step. However, as indicated in the earlier section, a pre-processing step to select variables for stepwise regression becomes necessary for the Apopka regression model for post-1990 discharge predictions, due to only 39 Apopka discharge values and a large number of independent variables. The preprocessing is done by selecting variables having significant p-values for partial correlation coefficients and low correlation coefficients amongst each other. On the other hand, application of standard multivariate linear regression would require that the variables to be included in the model be specified a priori. A careful examination of correlation and partial correlation coefficients is warranted in such cases to assist in the parsimonious selection of predictor variables and to avoid over-parameterization of the model. An alternative would be to use a data reduction technique such as principal component analysis (PCA) to combine the independent variables into principal components and then apply regression to the principal components.

The workflow for modeling the spring discharge can be summarized as follows:

- Split the period of record into a late-time period, where detailed groundwater level measurements are available, and an early time period where only limited or no groundwater level measurements are available.

- For each period, organize the spring discharge data (response variable) and the corresponding moving averages of groundwater levels, lake levels, precipitation, discharge at same spring and discharge at adjacent springs (predictors).

- Retain only those predictor variables for which the number of data points is at least 80% of the number of spring discharge measurements. This threshold has been applied to ensure that the characteristics of the spring discharge time series can be captured as much as possible by the regression model.

- Build a stepwise regression model between spring discharge (response) and some or all of the following predictors: discharge at same spring, discharge at adjacent springs, precipitation, lake levels and groundwater levels.

An important point to note here is that these regression models are being built with the "best available data." The quality of the model therefore depends on data coverage, presence of groundwater monitoring wells and lake levels in the immediate vicinity, and availability of discharge measurements at nearby springs that can be used as ancillary data sources.

4.2 Regression Models for Apopka Spring

Two distinct prediction periods can be identified for Apopka Spring:

- post-1990 period, when water level measurements from groundwater wells L-0062, L-0199 and Lake Apopka are available, along with precipitation measurements from Clermont 9 S and discharge from Bugg Spring, and
- pre-1990 period, when water level measurements are available from groundwater well L-0062 and Lake Apopka; along with precipitation measurements from Clermont 9 S.

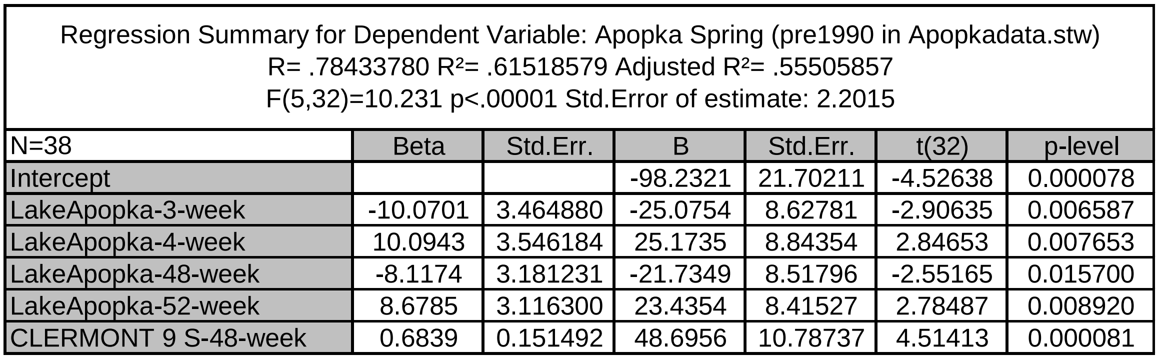
Stepwise regression analyses were performed on separate datasets for both of these prediction periods and the results are presented below. The stepwise regression analysis of the dataset for pre-1990 Apopka discharge predictions produced the following model:

$$\begin{aligned} \text{Apopka} = \text{LakeApopka.3.week} + \text{LakeApopka.4.week} + \text{LakeApopka.48.week} + \\ \text{LakeApopka.52.week} + \text{Clermont.9.S.48.week} \end{aligned} \tag{3}$$

The multiple R^2 for this regression model was 0.6151. The standard error of estimate was 2.2015. The F-statistic was 10.231, and the p-value was <0.00001. Estimated regression coefficients and their statistics are given below in Table 7.

In Table 7, the "B" column contains the regression coefficients in actual units. The "beta" column denotes the standardized regression coefficients (*SRC*) that would have resulted if the predictor variables had been normalized to zero mean and unit standard deviation. The absolute value of the *SRC*s can be used as an indicator of variable importance (Draper and Smith, 1981). Thus, the most important predictor variables can be identified as [LakeApopka 4-week], [LakeApopka 3-week] and [LakeApopka 52-week].

Table 7 Apopka – pre-1990 period – regression coefficient statistics.



Regression Summary for Dependent Variable: Apopka Spring (pre1990 in Apopkadata.stw)
R= .78433780 R²= .61518579 Adjusted R²= .55505857
F(5,32)=10.231 p<.00001 Std.Error of estimate: 2.2015

N=38	Beta	Std.Err.	B	Std.Err.	t(32)	p-level
Intercept			-98.2321	21.70211	-4.52638	0.000078
LakeApopka-3-week	-10.0701	3.464880	-25.0754	8.62781	-2.90635	0.006587
LakeApopka-4-week	10.0943	3.546184	25.1735	8.84354	2.84653	0.007653
LakeApopka-48-week	-8.1174	3.181231	-21.7349	8.51796	-2.55165	0.015700
LakeApopka-52-week	8.6785	3.116300	23.4354	8.41527	2.78487	0.008920
CLERMONT 9 S-48-week	0.6839	0.151492	48.6956	10.78737	4.51413	0.000081

Figure 6 shows a comparison between the observed and fitted values of the regression model for pre-1990 Apopka discharge predictions. The scatter in the data is consistent with a final R^2 of 0.6151. Note also the resulting under prediction of some high discharge values and over prediction of some low discharge values (i.e., the outliers in Figure 6). Also shown in Figure 6 are the confidence bands associated with the regression line. These bands, which are a function of the standard error of estimate and the number of data points, depict the uncertainty in placing the best-fit line through the data cloud.

Figure 7 shows a normal probability plot of the residuals of the Apopka regression model for pre-1990 Apopka discharge predictions. The plot shows deviations from linearity at some residuals. This is primarily due to the low number of data points available from Apopka discharge for statistical modeling.

The stepwise regression analysis of the dataset for post-1990 Apopka discharge predictions produced the following model:

$$\begin{gathered}\text{Apopka} = \text{L0199.2.week} + \text{L0199.6.week} + \text{LakeApopka} + \text{LakeApopka.3.week} + \\ \text{LakeApopka.8.week} + \text{LakeApopka.24.week} + \text{LakeApopka.48.week} + \text{Clermont.9.S.2.week} + \\ \text{Clermont.9.S.3.week} + \text{Clermont.9.S.24.week} + \text{Clermont.9.S.48.week} + \text{BuggSpring.48.week} \\ + \text{L0062.52.week} \qquad (4)\end{gathered}$$

The multiple R^2 for this regression model was 0.7933. The standard error of estimate was 1.8627. The F-statistic was 7.0886, and the p-value was <0.00002. Estimated regression coefficients and their statistics are given in Table 8.

In Table 8, the "B" column contains the regression coefficients in actual units. The "beta" column denotes the standardized regression coefficients (*SRC*) that would have resulted if the predictor variables had been normalized to zero mean and unit standard deviation. The most important predictor variables, identified on the basis of the absolute value of SRC, are [L-0199 2-week], [LakeApopka 8-week] and [L-0199 6-week].

Table 8 Apopka – post-1990 period – regression coefficient statistics.

Regression Summary for Dependent Variable: Apopka Spring (post1990 in Apopkadata.stw)
R= .89071554 R^2= .79337418 Adjusted R^2= .68145186
F(13,24)=7.0886 p<.00002 Std.Error of estimate: 1.8627

N=38	Beta	Std.Err.	B	Std.Err.	t(24)	p-level
Intercept			-107.819	52.47515	-2.05467	0.050953
L-0199-2-week	6.15084	2.465612	9.217	3.69456	2.49465	0.019890
L-0199-6-week	-4.93606	2.609948	-7.369	3.89629	-1.89125	0.070721
LakeApopka	-1.52663	0.882302	-3.987	2.30406	-1.73028	0.096420
LakeApopka-3-week	-3.48564	2.029968	-8.680	5.05477	-1.71709	0.098842
LakeApopka-8-week	5.01358	2.081273	12.612	5.23546	2.40890	0.024036
LakeApopka-24-week	-2.76293	1.223492	-7.030	3.11305	-2.25824	0.033299
LakeApopka-48-week	1.05970	0.641911	2.837	1.71876	1.65085	0.111795
CLERMONT 9 S-2-week	0.62843	0.296336	9.414	4.43916	2.12067	0.044478
CLERMONT 9 S-3-week	-0.71610	0.332911	-14.661	6.81564	-2.15102	0.041755
CLERMONT 9 S-24-week	-0.33733	0.194718	-15.305	8.83471	-1.73242	0.096034
CLERMONT 9 S-48-week	0.69695	0.225189	49.628	16.03518	3.09495	0.004947
Bugg Spring-48-week	-1.23644	0.254254	-2.372	0.48782	-4.86301	0.000059
L-0062-52-week	1.38363	0.405271	3.055	0.89476	3.41409	0.002277

Figure 8 shows a comparison between the observed and fitted values of the regression model for post-1990 Apopka discharge predictions. The scatter in the data is consistent with a final R^2 of 0.7933. Note also the resulting under prediction of some high discharge values and over prediction of some low discharge values (i.e., the outliers in Figure 8). Also shown in Figure 8 are the confidence bands associated with the regression line. These bands, which are a function of the standard error of estimate and the number of data points, depict the uncertainty in placing the best-fit line through the data cloud.

Figure 9 shows a normal probability plot of the residuals of the Apopka regression model for post-1990 Apopka discharge predictions. The linearity of the data suggests that standard assumptions for normally distributed errors in a multivariate linear regression model have been satisfied and the model is properly parameterized. The presence of moving averages of Bugg Spring and L-0199 as variables in the model helps improve the residual plot.

To compare observed versus predicted discharges, it is also useful to consider the variance values for the two records. The F-test for variance equality is often employed for this purpose. This test makes a statistical comparison between the variances of two data sets through the calculation of three values (Ott, 2006):

- Calculated F-value: depends on the variance values for the observed and predicted discharge values and the two sample sizes,
- Critical F-value: depends on the two sample sizes and the desired significance level for the test, and
- P-value: calculated based on the difference between the calculated and critical F-values.

If the Calculated F-value is greater than the Critical F-value then, reject H_0 (the null hypothesis which states that the standard deviations of two normally distributed populations are equal, and thus that they have similar spreads) at the chosen level of confidence (alpha = 0.05). If this is the case then look at the P-value to evaluate the chances of observing an F-value that is greater than the calculated value.

In general, it is expected that regression-predicted values are generally smoother than actual observed discharge values. To quantify the effects of this smoothing on the generated period of record, two tools are used, a quantitative evaluation and visual comparison. The quantitative evaluation is the Kolmogorov-Smirnov (K-S) test which evaluates the differences between the empirical distribution functions for the observed and predicted time-series (D'Agostino and Stephens, 1986). Under the null hypothesis that the two cumulative distribution functions are identical, the test statistic D for this test is the greatest absolute vertical distance between the two empirical distribution functions. This test statistic is not dependent on the two underlying distributions. Therefore the p-value for this test is only dependent on the two sample sizes, which can be different.

The K-S D statistic can be used to evaluate if the two cumulative distributions functions (CDFs) are statistically similar. Another qualitative tool often employed to compare two data sets is the box-whisker plot (also known in the literature as the box plot, Ott, 2006). This plot is a convenient way of graphically depicting the location and spread of the two (or more) data sets. The plot shows the smallest observation, lower quartile (Q1), median, upper quartile (Q3), and largest observation. Furthermore, the plots show which observations, if any, are considered to be outliers. These plots visually show different types of populations, without any assumptions of the statistical distribution or requirements about the sample sizes. The box size (difference between Q3 and Q1) helps indicate variance. Skew is also graphically shown through (1) the location of the median in relation to Q1 and Q3, (2) the maximum and minimum values, and (3) the number of value of outliers.

Table 9 shows the F-test and K-S test between observed Apopka Spring time-series and predicted Apopka Spring time-series on days corresponding to observed data. Results for the F-test indicate that there is no significant difference between the two variances; with a 28% chance of observing the calculated F-value under the equal variance hypothesis for this sample size. Similar results are indicated by the K-S D statistic which shows a p-value of about 1.0, indicating a probability of almost 100% that the two empirical CDFs are identical.

Figure 10 shows the box-whisker plots for three data sets:

(1) observed discharge values at Apopka Spring,

(2) regression-predicted values for the same dates at which observed discharge value are available. These predicted values come from two different regression models as described above, and

(3) regression-predicted values from the two regression models for each day in the period of record.

The plots show that the observed discharge values at Apopka Spring show slightly higher variability than the regression-predicted values (data sets 1 and 2). However, data set 3, which shows a complete record of pooled model predictions, shows higher variability than data set 2. This shows that the regression predictions show higher variability than the observed values. It is expected, however, that more variance would have been observed if more observations had been made in the same time period. In conclusion, the regression-predicted values show a similar range of variability as the observed discharge values with the complete daily predicted record showing plausible variability.

Table 9 Apopka Spring - 1959-2005 – Observed and Regression-Predicted Variance Statistics.

	Apopka(observed)	*Apopka(predicted)*
Mean	27.29	27.26
Variance	11.16	9.24
Observations	39	39
df	38	38
F	1.21	
P(F<=f) one-tail	0.28	
F Critical one-tail	1.72	
K-S D statistic	0.08	
p-value for K-S test	1.00	

* df are the degrees of freedom which are equal to the sample size minus 1 for the F-test.

4.3 Regression Models for Bugg Spring

Two distinct prediction periods can be identified for Bugg Spring:

- post-1990 period, when water level measurements from groundwater wells L-0096, L-0703R, and L-0054R are available, along with precipitation measurements from Bushnell 2 E and discharge from Bugg Spring, and
- pre-1990 period, when water level measurements are available from groundwater well L-0054R; along with precipitation measurements from Bushnell 2 E.

Stepwise regression analyses were performed on separate datasets for both of these prediction periods and the results are presented below. The stepwise regression analysis of the dataset for pre-1990 Bugg discharge predictions produced the following model:

$$\begin{gathered}\text{Bugg} = \text{Bushnell.2.E.3.week} + \text{Bushnell.2.E.4.week} + \text{Bushnell.2.E.12.week} + \\ \text{Bushnell.2.E.24.week} + \text{Bushnell.2.E.48.week} + \\ \text{L0054R.24.week} + \text{L0054R.52.week}\end{gathered} \tag{5}$$

The multiple R^2 for this regression model was 0.5651. The standard error of estimate was 1.5132. The F-statistic was 61.083, and the p-value was <0.0000. Estimated regression coefficients and their statistics are given below in Table 10.

In Table 10, the “B” column contains the regression coefficients in actual units. The “beta” column denotes the standardized regression coefficients (*SRC*) that would have resulted if the predictor variables had been normalized to zero mean and unit standard deviation. The most important predictor variables can be identified as [L0054R 24-week], [L0054R 52-week] and [Bushnell 2 E 48-week].

Table 10 Bugg – pre-1990 period – regression coefficient statistics.

Regression Summary for Dependent Variable: Bugg Spring (pre1990 in Buggdata.stw)
R= .75176316 R²= .56514785 Adjusted R²= .55589568
F(7,329)=61.083 p<0.0000 Std.Error of estimate: 1.5132

N=337	Beta	Std.Err.	B	Std.Err.	t(329)	p-level
Intercept			-3.62809	2.866350	-1.26575	0.206498
BUSHNELL 2 E-3-week	-0.145905	0.089522	-2.46223	1.510735	-1.62982	0.104096
BUSHNELL 2 E-4-week	0.227605	0.096028	4.19801	1.771167	2.37019	0.018355
BUSHNELL 2 E-12-week	0.233836	0.065313	6.02972	1.684167	3.58024	0.000395
BUSHNELL 2 E-24-week	0.107880	0.056050	4.20063	2.182466	1.92472	0.055127
BUSHNELL 2 E-48-week	0.328875	0.059642	27.22634	4.937551	5.51414	0.000000
L-0054R-24-week	0.796893	0.127261	0.83664	0.133608	6.26190	0.000000
L-0054R-52-week	-0.624932	0.123536	-0.69533	0.137452	-5.05872	0.000001

Figure 11 shows a comparison between the observed and fitted values of the regression model for pre-1990 Bugg discharge predictions. The scatter in the data is consistent with a final R^2 of 0.5651. Note also the resulting under prediction of some high discharge values and over prediction of some low discharge values (i.e., the outliers in Figure 11). Also shown in Figure 11 are the confidence bands associated with the regression line. These bands, which are a function of the standard error of estimate and the number of data points, depict the uncertainty in placing the best-fit line through the data cloud.

Figure 12 shows a normal probability plot of the residuals of the Bugg regression model for pre-1990 Bugg discharge predictions. The linearity of the data suggests that standard assumptions for normally distributed errors in a multivariate linear regression model have been satisfied and the model is properly parameterized. There are, however, minor deviations from linearity at high and low values of residuals.

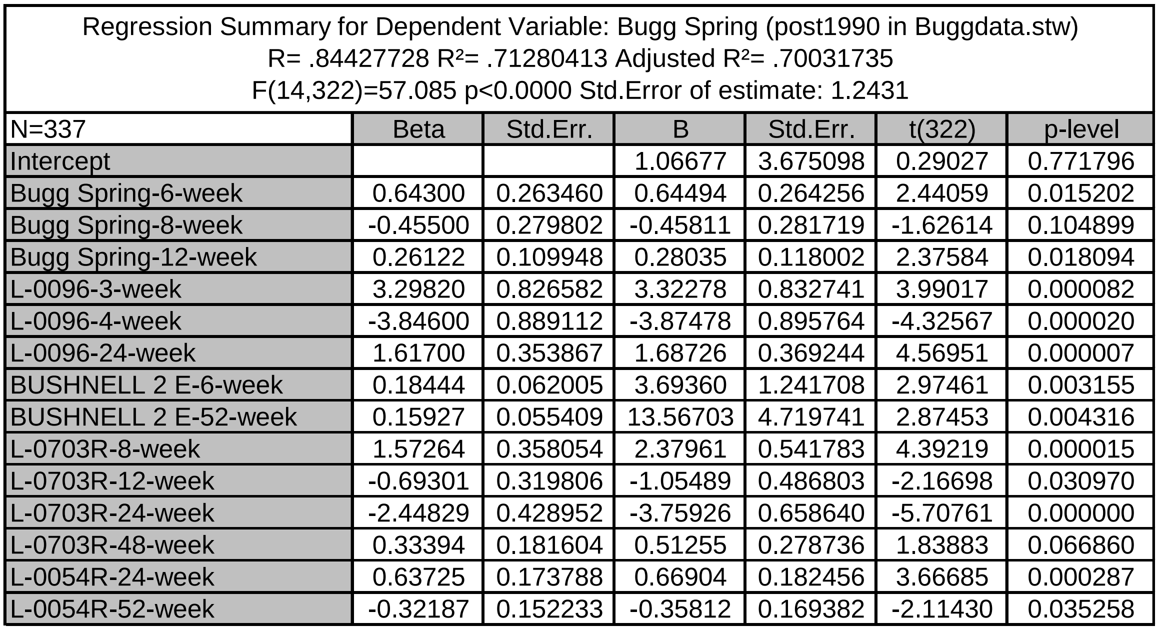
The stepwise regression analysis of the dataset for post-1990 Bugg discharge predictions produced the following model:

$$\text{Bugg} = \text{Bugg.6.week} + \text{Bugg.8.week} + \text{Bugg.12.week} + \text{L0096.3.week} + \text{L0096.4.week} + \text{L0096.24.week} + \text{Bushnell.2.E.6.week} + \text{Bushnell.2.E.52.week} + \text{L0703R.8.week} + \text{L0703R.12.week} + \text{L0703R.24.week} + \text{L0703R.48.week} + \text{L0054R.24.week} + \text{L0054R.52.week} \quad (6)$$

The multiple R^2 for this regression model was 0.7128. The standard error of estimate was 1.2431. The F-statistic was 57.085, and the p-value was <0.0000. Estimated regression coefficients and their statistics are given below in Table 11.

In Table 11, the “B” column contains the regression coefficients in actual units. The “beta” column denotes the standardized regression coefficients (*SRC*) that would have resulted if the predictor variables had been normalized to zero mean and unit standard deviation. The most important predictor variables, identified on the basis of the absolute value of SRC, are [L-0096 4-week], [L-0096 3-week], and [L-0703R 24-week].

Table 11 Bugg – post-1990 period – regression coefficient statistics.



Regression Summary for Dependent Variable: Bugg Spring (post1990 in Buggdata.stw)
R= .84427728 R^2= .71280413 Adjusted R^2= .70031735
F(14,322)=57.085 p<0.0000 Std.Error of estimate: 1.2431

N=337	Beta	Std.Err.	B	Std.Err.	t(322)	p-level
Intercept			1.06677	3.675098	0.29027	0.771796
Bugg Spring-6-week	0.64300	0.263460	0.64494	0.264256	2.44059	0.015202
Bugg Spring-8-week	-0.45500	0.279802	-0.45811	0.281719	-1.62614	0.104899
Bugg Spring-12-week	0.26122	0.109948	0.28035	0.118002	2.37584	0.018094
L-0096-3-week	3.29820	0.826582	3.32278	0.832741	3.99017	0.000082
L-0096-4-week	-3.84600	0.889112	-3.87478	0.895764	-4.32567	0.000020
L-0096-24-week	1.61700	0.353867	1.68726	0.369244	4.56951	0.000007
BUSHNELL 2 E-6-week	0.18444	0.062005	3.69360	1.241708	2.97461	0.003155
BUSHNELL 2 E-52-week	0.15927	0.055409	13.56703	4.719741	2.87453	0.004316
L-0703R-8-week	1.57264	0.358054	2.37961	0.541783	4.39219	0.000015
L-0703R-12-week	-0.69301	0.319806	-1.05489	0.486803	-2.16698	0.030970
L-0703R-24-week	-2.44829	0.428952	-3.75926	0.658640	-5.70761	0.000000
L-0703R-48-week	0.33394	0.181604	0.51255	0.278736	1.83883	0.066860
L-0054R-24-week	0.63725	0.173788	0.66904	0.182456	3.66685	0.000287
L-0054R-52-week	-0.32187	0.152233	-0.35812	0.169382	-2.11430	0.035258

Figure 13 shows a comparison between the observed and fitted values of the regression model for post-1990 Bugg discharge predictions. The scatter in the data is consistent with a final R^2 of 0.7128. Note also the resulting under prediction of some high discharge values and over prediction of some low discharge values (i.e., the outliers in Figure 13). Also shown in Figure 13 are the confidence bands associated with the regression line. These bands, which are a function of the standard error of estimate and the number of data points, depict the uncertainty in placing the best-fit line through the data cloud.

Figure 14 shows a normal probability plot of the residuals of the Apopka regression model for post-1990 Bugg discharge predictions. The linearity of the data, except at high and low residuals, suggests that standard assumptions for normally distributed errors in a multivariate linear regression model have been satisfied and the model is properly parameterized.

To compare observed versus predicted discharges, the same methods described before for Apopka Spring are used for Bugg Spring. Results for the F-test and K-S D statistic are shown in Table 12. Results for the F-test indicate that there is a statistically significant difference between the two variances; with values of 5.33 and 3.40 for the observed and regression-predicted values, respectively. The K-S D statistic shows a similar significant difference between the two empirical CDFs.

As mentioned before for Apopka Spring, the F-test and the K-S D statistic do not show the nature of the difference between the two time series. To provide some insight into these differences, Figure 15 shows the box-whisker plots for the observed and regression-predicted discharge values (along with the complete regression-predicted period of record). The plots show that the differences between the observed and predicted values are largely due to the existence of more outliers and extreme values in the observed time series. The interquartile range (25%-75% box in Figure 15) is very similar for the data sets 1 and 2 (observed and regression-model-predicted values), with a difference of less than 0.2 cfs at the lower and upper levels. The 95% non-outlier range in Figure 15 also shows that the two data sets are similar at the upper level but the regression models display less value at the lower range of observed spring discharge values. The largest difference between the data sets appears to be due to 3 outliers in the observed Apopka Spring discharge values.

As with Apopka Spring, data set 3, which shows a complete record of pooled model predictions, shows much more variability than data set 2, with an overall variability that is slightly lower than the observed record? Most of the difference however is at the lower range of observed discharge values. It is expected, however, that more variance would have been observed if more observations had been made in the same time period. In conclusion, the regression-predicted values show a reasonably similar range of variability as the observed discharge values with the complete daily predicted record showing plausible variability.

Table 12 Bugg Spring - Observed and Regression-Predicted Variance Statistics.

	Bugg(observed)	*Bugg(predicted)*
Mean	11.46	10.41
Variance	5.33	3.40
Observations	349	11721
df	348	11720
F	1.57	
P(F<=f) one-tail	0.00	
F Critical one-tail	1.13	
K-S D statistic	0.32	
p-value for K-S test	0.00	

5.0 PREDICTION OF DAILY DISCHARGE AND FLOW DURATION

5.1 *Daily Discharge Predictions and Flow Duration Curves for Apopka Spring*

Predictions of daily discharge and flow duration curves for Apopka are carried out with the help of Eq. (3) for the pre-1990 period and Eq. (4) for the post-1990 period. Figures 16 and 17 show these daily predictions juxtaposed with actual measurements of Apopka discharge (at an average frequency of 75 days). The agreement between both the time series in Figure 16 is quite good and the absence of any significant divergent trends indicates that the linear model is able to capture the general trend of the spring discharge.

The absence of actual observations of Apopka Spring discharge during the 1949-1990 period preclude a meaningful evaluation of the reliability of the daily predictions shown in Figure 17, generated using Eq. (3).

Figure 18(a) shows the Apopka (7/18/1997 to 12/31/2005) flow duration curve showing comparison between observed data and the model daily discharge predictions. The observed and simulated discharge flow duration curves, for the period of record of Apopka Spring data, match well except at extreme low and high discharge values. Figure 18(b) shows the flow duration curve, i.e., discharge versus percent exceedance for the long-term simulation, for a period from 6/2/1949 to 12/31/2005, generated from the results of the statistical modeling. The confidence intervals on the predicted daily discharge are calculated based on the standard error of estimate from the corresponding regression models (Eq. 3 and Eq. 4). As such, they reflect only the uncertainty on the mean predictions, and do not include the effects of any additional sources of uncertainty such as measurement errors.

The corresponding high- and low-flow frequency analyses for the system (frequency of spring discharge for durations of 1 month, 2 months, 3 months, 4 months, 6 months and 1 year) are shown in Figure 19.

5.2 Daily Discharge Predictions and Flow Duration Curves for Bugg Spring

Predictions of daily discharge and flow duration curves for Bugg are carried out with the help of Eq. (5) for the pre-1990 period and Eq. (6) for the post-1990 period. Figures 20 and 21 show these daily predictions juxtaposed with actual measurements of Bugg discharge (at an average frequency of 15 days). The agreement between both the time series in Figure 20 is quite good and the absence of any significant divergent trends, except between 2004 and 2005, indicates that the linear model is able to capture the general trend of the spring discharge.

The absence of actual observations of Bugg Spring discharge during the 1973-1990 period preclude a meaningful evaluation of the reliability of the daily predictions shown in Figure 21, generated using Eq. (5).

Figure 22(a) shows the Bugg (6/1/2000 to 11/28/2005) flow duration curve showing comparison between observed data and the model daily discharge predictions. This plot compares the observed and the simulated daily discharge flow duration curves, for the period of record where Bugg data has the highest data frequency (refer Figure 20). Figure 22(b) shows the flow duration curve, i.e., discharge versus percent exceedance for the long-term simulation generated from the results of the statistical modeling. The confidence intervals on the predicted daily discharge are calculated based on the standard error of estimate from the corresponding regression models (Eq. 5 and Eq. 6). As such, they reflect only the uncertainty on the mean predictions, and do not include the effects of any additional sources of uncertainty such as measurement errors.

The corresponding high- and low-flow frequency analyses for the system (frequency of spring discharge for durations of 1 month, 2 months, 3 months, 4 months, 6 months and 1 year) are shown in Figure 23.

6.0 CONCLUSIONS AND RECOMMENDATIONS

This document presents an evaluation of the spring discharge data for Apopka and Bugg springs; groundwater levels at adjacent monitoring wells, lake levels at nearby lakes and precipitation measurements at nearby rain gage stations. Based on this evaluation, a regression modeling methodology is developed and applied for generating daily spring discharge records at Apopka and Bugg springs. Usage notes for the regression models are provided in Appendix A. Flow duration curves are also generated along with high- and low-frequency analyses for set durations from the simulated daily spring discharge. The following general conclusions can be made based on this study.

- Most measurements of spring discharge and groundwater level are at a frequency of ~30 days greater – necessitating the generation of moving averages with commensurate lags to be used as surrogate predictor variables.
- Typically, two regression models of spring discharge are needed: (a) one for the period when daily groundwater levels, lake levels and rainfall data are available, and (b) one for the period when rainfall data are supplemented with lake levels and perhaps low data frequency groundwater levels from one or two long-term monitoring wells.
- Stepwise regression is a good starting point for regression modeling – as indicated by the linearity of the residuals in a probability plot and the reasonable nature of daily discharge predictions compared to actual observations recorded at less frequent intervals.
- Daily discharge predictions can be made for Apopka as far back in time as 1949. Comparable predictions can be made until 1973 for Bugg Spring primarily due to the inclusion of long-term monitoring well L-0054R which goes back only till 1973.

Based on the data evaluation, regression model building and discharge prediction exercises undertaken during this study, the following recommendations are offered with respect to the applicability of the modeling tool.

- The model of spring discharge conditioned on groundwater levels, lake levels, rainfall and spring discharge is of a higher reliability, and should be used as the primary model for setting criteria and/or thresholds in the MFL program.

- The model of spring discharge based only on rainfall, lake levels and groundwater levels (when available) is of lower reliability and should be used only as a secondary model for estimating long-term average behavior and any associated uncertainty.

- The generation of daily spring discharge based only on rainfall records and perhaps the discharge at an adjacent spring does not appear to a feasible proposition be of limited usefulness. It is recommended that daily spring discharge prediction exercises be limited to situations used cautiously where ancillary groundwater level measurements are not available.

In summary, we note that reasonable predictions of daily discharge have been made for both springs of interest using the best available data, with the corresponding periods of record being ~55 years for Apopka Spring and ~30 years for Bugg Spring.

The daily period of record generated by the multiple regression models provides an estimate for the historic time series of spring discharge values. These estimated discharge values are developed for uses where such a time series is required, such as a frequency analysis of historic flows for Minimum Flows and Levels (MFL) determinations. It must be explicitly stated that the presented multiple regression models are not physical and should not be used for predictive purposes or to interpret the relationships between spring discharge values and explanatory variables such as groundwater levels, recorded rainfall, or recorded discharges at nearby springs. A specific caution is made that predictions achieved by altering the explanatory variables from their observed values and re-generating the spring discharge time series entail assumptions not supported here.

7.0 REFERENCES

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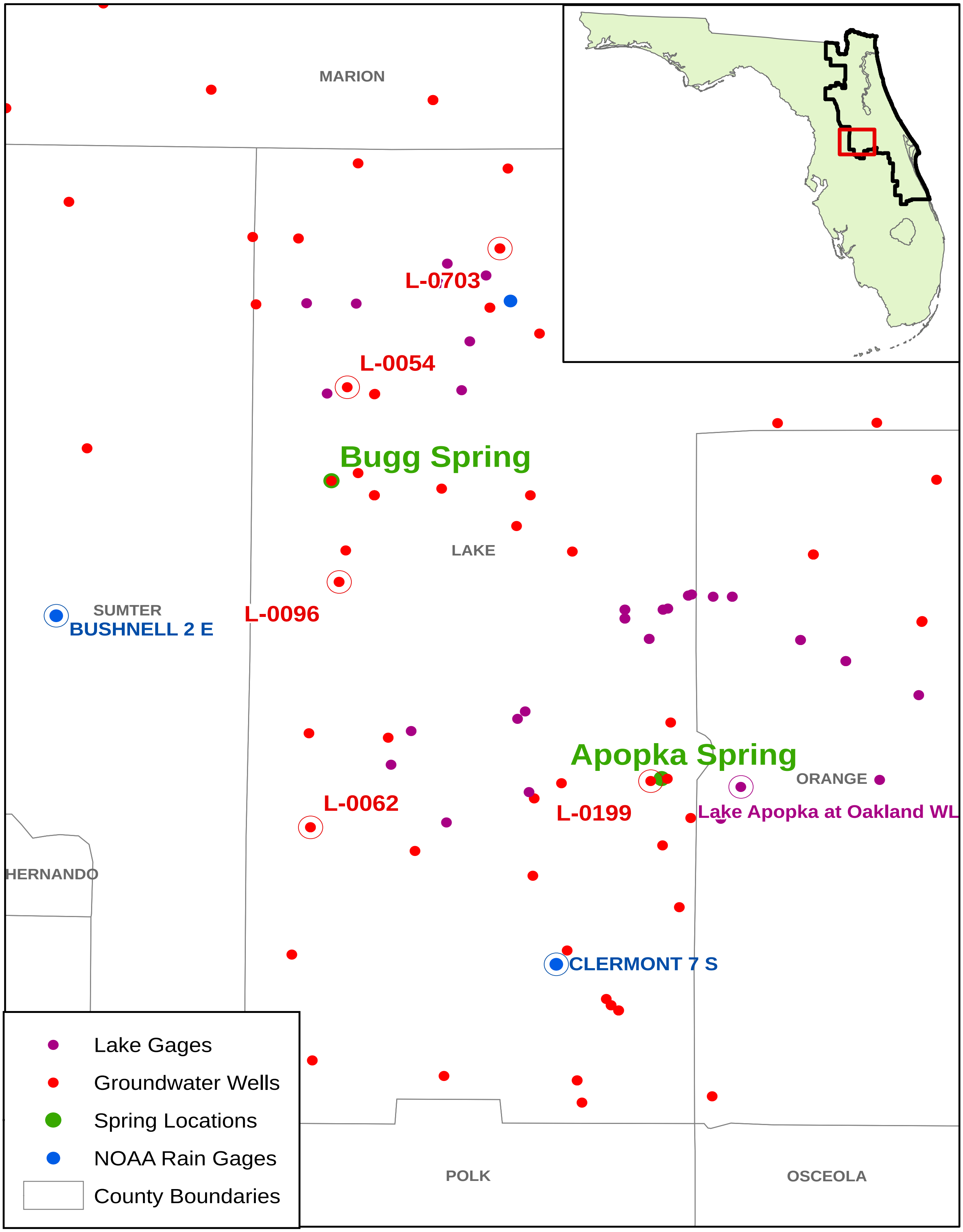
FIGURES



Date: June 26, 2006

File: Fig 1.pdf

Location of springs, lake gage and groundwater monitoring wells in region of interest.

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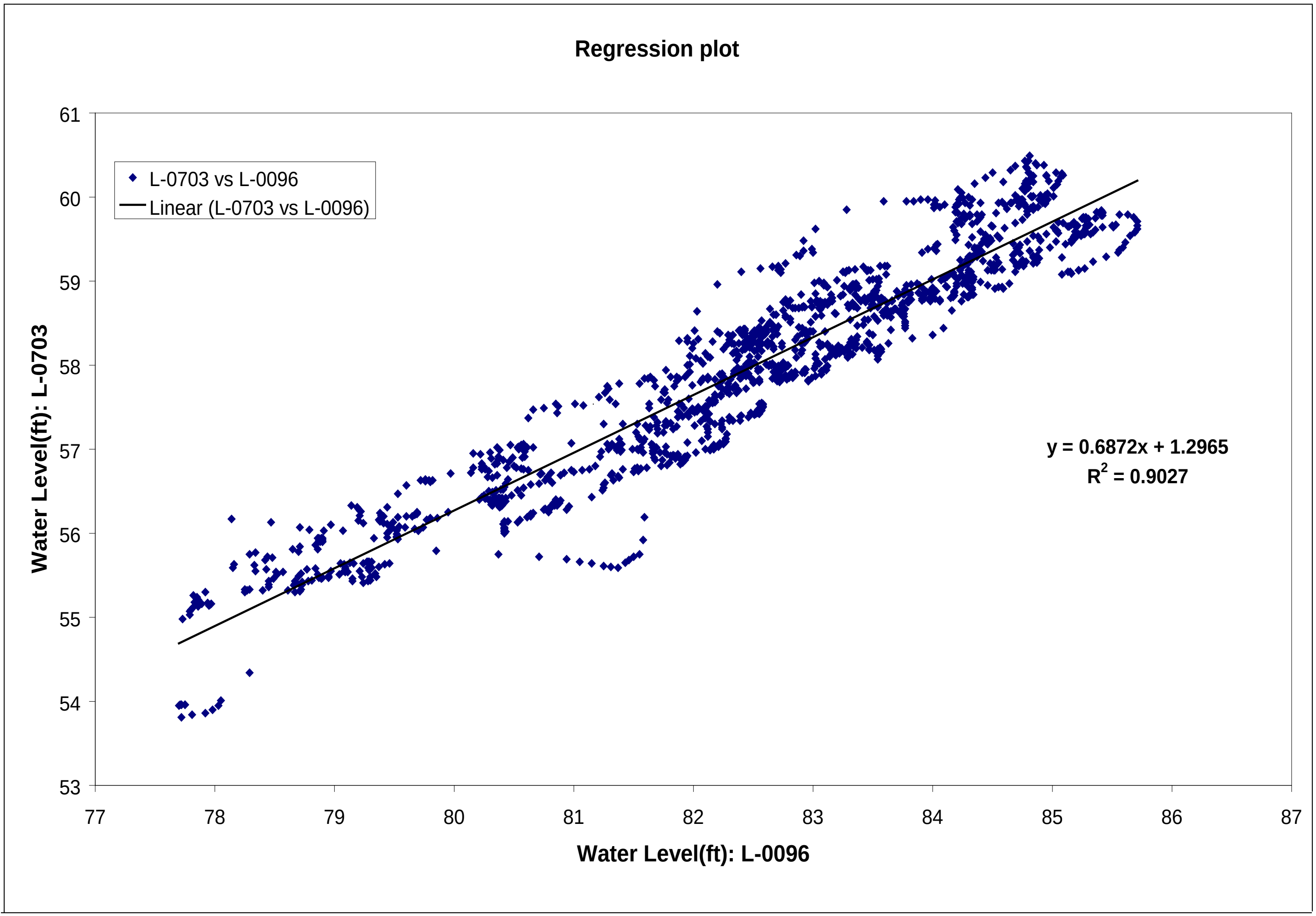
Figure 1



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Regression plot: L-0703 vs L-0096.

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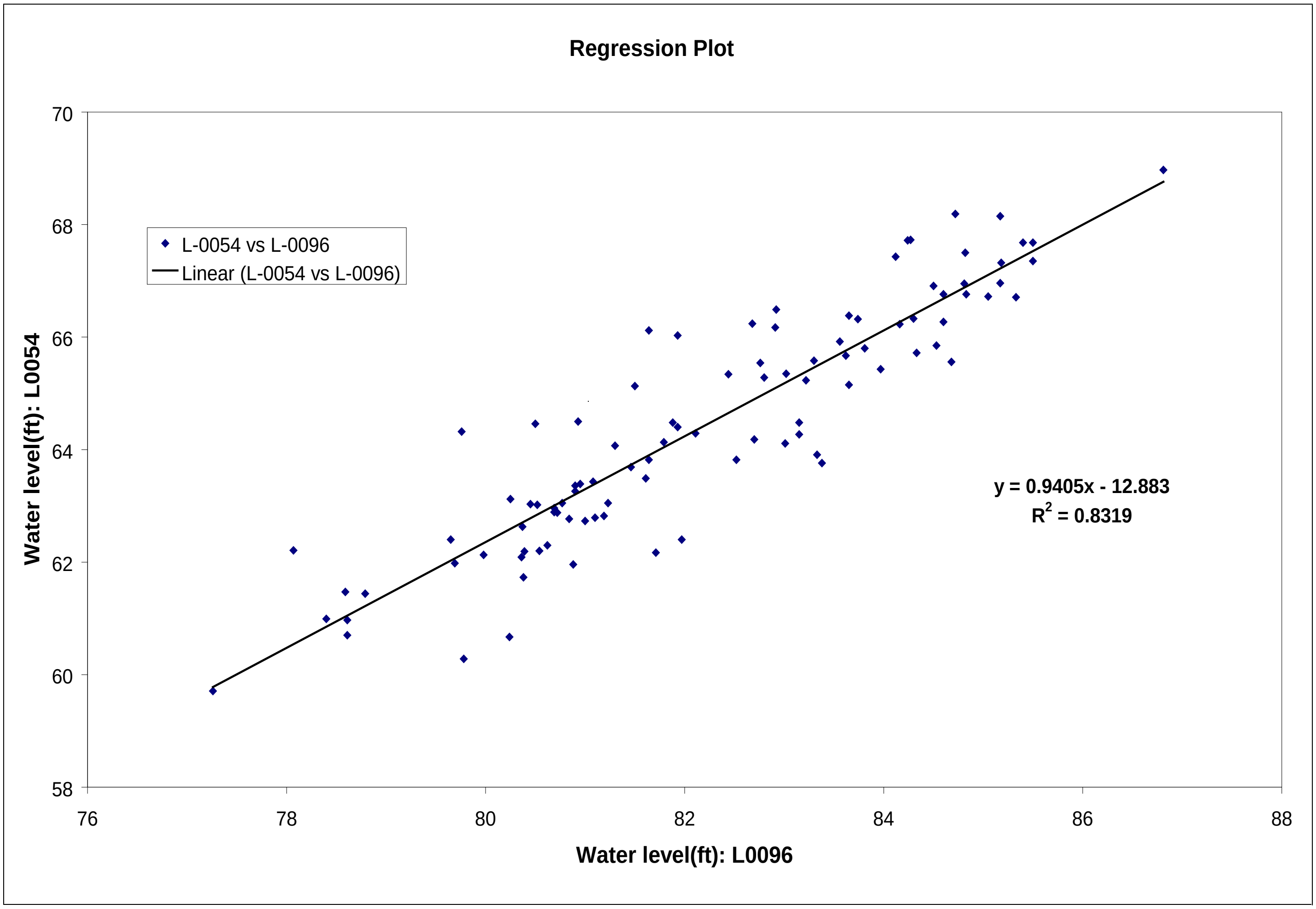
Figure 2



Date: June 26, 2006

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Regression plot: L-0054 vs L-0096.

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Figure 3

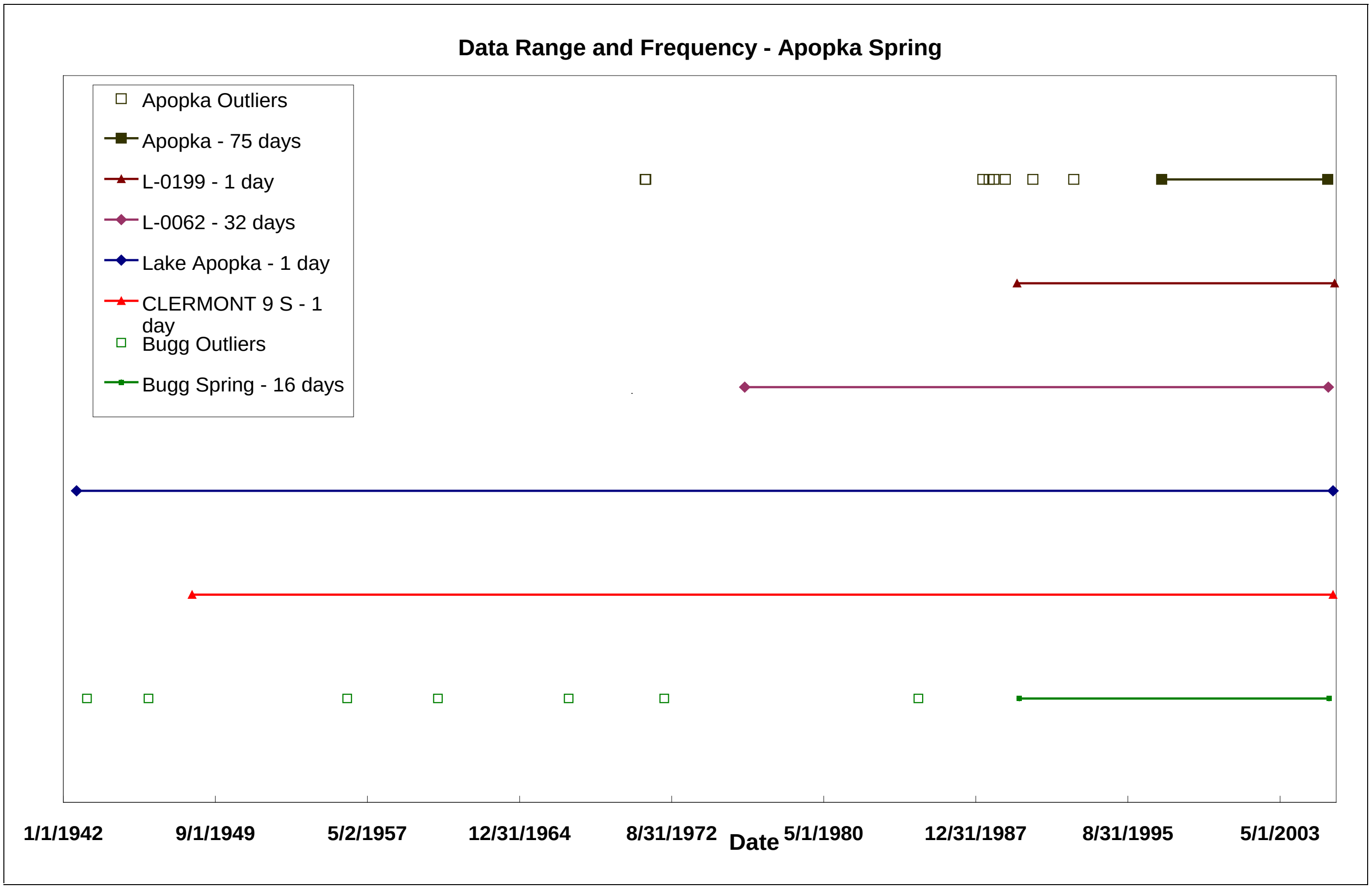

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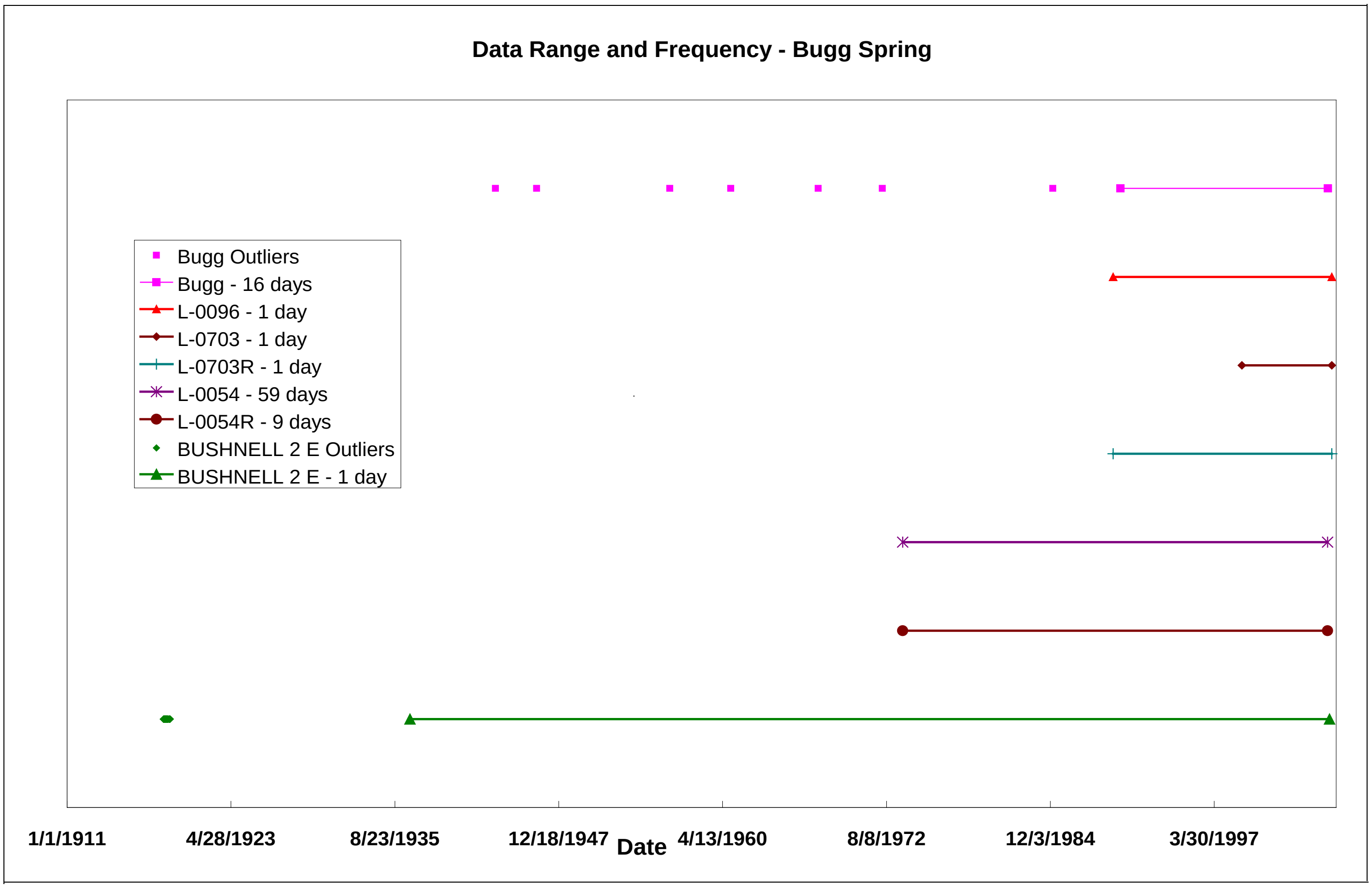
Figure 4



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Overlap between various data types, Bugg Spring.

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Figure 5

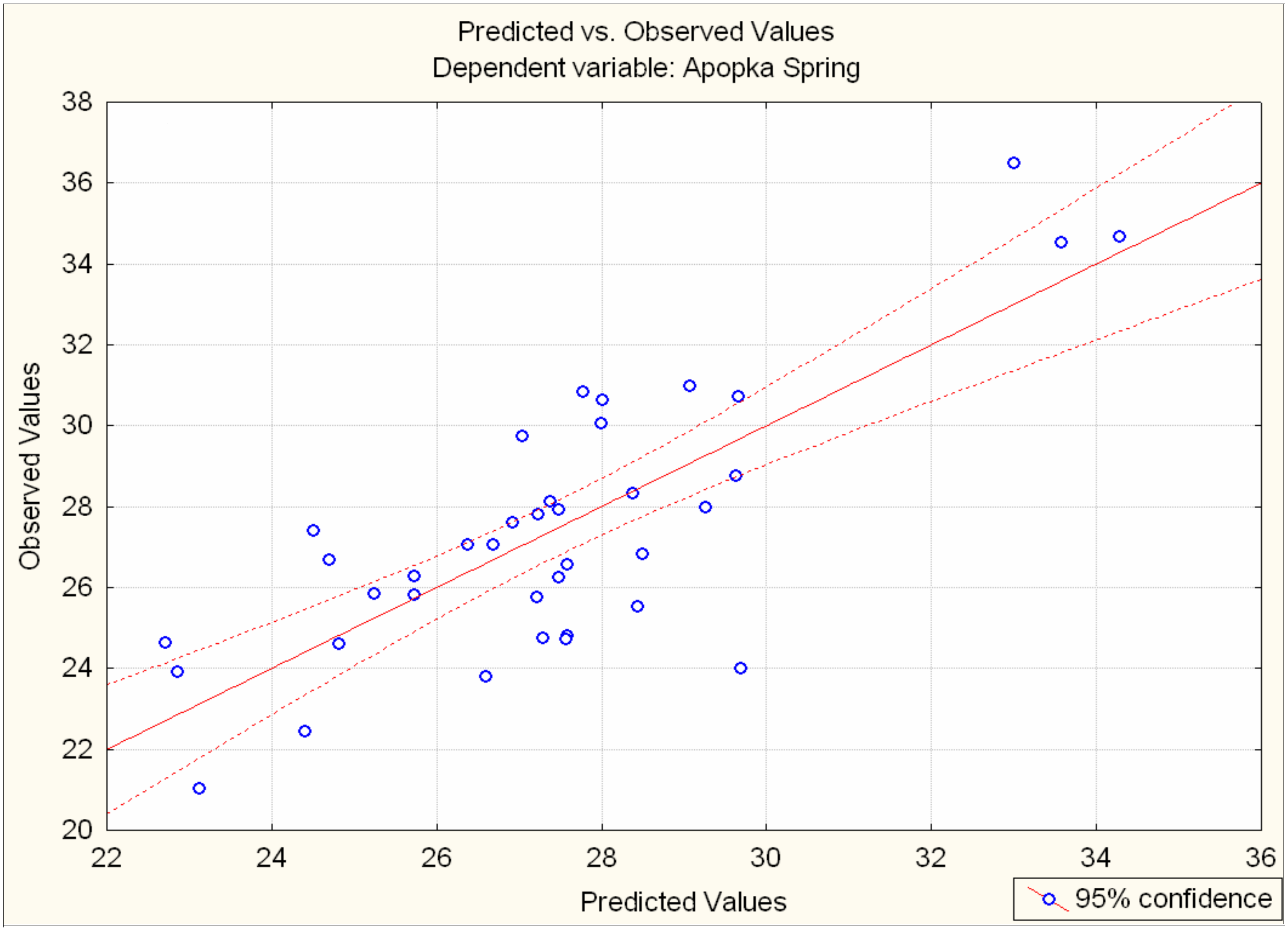

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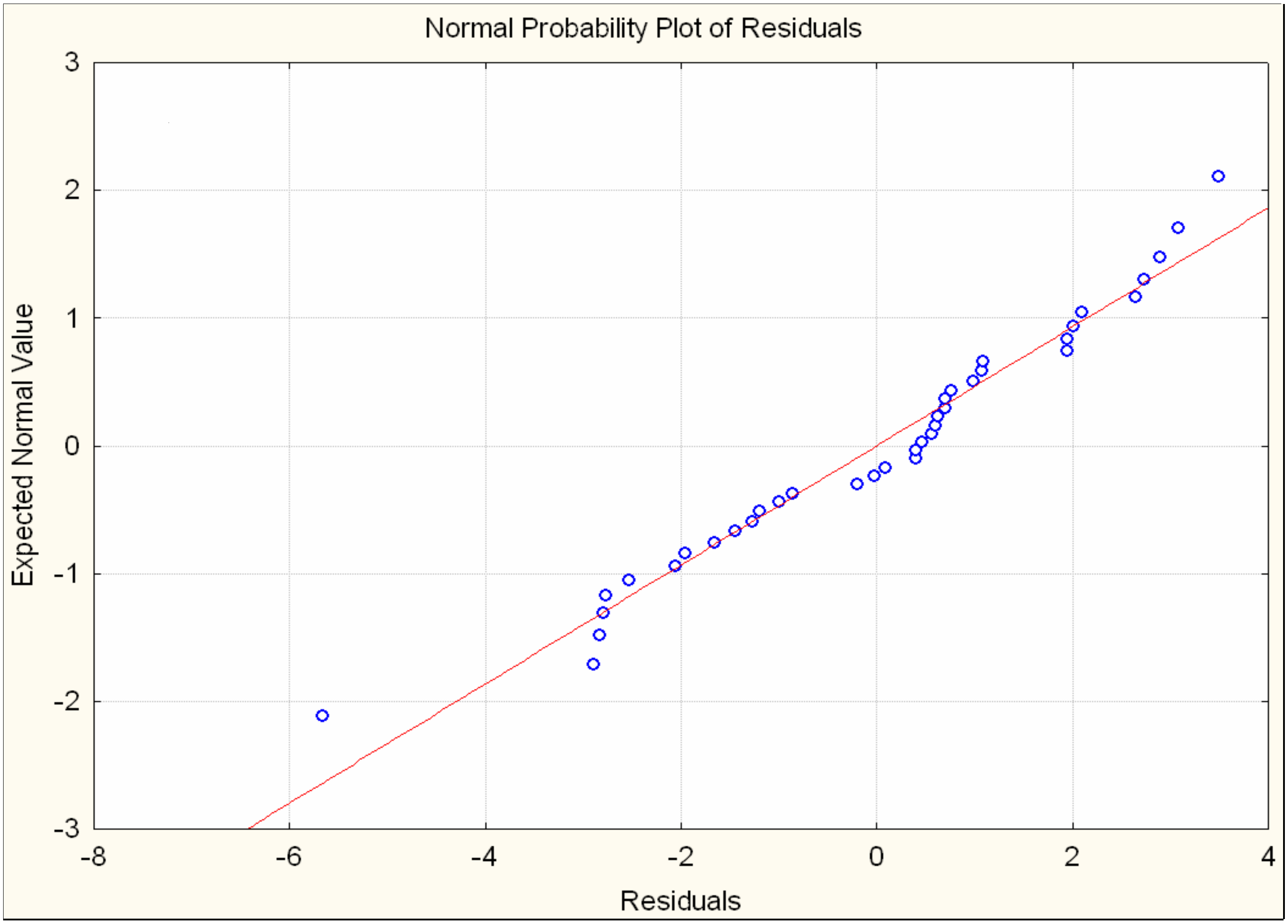
Figure 6



Date: June 26, 2006

File: Fig 7.pdf

Apopka - pre-1990 - normal probability plot of residuals.

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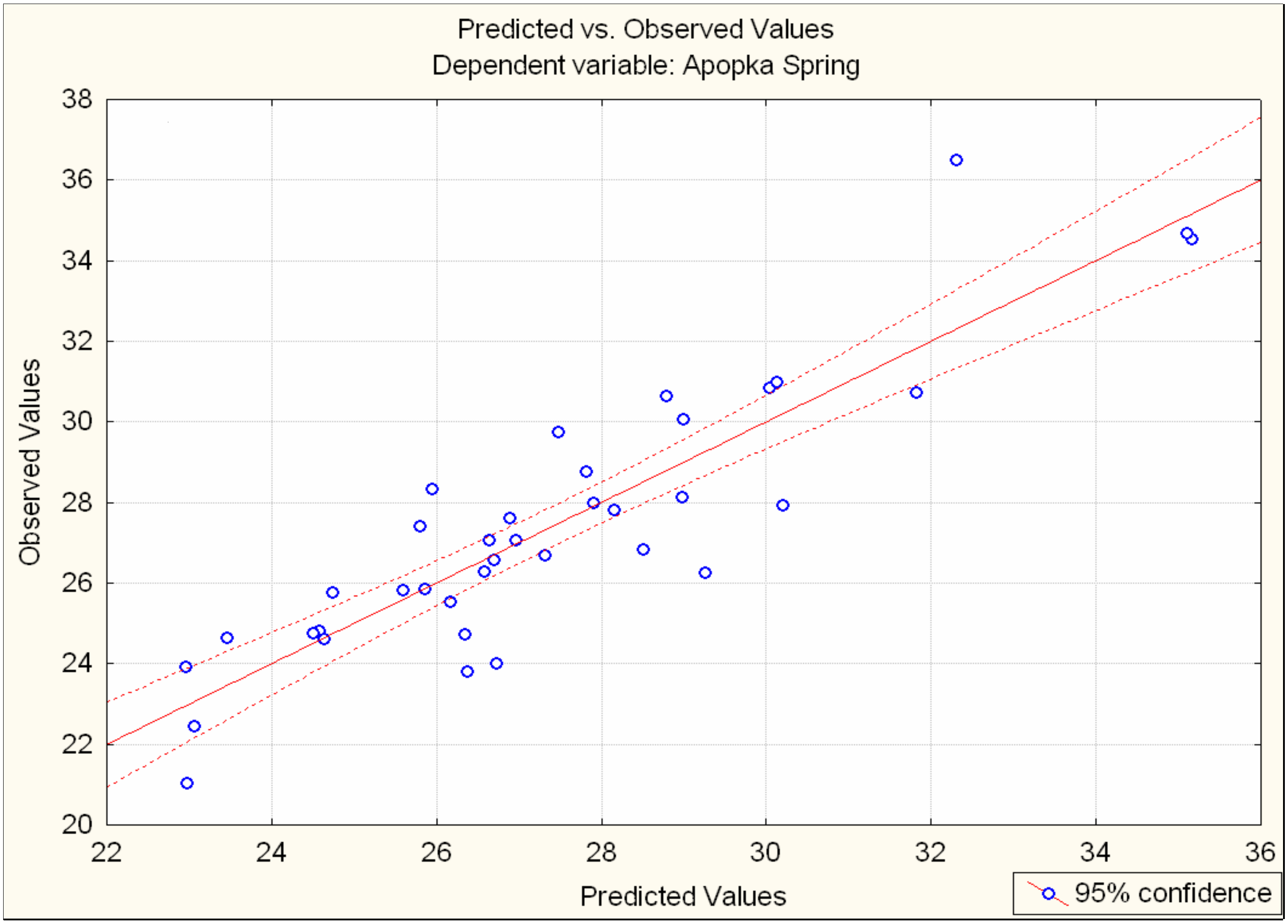
Figure 7



Date: June 26, 2006	Apopka - post-1990 - comparison of observed and predicted values.
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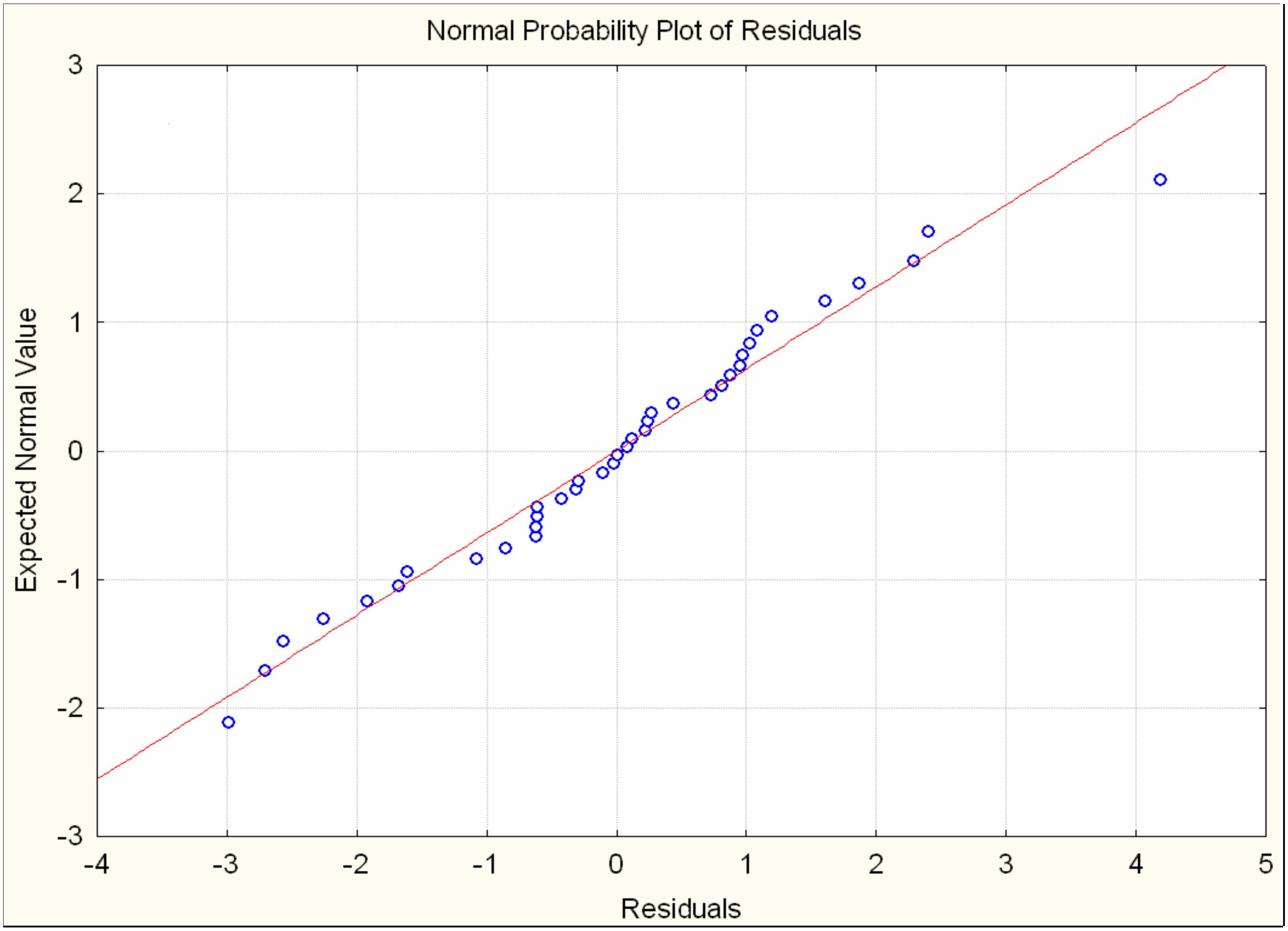
Figure 8



Date: June 26, 2006	Apopka - post-1990 - normal probability plot of residuals.
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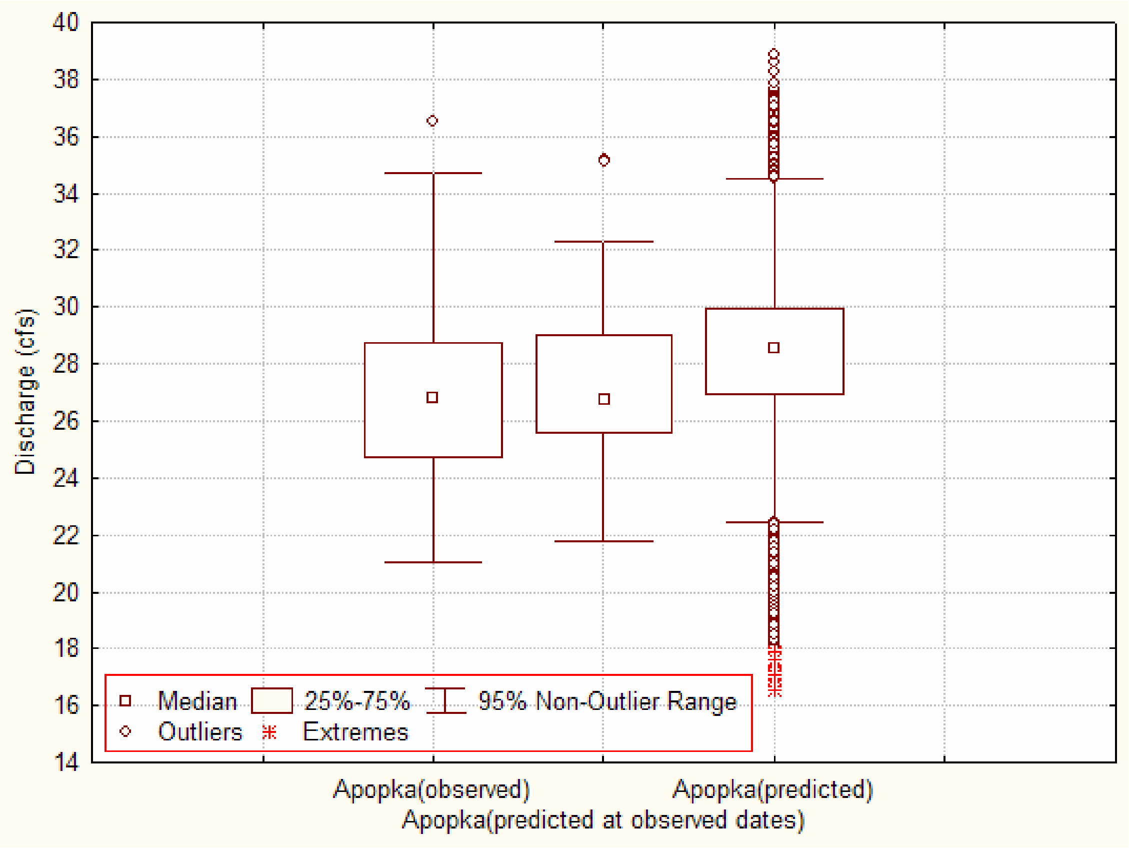
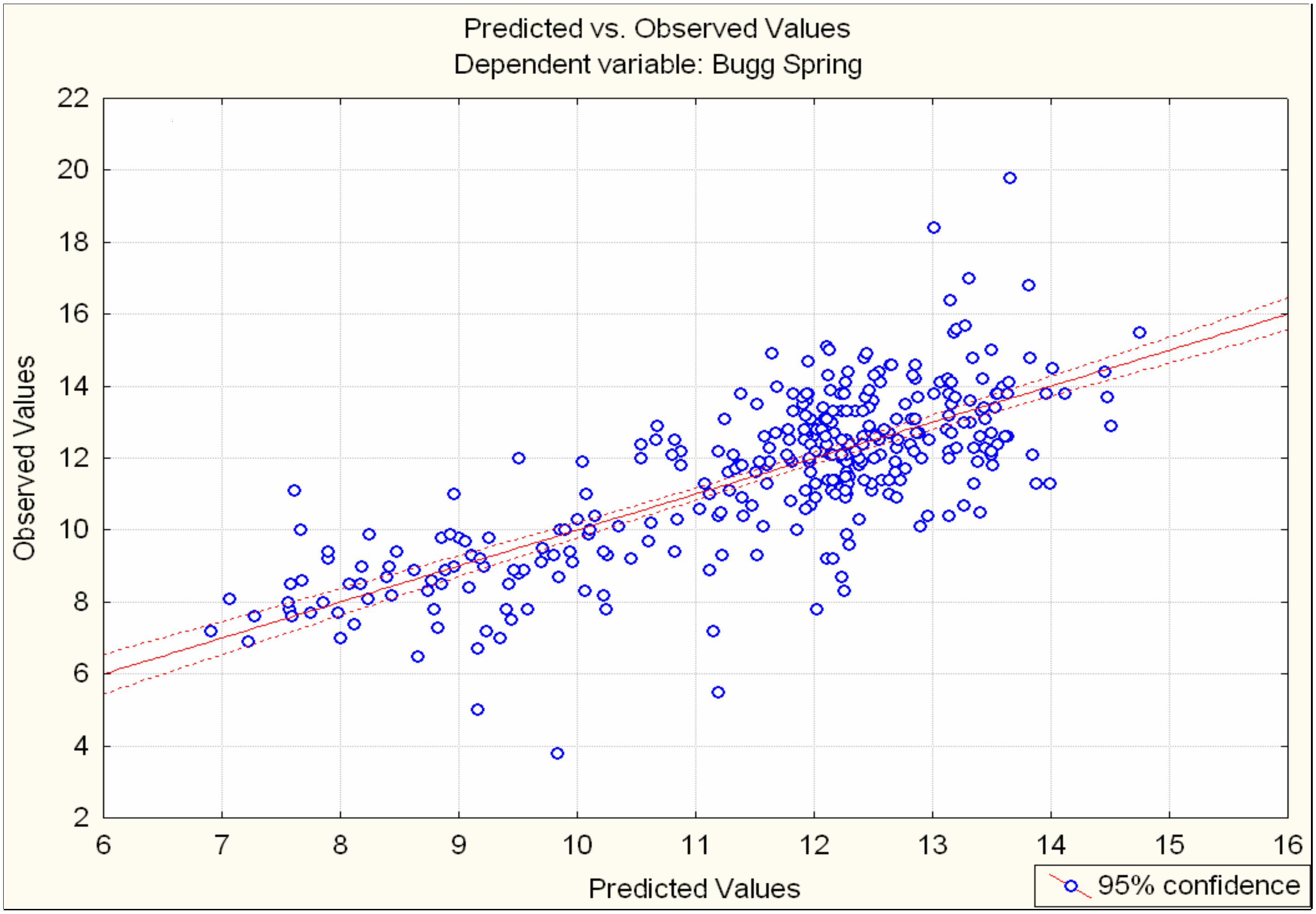
Figure 9



Date: June 13, 2007	**Box-Whisker Plots for Observed and Regression-Predicted Discharge Value for Apopka Spring Regression Models.**	
File: Fig 10.pdf		
INTERA	St. Johns River Water Management District Palatka, Florida	Figure 10



Date: June 26, 2006

File: Fig 11.pdf

Bugg - pre-1990 - comparison of observed and predicted values.

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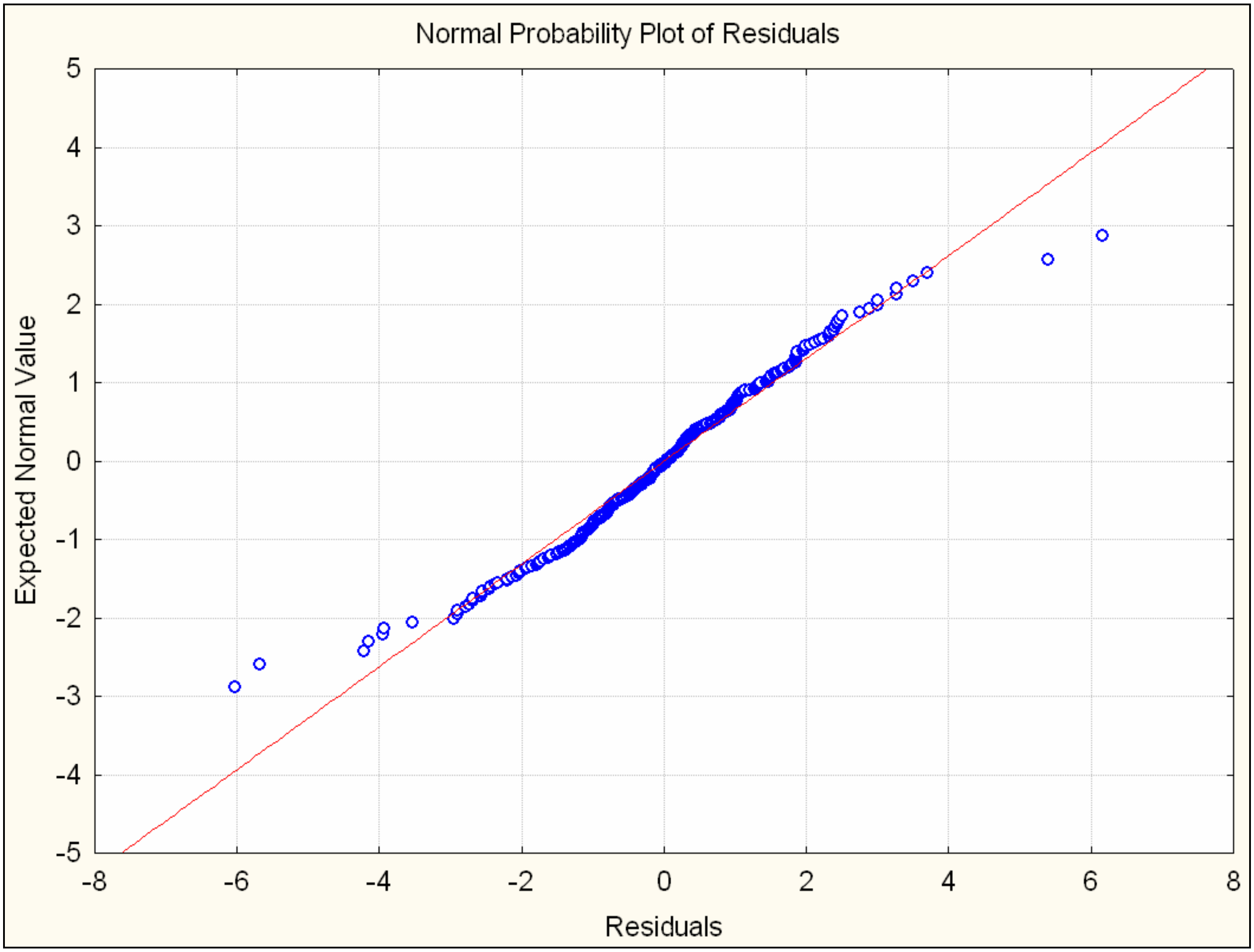
Figure 11



Date: June 26, 2006

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Bugg - pre-1990 - normal probability plot of residuals.

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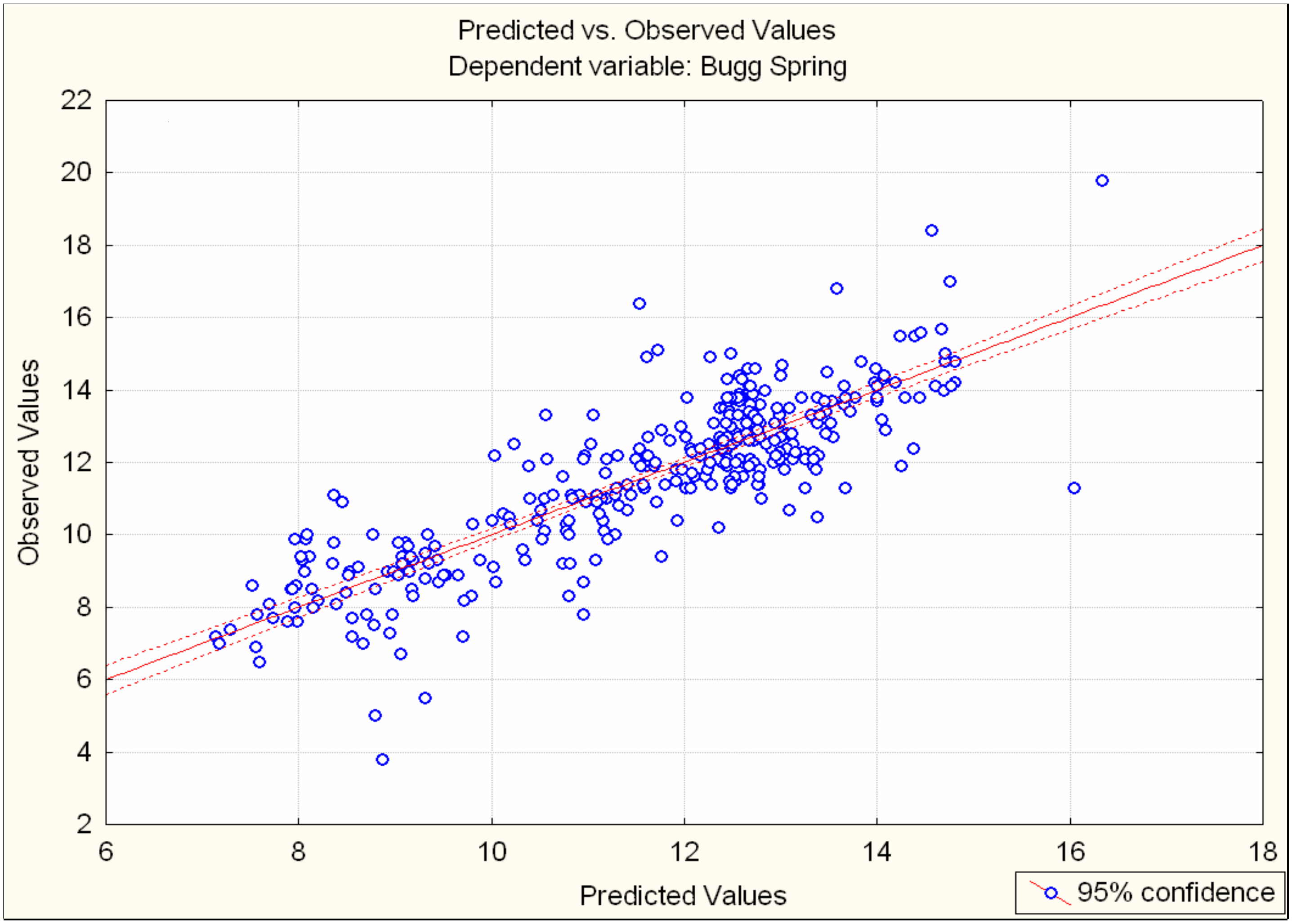
Figure 12



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Bugg - post-1990 - comparison of observed and predicted values.

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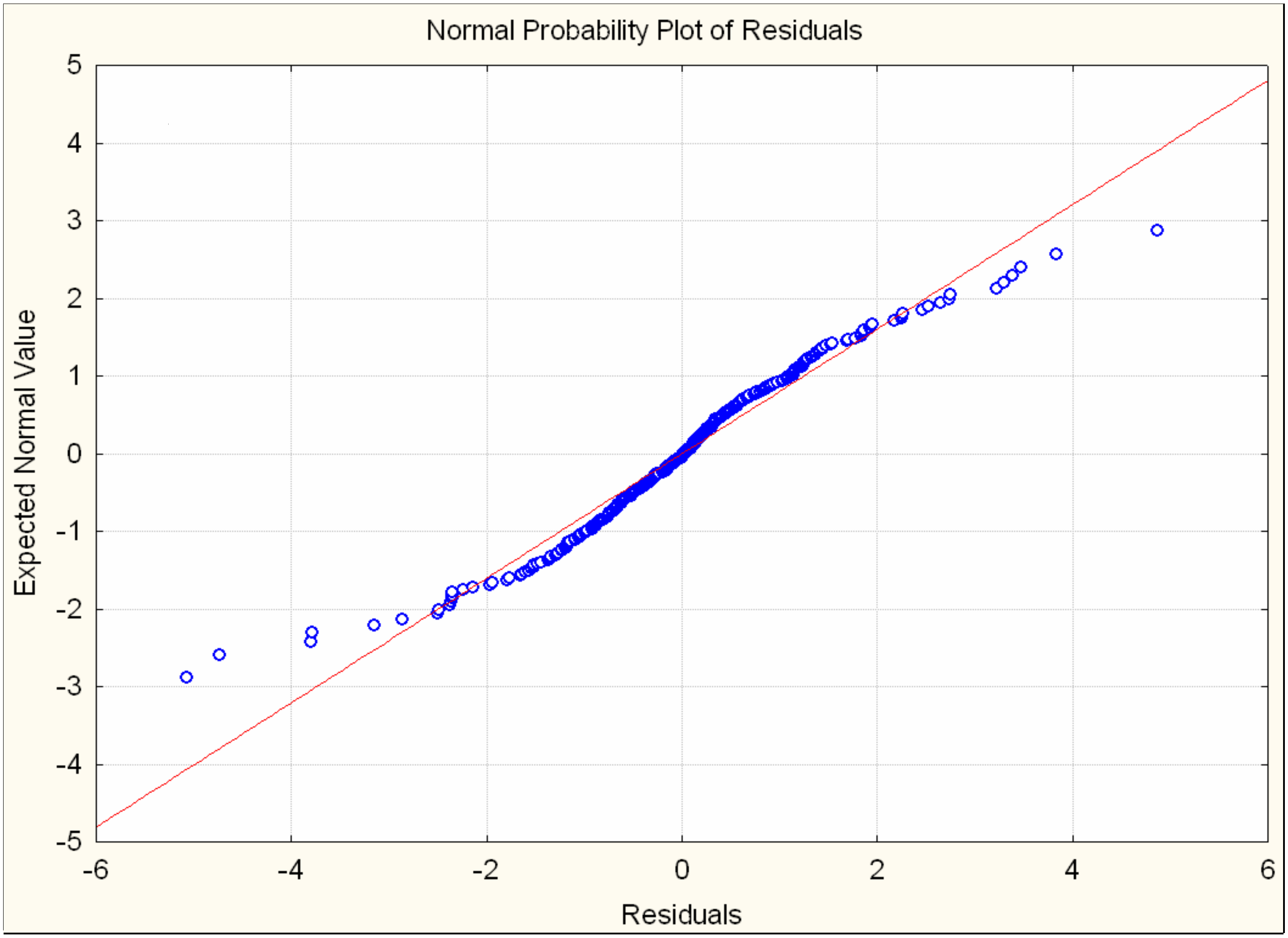
Figure 13



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Bugg - post-1990 - normal probability plot of residuals.

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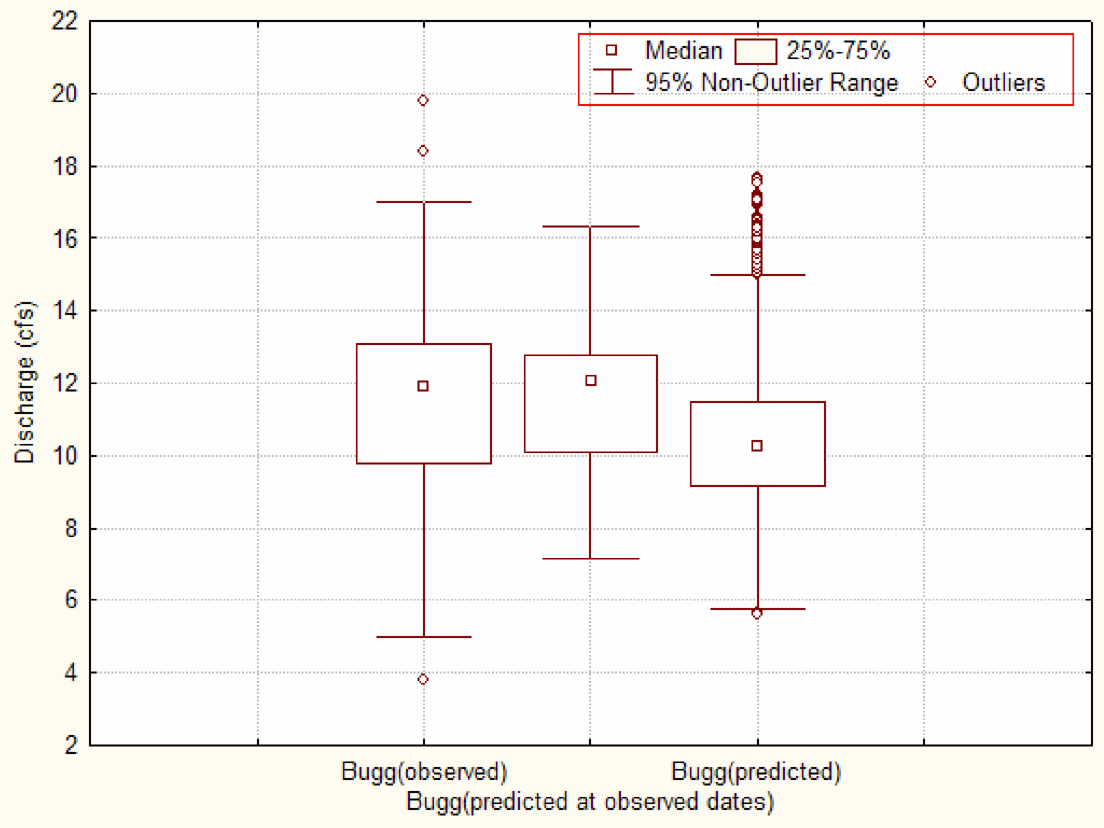
Figure 14



Date: June 13, 2007

File: Fig 15.pdf

Box-Whisker Plots for Observed and Regression-Predicted Discharge Value for Bugg Spring Regression Models.

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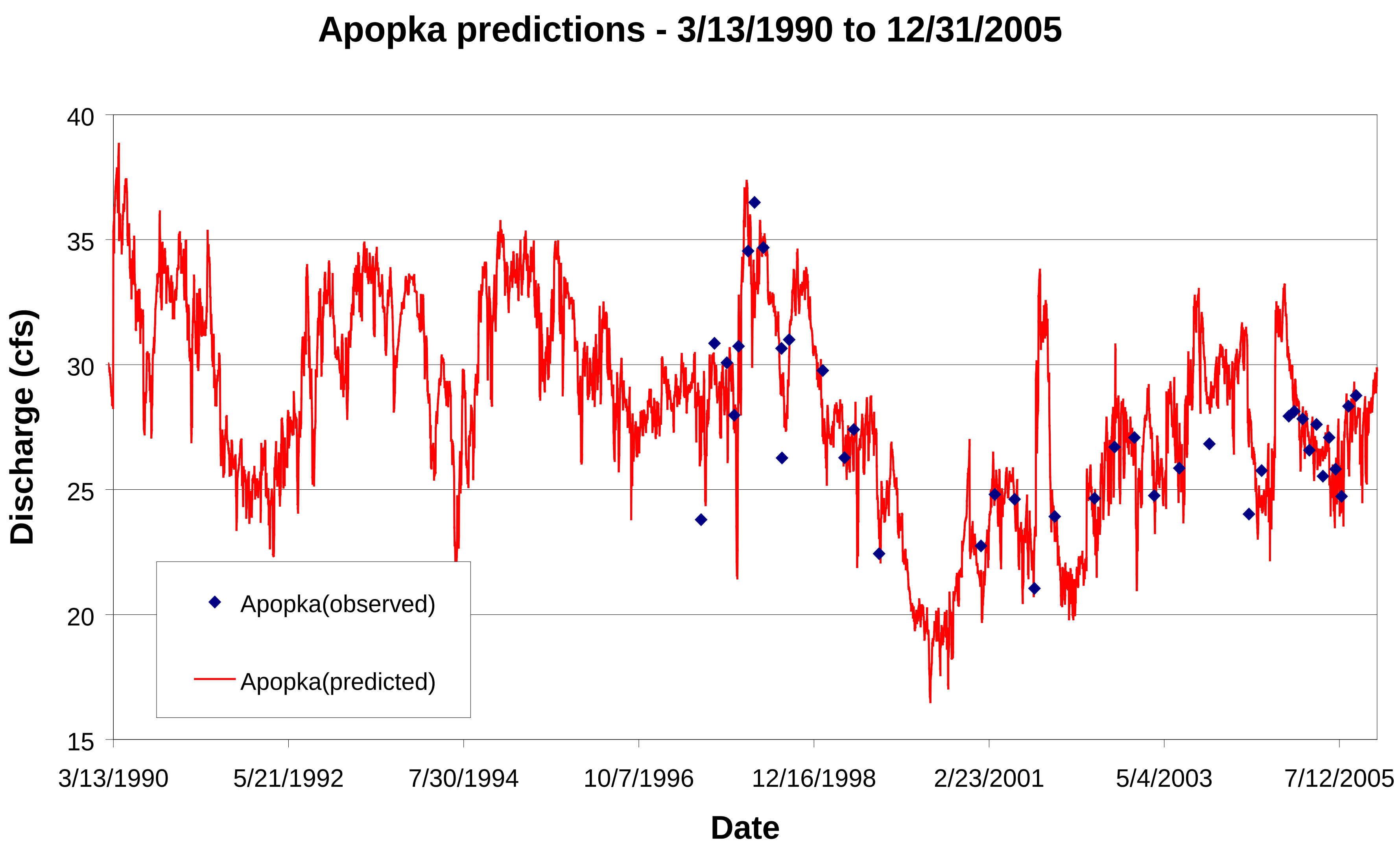
Figure 15



Date: June 26, 2006 File: Fig16.pdf	Daily discharge predictions for Apopka, 1990-2005.

INTERA

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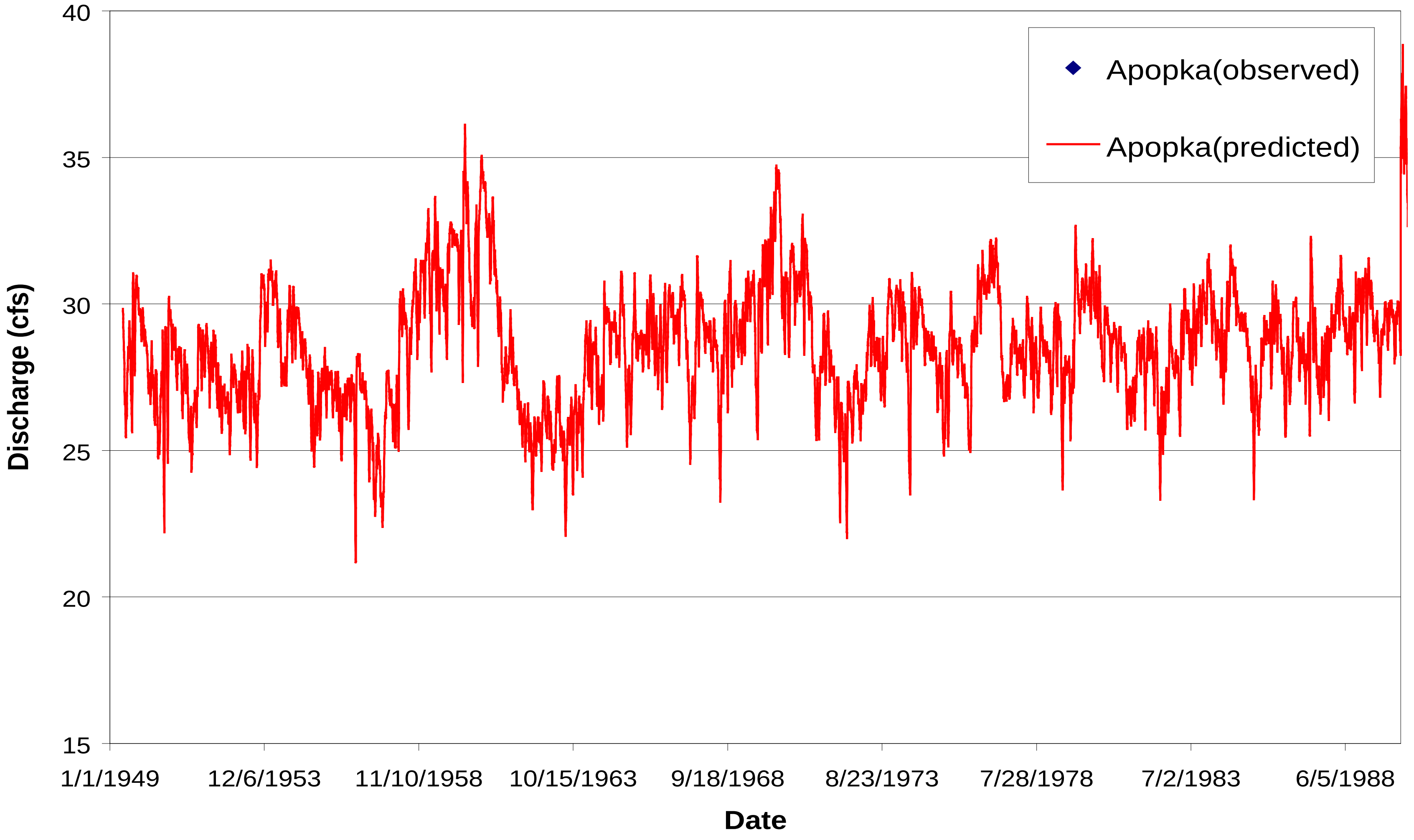
Figure 16

Apopka predictions - 6/2/1949 to 3/12/1990



Date: June 26, 2006	Daily discharge predictions for Apopka, 1949-1990.
File: Fig17.pdf	

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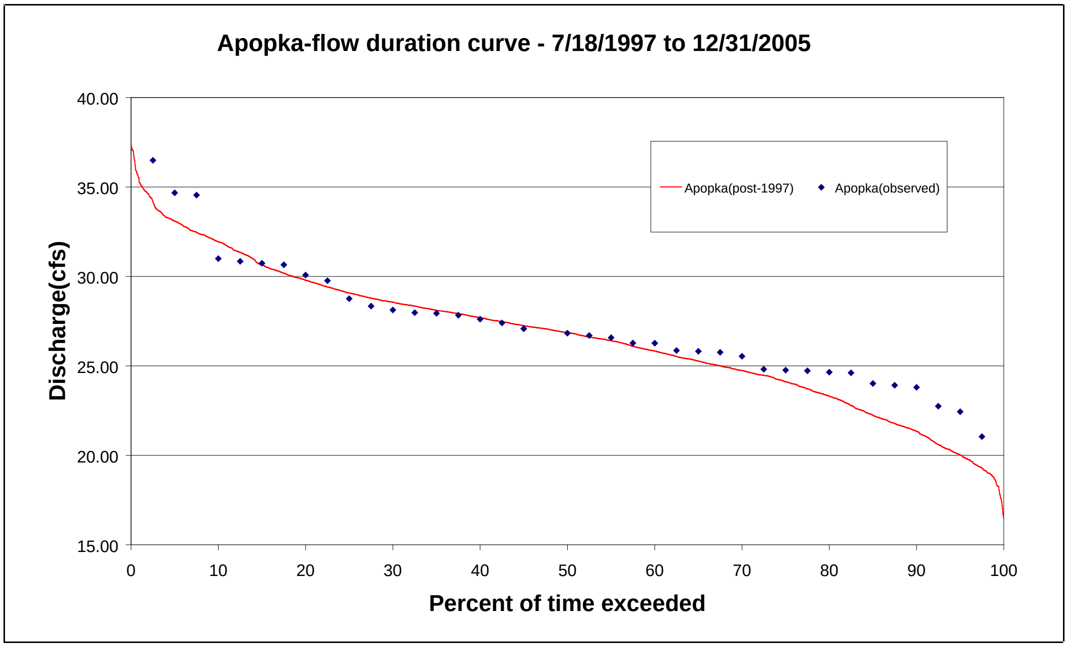
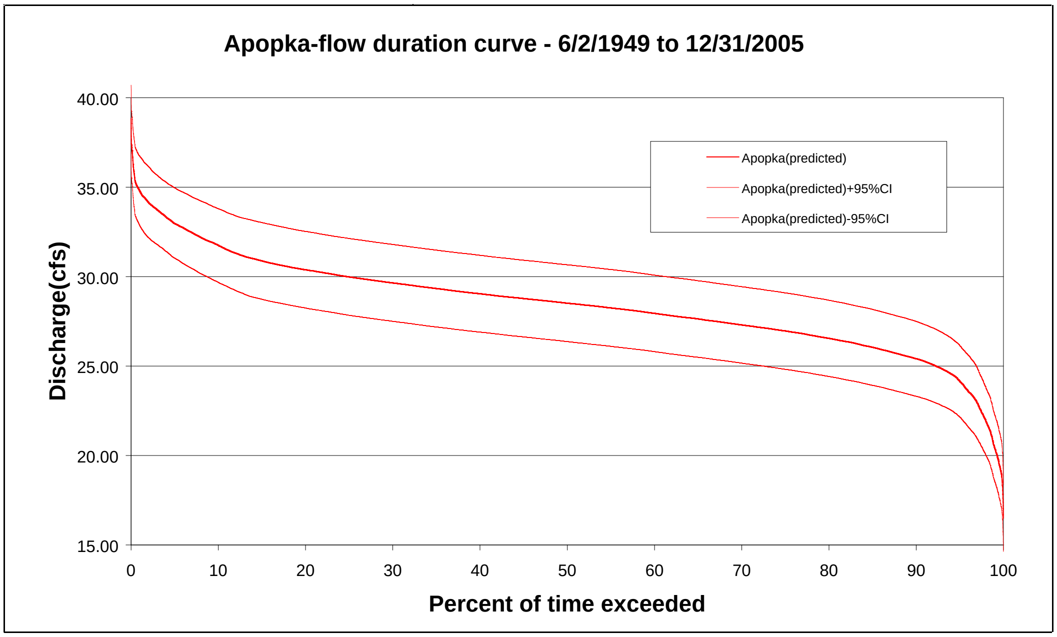
Palatka, Florida

Figure 17

(a) Apopka (7/18/1997 to 12/31/2005) flow duration curve showing comparison between observed data and model predictions



(b) Apopka (6/2/1949 to 12/31/2005) flow duration curve for the entire period of record based on model predictions



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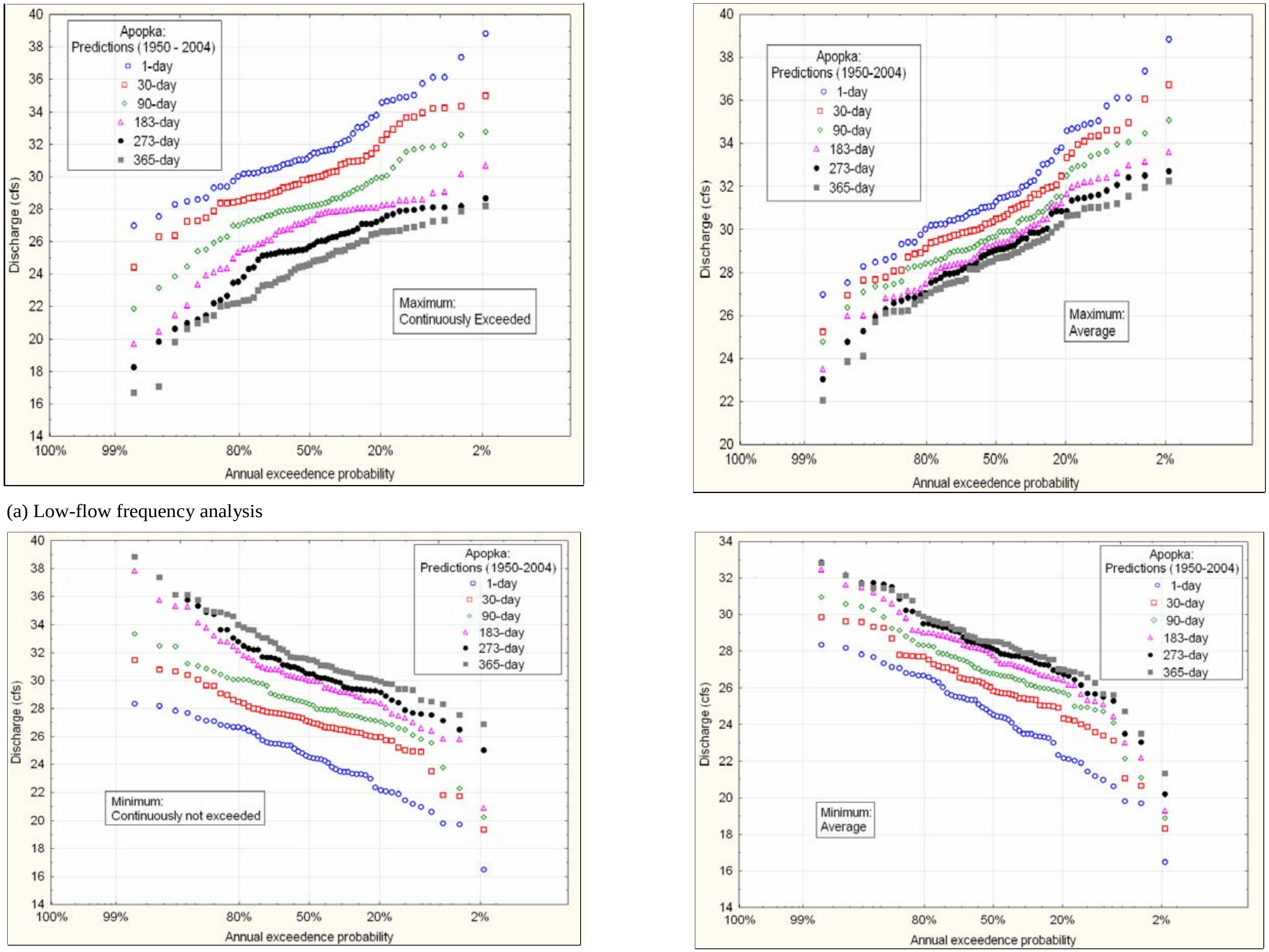
File: Fig 18.pdf	
INTERA	St. Johns River Water Management District Palatka, Florida — Figure 18



(a) High-flow frequency analysis

(a) Low-flow frequency analysis

Date: June 26, 2006	High- and low-frequency analysis of discharge for Apopka Spring.
File: Fig19.pdf	

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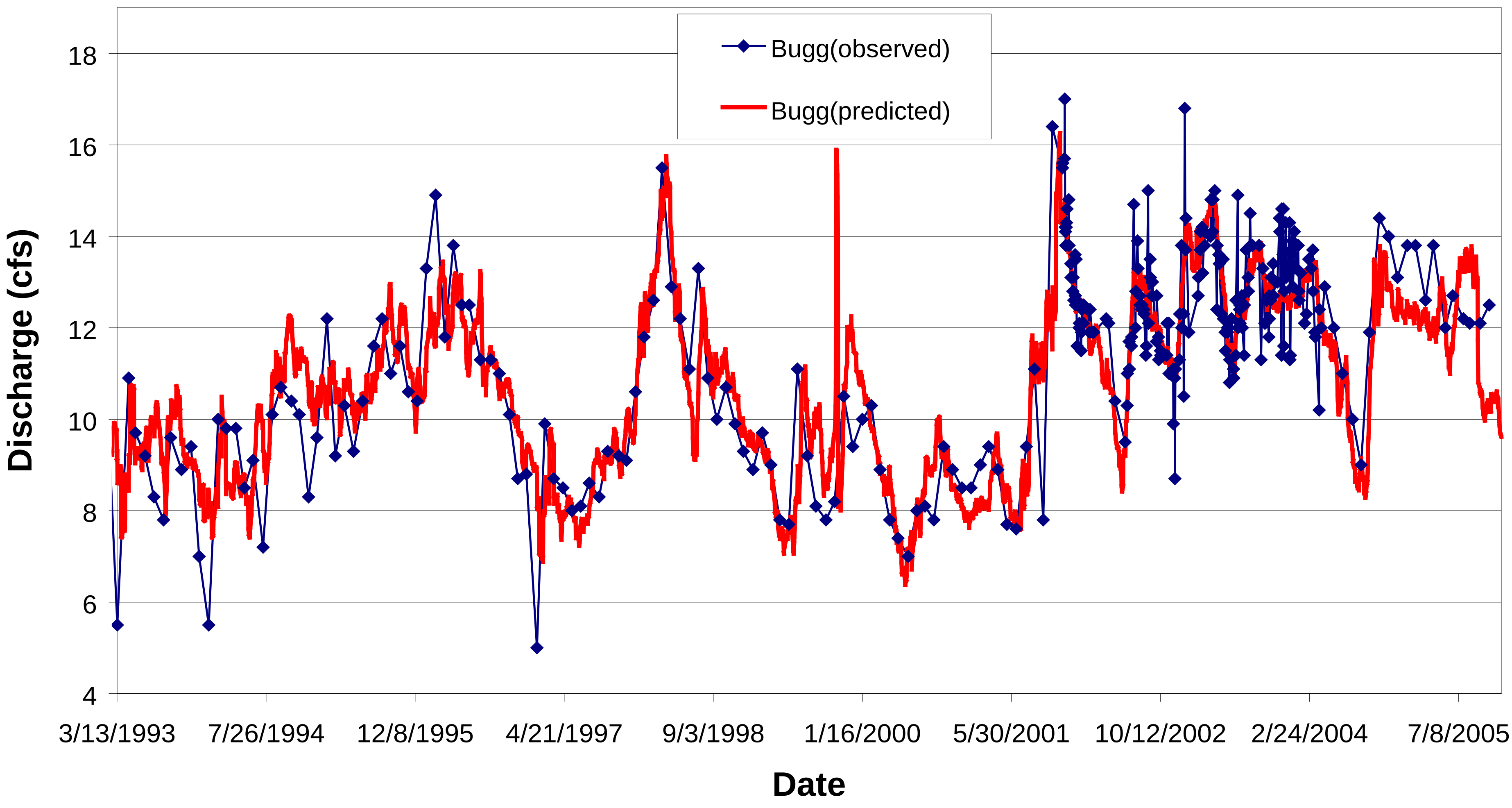
Figure 19

Bugg-prediction - 3/13/1990 - 11/28/2005



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File: Fig20.pdf

Daily discharge predictions for Bugg, 1990-2005.

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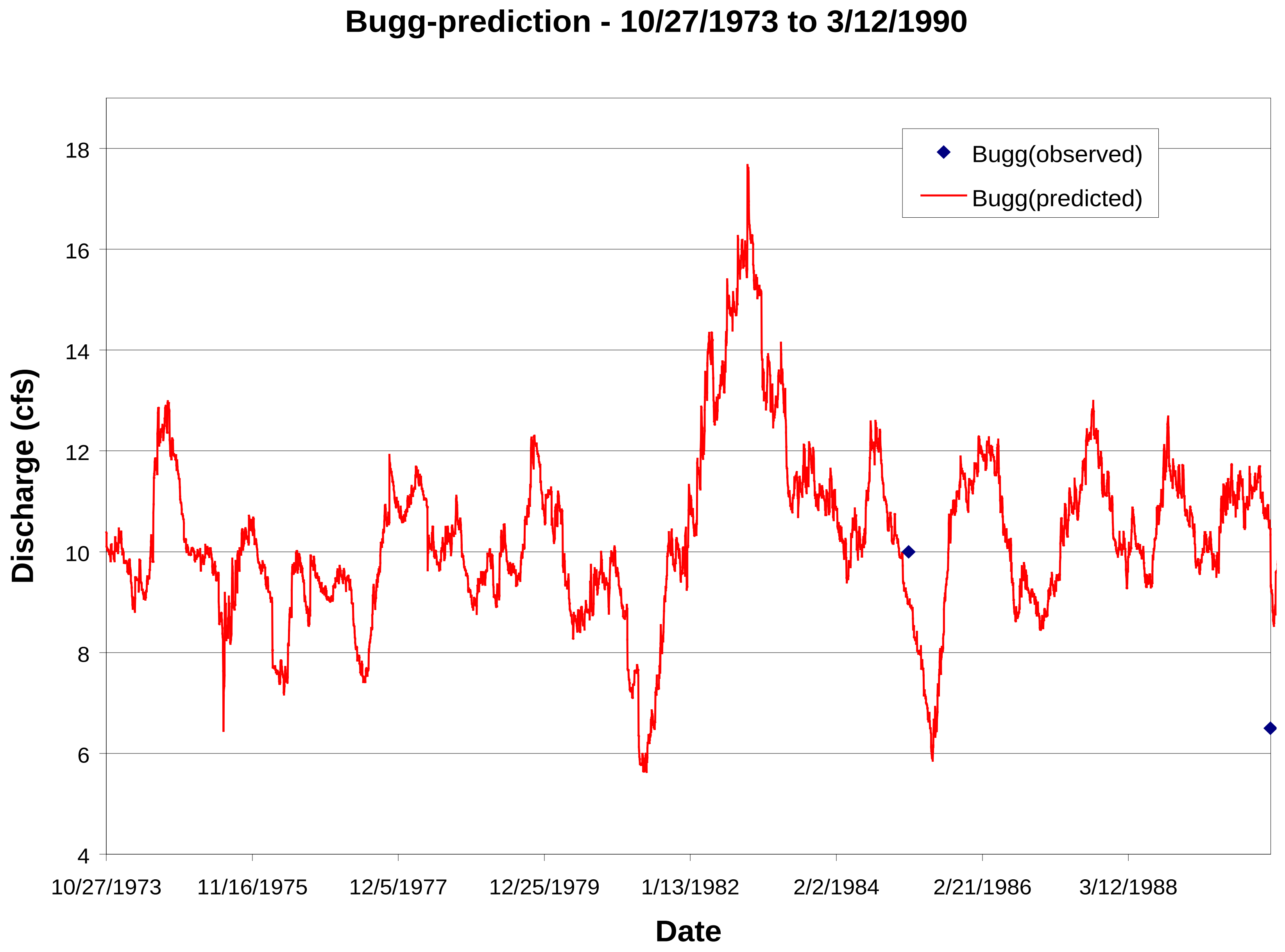
Figure 20



Date: June 26, 2006

File: Fig21.pdf

Daily discharge predictions for Bugg, 1973-1990.

INTERA

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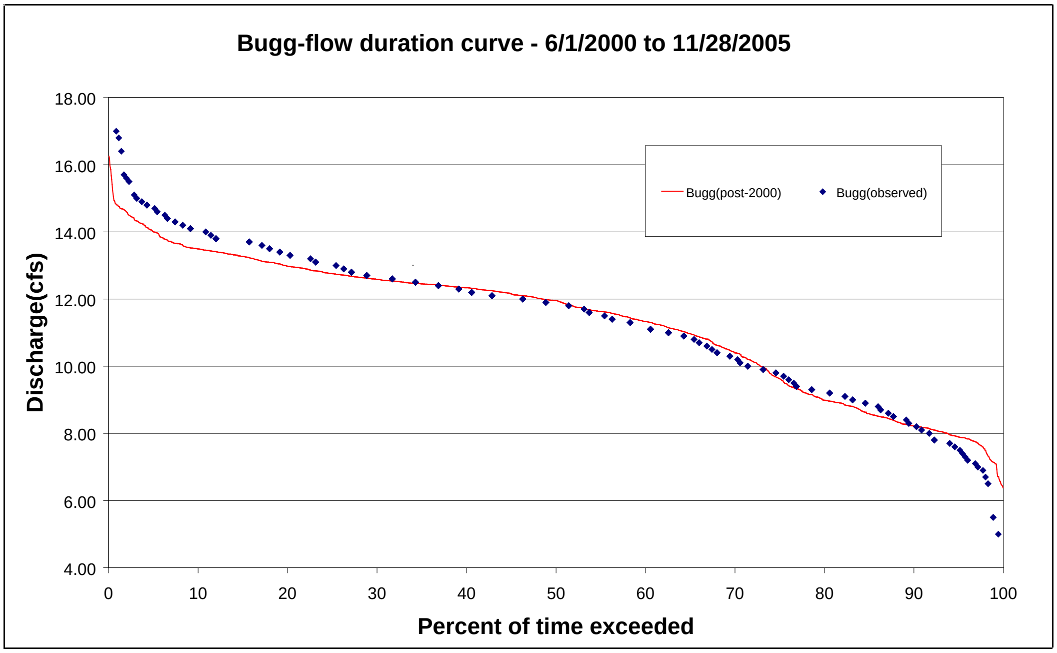
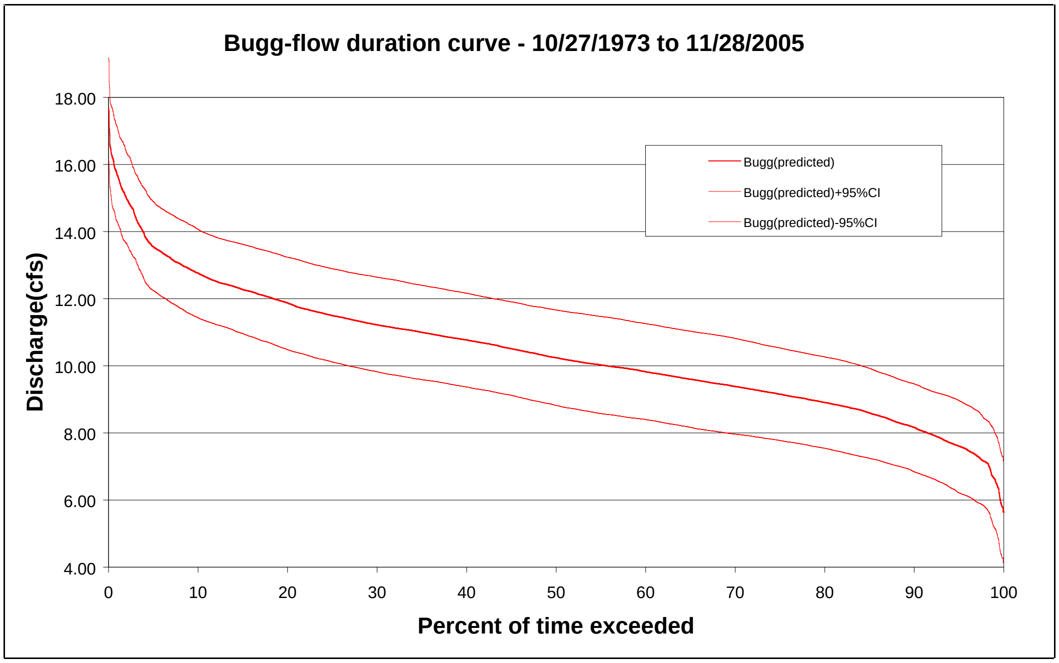
Figure 21

(a) Bugg (6/1/2000 to 11/28/2005) flow duration curve showing comparison between observed data and model predictions



(b) Bugg (10/27/1973 to 11/28/2005)) flow duration curve for the entire period of record based on model predictions



Date: June 26, 2006	Flow duration curves for Bugg Spring.
File: Fig 22.pdf	

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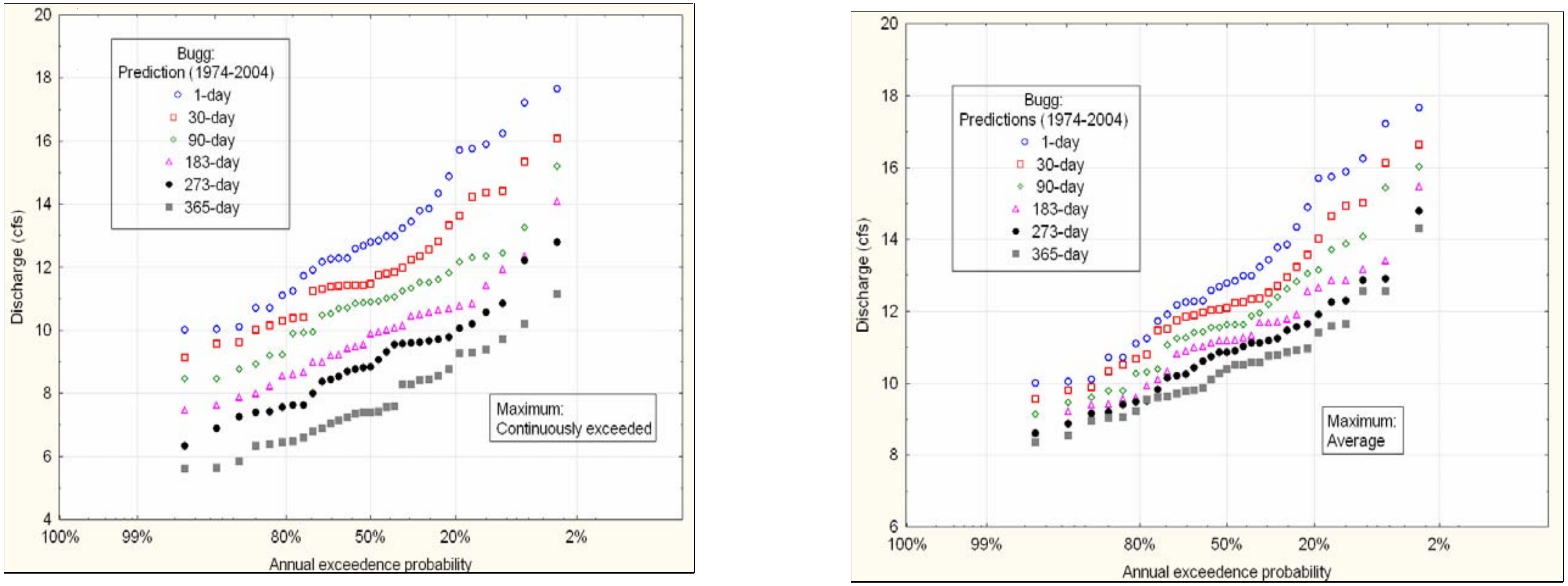
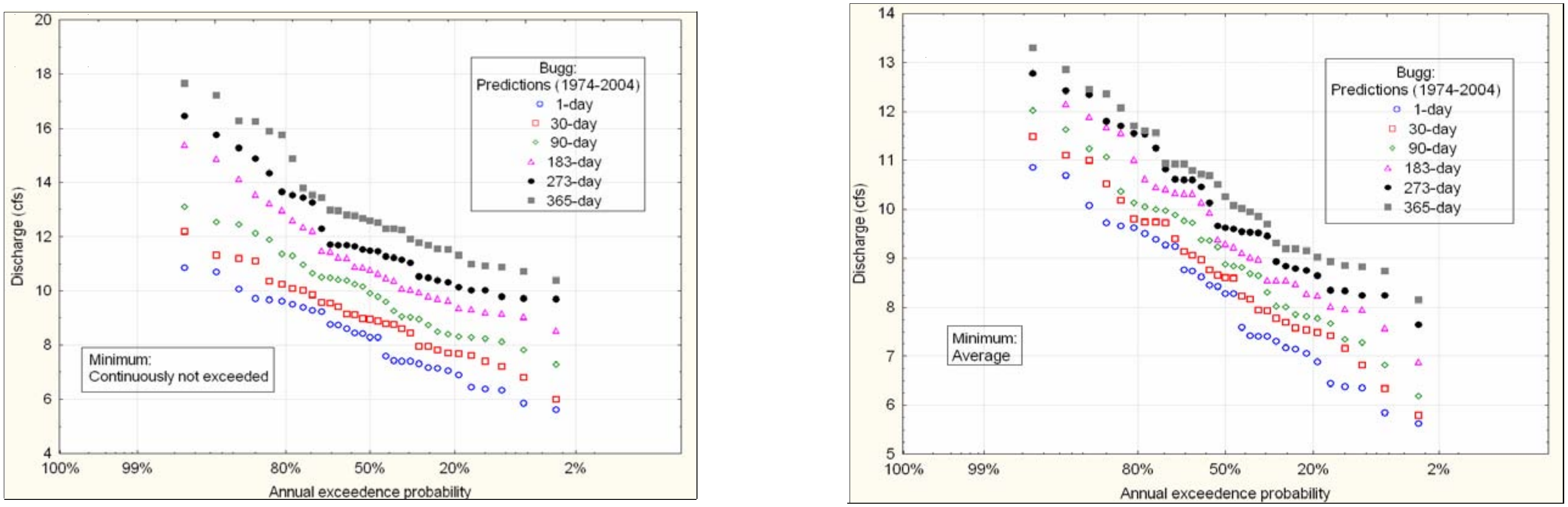
Figure 22

(a) High-flow frequency analysis



(a) Low-flow frequency analysis



Date: June 26, 2006	High- and low-frequency analysis of discharge for Bugg Spring.
File: Fig23.pdf	

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Figure 23

APPENDIX A
Model Usage Notes

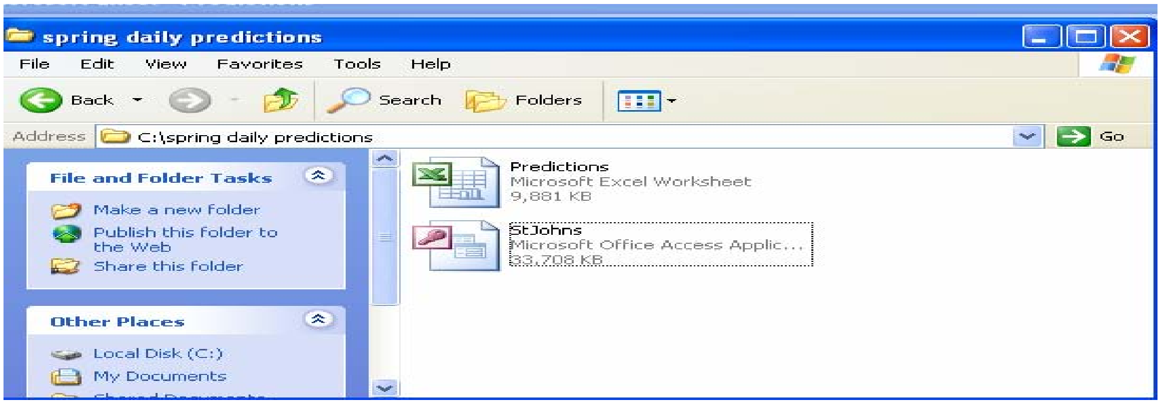
APPENDIX A: Model Usage Notes

This Appendix describes the structure and operation of an ACCESS database created to facilitate predictive applications of the statistical spring discharge models described earlier in Section 4. An example using Bugg spring data is also presented.

1. *Folde*r: **Spring Daily Predictions** –

The folder **Spring Daily Predictions** has two files as shown below:

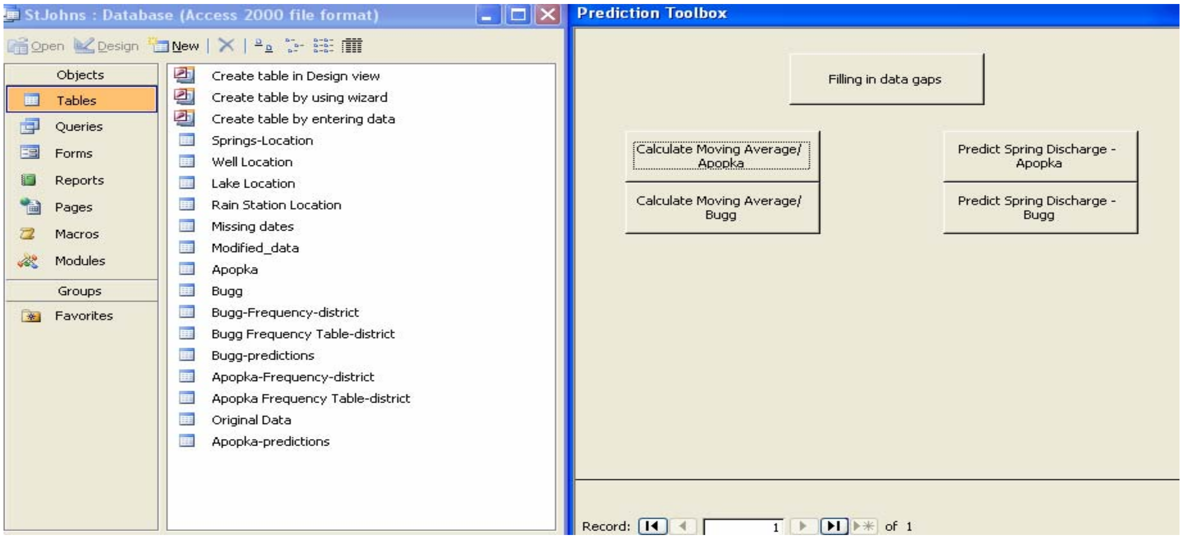
- **St.Johns.mdb**
- **Predictions.xls**



Predictions
Microsoft Excel Worksheet
9,881 KB

StJohns
Microsoft Office Access Applic...
33,708 KB

After building the statistical models in STATISTICA, **St.Johns.mdb – an ACCESS database** was built for applying the statistical models to generate daily predictions for both springs. A screenshot of the database is shown below.


StJohns : Database (Access 2000 file format)
Open
Design
New
Objects
Tables
Queries
Forms
Reports
Pages
Macros
Modules
Groups
Favorites
Prediction Toolbox
Filling in data gaps
Calculate Moving Average/ Apopka
Predict Spring Discharge - Apopka
Calculate Moving Average/ Bugg
Predict Spring Discharge - Bugg
Record: 1 of 1

Create table in Design view
Create table by using wizard
Create table by entering data
Springs-Location
Well Location
Lake Location
Rain Station Location
Missing dates
Modified_data
Apopka
Bugg
Bugg-Frequency-district
Bugg Frequency Table-district
Bugg-predictions
Apopka-Frequency-district
Apopka Frequency Table-district
Original Data
Apopka-predictions

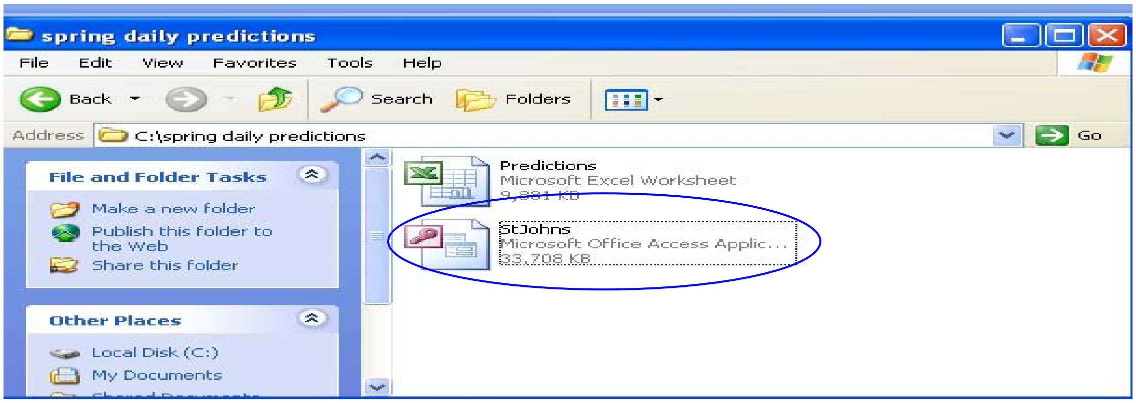
On the left, are the different tables present in the database and on the right is a prediction toolbox. The prediction toolbox executes ACCESS queries and/or VISUAL BASIC APPLICATION Modules, on the click of different buttons. **Predictions.xls – EXCEL file** is used to graphically display the daily predictions and frequency analysis generated in

St.Johns.mdb. The next few pages will walk the user through using the toolbox for generating daily predictions and frequency analysis with the help of an example. It will also guide the user on how to save the results for different cases.

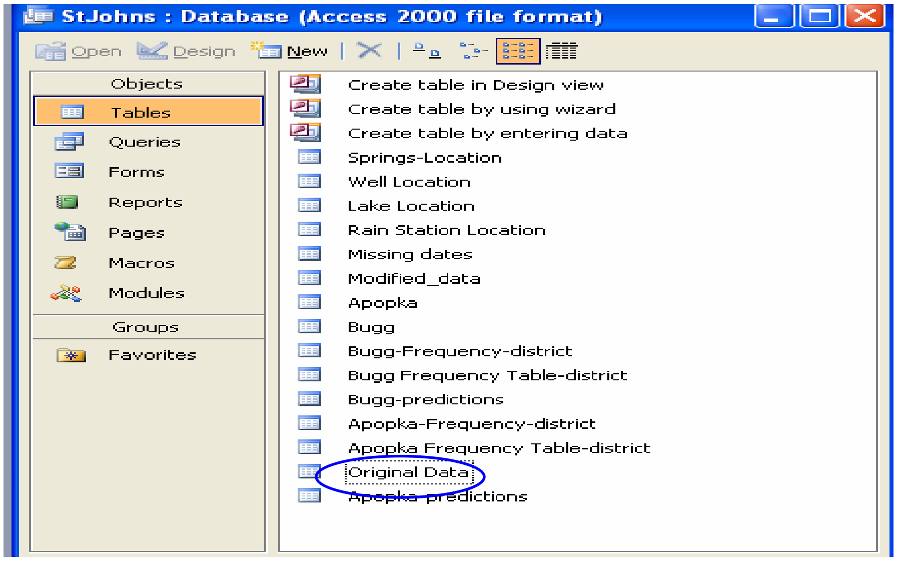
In the example below, our primary task would be to get Bugg spring daily predictions from 10/27/1973 to 11/28/2005.

2. Open St.Johns.mdb

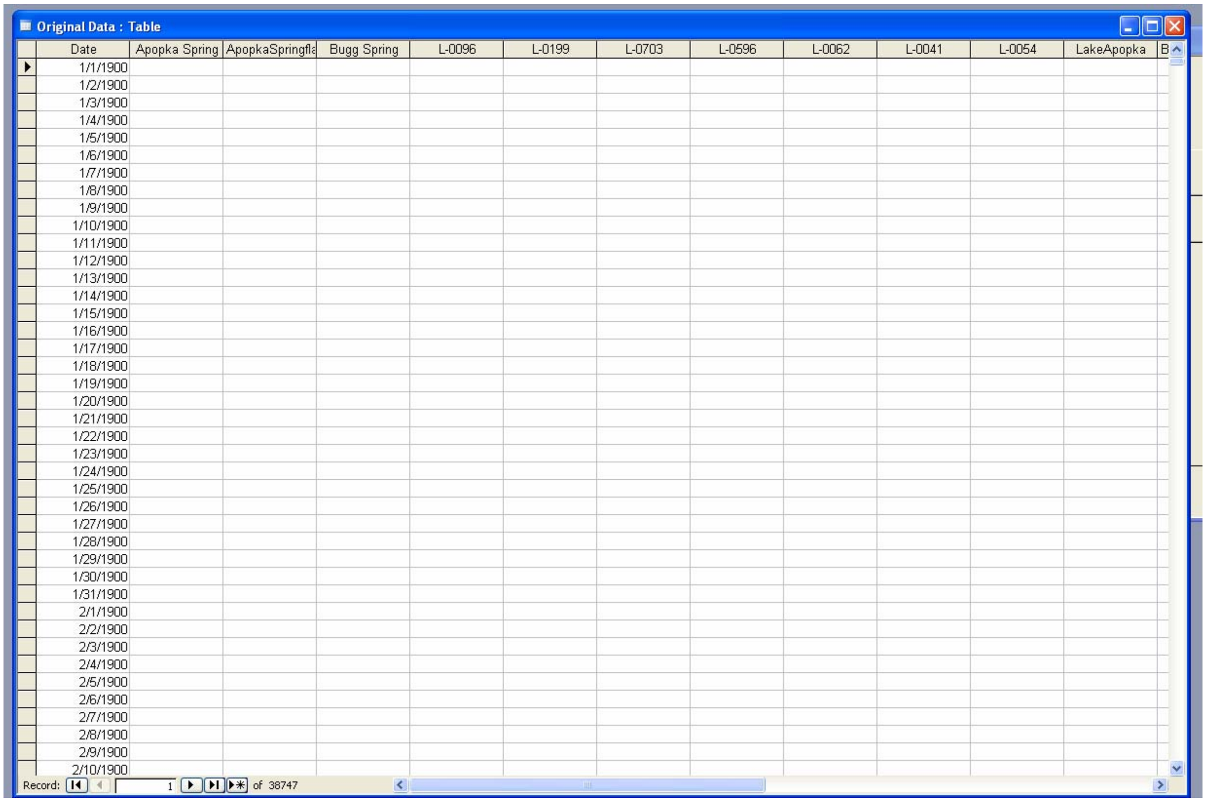
Open **St.Johns.mdb** (highlighted below) by double clicking the file.



The original spring discharge, groundwater elevation, lake level and precipitation data reside in the "**Original Data**" ACCESS data table. The screenshot below indicates the **Original Data** table within the database.



Double-clicking this table would open the **Original Data** table as shown below.



Original Data : Table

Date	Apopka Spring	ApopkaSpringfla	Bugg Spring	L-0096	L-0199	L-0703	L-0596	L-0062	L-0041	L-0054	LakeApopka	B
1/1/1900												
1/2/1900												
1/3/1900												
1/4/1900												
1/5/1900												
1/6/1900												
1/7/1900												
1/8/1900												
1/9/1900												
1/10/1900												
1/11/1900												
1/12/1900												
1/13/1900												
1/14/1900												
1/15/1900												
1/16/1900												
1/17/1900												
1/18/1900												
1/19/1900												
1/20/1900												
1/21/1900												
1/22/1900												
1/23/1900												
1/24/1900												
1/25/1900												
1/26/1900												
1/27/1900												
1/28/1900												
1/29/1900												
1/30/1900												
1/31/1900												
2/1/1900												
2/2/1900												
2/3/1900												
2/4/1900												
2/5/1900												
2/6/1900												
2/7/1900												
2/8/1900												
2/9/1900												
2/10/1900												

Record: 1 of 38747

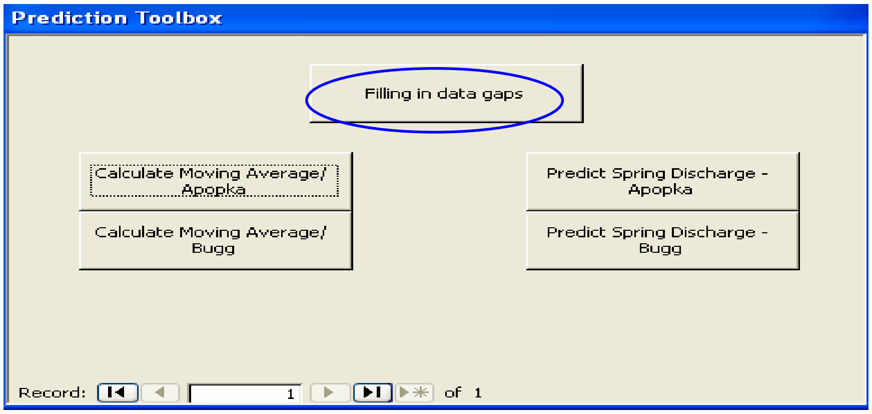
The table has 38747 records for dates ranging from 1/1/1900 to 1/31/2006. If the user wants to change a particular data time series, pasting the new time series (with dates from 1/1/1900 to 1/31/2006) over the old one is one of the ways to do it.

If the user has another ACCESS database with new time series data, it can be added to the **Original Data** table using an *Append Query*. *Append Query* allows the user to append one or more columns to the **Original Data** table. For example, if a new time series for L-0096 becomes available, append the new data column as *L-0096(new)* using the *Append Query*. Then delete the old *L-0096* column from **Original Data** table and rename L-0096(new) as L-0096. If data is not available for a particular date, the user can leave it blank as seen in **Original Data** table for different variables.

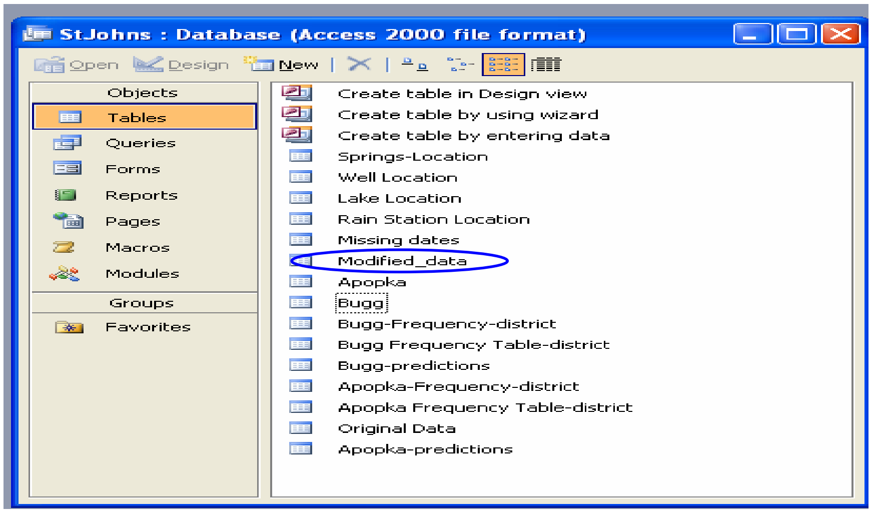
3. Data Gap Filling to create "Modified Data" Table

Gaps in the data (over continuous periods) are filled by regressing against more frequently observed data for a related variable. The need to fill data gaps for some wells arises during the calculation of moving averages. For example, groundwater elevations at L-0703 can be predicted from water levels at L-0096 using a simple linear regression model. Such relationships, developed for well pairs L-0703/L-0096 and L-0054/L-0096 have been pre-programmed, and are invoked to fill in the gaps in the **Original Data** table.

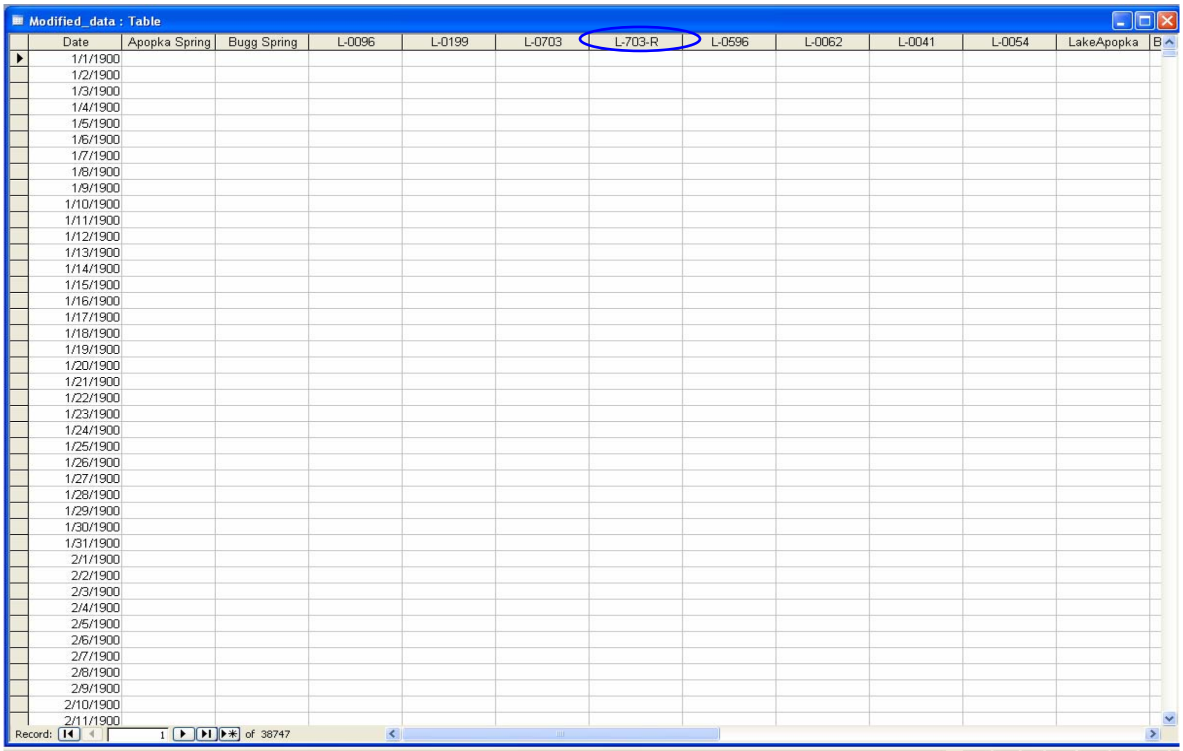
Therefore the next step is clicking the "Filling in data gaps" button on the prediction toolbox.


Prediction Toolbox
Filling in data gaps
Calculate Moving Average/ Apopka
Predict Spring Discharge - Apopka
Calculate Moving Average/ Bugg
Predict Spring Discharge - Bugg
Record: 1 of 1

Clicking this button creates a **Modified_data** table as highlighted below:



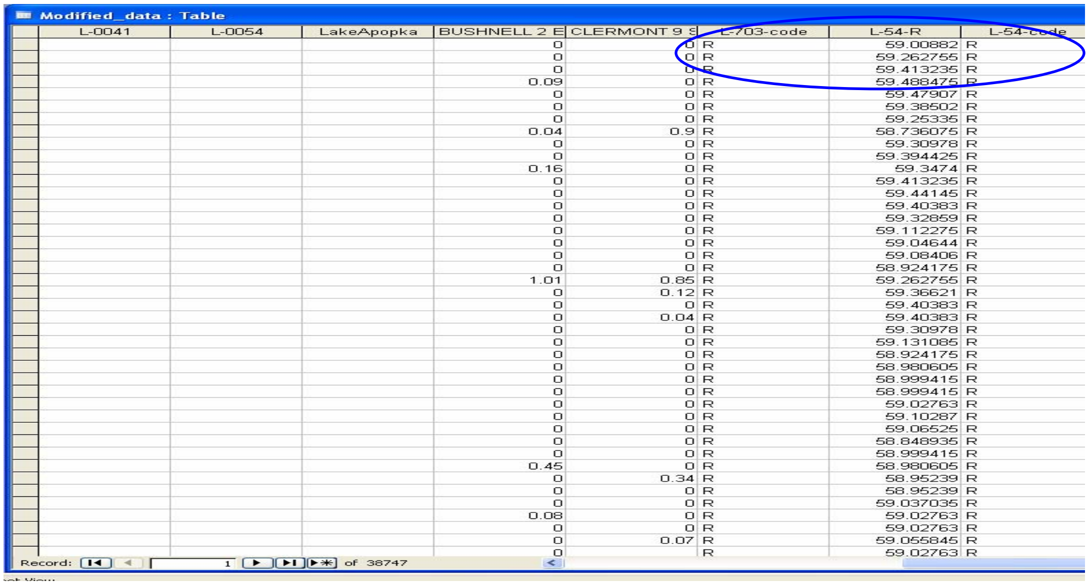
Open the **Modified_data** table by double-clicking on it. Below is the screenshot:



Date	Apopka Spring	Bugg Spring	L-0096	L-0199	L-0703	L-703-R	L-0596	L-0062	L-0041	L-0054	LakeApopka	B
1/1/1900												
1/2/1900												
1/3/1900												
1/4/1900												
1/5/1900												
1/6/1900												
1/7/1900												
1/8/1900												
1/9/1900												
1/10/1900												
1/11/1900												
1/12/1900												
1/13/1900												
1/14/1900												
1/15/1900												
1/16/1900												
1/17/1900												
1/18/1900												
1/19/1900												
1/20/1900												
1/21/1900												
1/22/1900												
1/23/1900												
1/24/1900												
1/25/1900												
1/26/1900												
1/27/1900												
1/28/1900												
1/29/1900												
1/30/1900												
1/31/1900												
2/1/1900												
2/2/1900												
2/3/1900												
2/4/1900												
2/5/1900												
2/6/1900												
2/7/1900												
2/8/1900												
2/9/1900												
2/10/1900												
2/11/1900												

Record: 1 of 38747

The user would notice some new variables present in the **Modified_Table**. For example, we see L-703-R highlighted in the above screenshot. L-703-R has all the original well-data for L-0703 and some regressed data values from L-0096 using a simple linear regression model. Similarly, **Modified_Table** will also have L0054-R as new variable. **Modified_Table** also has additional columns called L-703-code and L-54-code, which flag the water-level data values filled by regression with letter "R". This is highlighted in screenshot below:

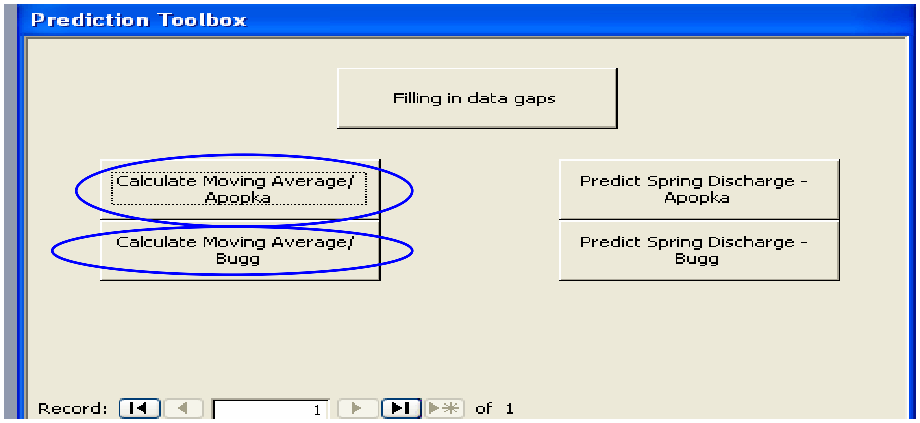


L-0041	L-0054	LakeApopka	BUSHNELL 2 E	CLERMONT 9 S	L-703-code	L-54-R	L-54-code
			0	0	R	59.00882	R
			0	0	R	59.262755	R
			0	0	R	59.413235	R
			0.09	0	R	59.488475	R
			0	0	R	59.47907	R
			0	0	R	59.38502	R
			0	0	R	59.25335	R
			0.04	0.9	R	58.736075	R
			0	0	R	59.30978	R
			0	0	R	59.394425	R
			0.16	0	R	59.3474	R
			0	0	R	59.413235	R
			0	0	R	59.44145	R
			0	0	R	59.40383	R
			0	0	R	59.32859	R
			0	0	R	59.112275	R
			0	0	R	59.04644	R
			0	0	R	59.08406	R
			0	0	R	58.924175	R
			1.01	0.85	R	59.262755	R
			0	0.12	R	59.36621	R
			0	0	R	59.40383	R
			0	0.04	R	59.40383	R
			0	0	R	59.30978	R
			0	0	R	59.131085	R
			0	0	R	58.924175	R
			0	0	R	58.980605	R
			0	0	R	58.999415	R
			0	0	R	58.999415	R
			0	0	R	59.02763	R
			0	0	R	59.10287	R
			0	0	R	59.06525	R
			0	0	R	58.848935	R
			0	0	R	58.999415	R
			0.45	0	R	58.980605	R
			0	0.34	R	58.95239	R
			0	0	R	58.95239	R
			0	0	R	59.037035	R
			0.08	0	R	59.02763	R
			0	0	R	59.02763	R
			0	0.07	R	59.055845	R
			0		R	59.02763	R

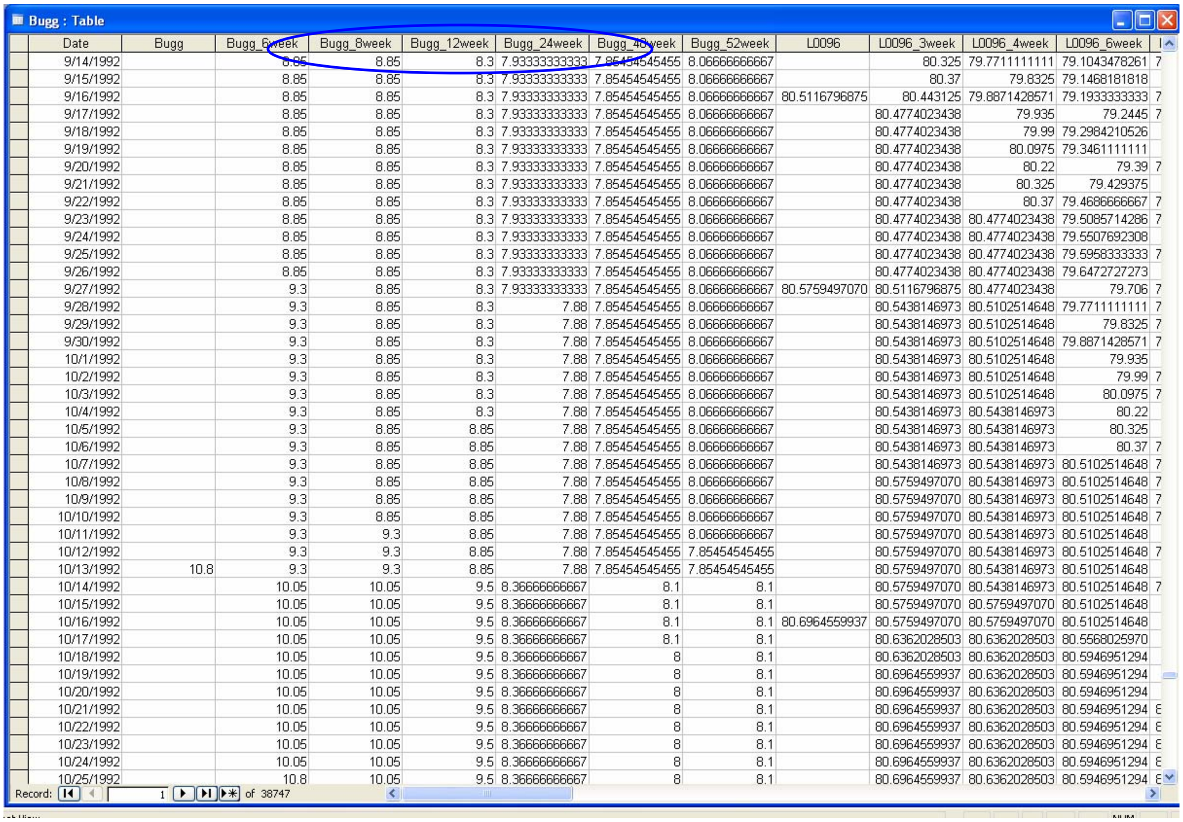
Record: 1 of 38747

4. Calculating moving average variables for each spring

The statistical models in the report show the use of moving averages of different variables (spring, groundwater level, lake level, and rainfall data) for predicting daily discharge for each spring. Computation of these variables, for each spring, is then performed by clicking the two buttons highlighted below.


Prediction Toolbox
Filling in data gaps
Calculate Moving Average/ Apopka
Calculate Moving Average/ Bugg
Predict Spring Discharge - Apopka
Predict Spring Discharge - Bugg
Record: 1 of 1

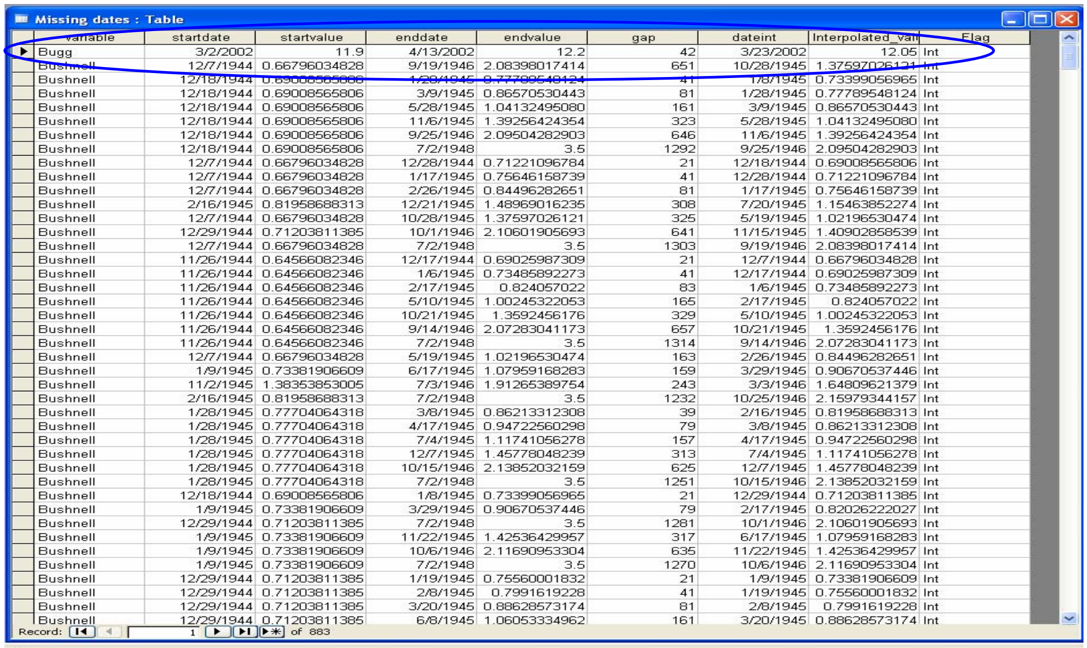
For example clicking on *Calculate Moving Average/Bugg* would fill the table **Bugg** present in the database. The screenshot below shows table **Bugg**:



Date	Bugg	Bugg_6week	Bugg_8week	Bugg_12week	Bugg_24week	Bugg_40week	Bugg_52week	L0096	L0096_3week	L0096_4week	L0096_6week
9/14/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.325	79.7711111111	79.1043478261
9/15/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.37	79.8325	79.1468181818
9/16/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667	80.5116796875	80.443125	79.8871428571	79.1933333333
9/17/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	79.935	79.2445
9/18/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	79.99	79.2984210526
9/19/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.0975	79.3461111111
9/20/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.22	79.39
9/21/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.325	79.429375
9/22/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.37	79.4686666667
9/23/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.4774023438	79.5085714286
9/24/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.4774023438	79.5507692308
9/25/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.4774023438	79.5958333333
9/26/1992		8.85	8.85	8.3	7.93333333333	7.85454545455	8.06666666667		80.4774023438	80.4774023438	79.6472727273
9/27/1992		9.3	8.85	8.3	7.93333333333	7.85454545455	8.06666666667	80.5759497070	80.5116796875	80.4774023438	79.706
9/28/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5102514648	79.7711111111
9/29/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5102514648	79.8325
9/30/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5102514648	79.8871428571
10/1/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5102514648	79.935
10/2/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5102514648	79.99
10/3/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5102514648	80.0975
10/4/1992		9.3	8.85	8.3	7.88	7.85454545455	8.06666666667		80.5438146973	80.5438146973	80.22
10/5/1992		9.3	8.85	8.85	7.88	7.85454545455	8.06666666667		80.5438146973	80.5438146973	80.325
10/6/1992		9.3	8.85	8.85	7.88	7.85454545455	8.06666666667		80.5438146973	80.5438146973	80.37
10/7/1992		9.3	8.85	8.85	7.88	7.85454545455	8.06666666667		80.5438146973	80.5438146973	80.5102514648
10/8/1992		9.3	8.85	8.85	7.88	7.85454545455	8.06666666667		80.5759497070	80.5438146973	80.5102514648
10/9/1992		9.3	8.85	8.85	7.88	7.85454545455	8.06666666667		80.5759497070	80.5438146973	80.5102514648
10/10/1992		9.3	8.85	8.85	7.88	7.85454545455	8.06666666667		80.5759497070	80.5438146973	80.5102514648
10/11/1992		9.3	9.3	8.85	7.88	7.85454545455	8.06666666667		80.5759497070	80.5438146973	80.5102514648
10/12/1992		9.3	9.3	8.85	7.88	7.85454545455	7.85454545455		80.5759497070	80.5438146973	80.5102514648
10/13/1992	10.8	9.3	9.3	8.85	7.88	7.85454545455	7.85454545455		80.5759497070	80.5438146973	80.5102514648
10/14/1992		10.05	10.05	9.5	8.36666666667	8.1	8.1		80.5759497070	80.5438146973	80.5102514648
10/15/1992		10.05	10.05	9.5	8.36666666667	8.1	8.1		80.5759497070	80.5759497070	80.5102514648
10/16/1992		10.05	10.05	9.5	8.36666666667	8.1	8.1	80.6964559937	80.5759497070	80.5759497070	80.5102514648
10/17/1992		10.05	10.05	9.5	8.36666666667	8.1	8.1		80.6362028503	80.6362028503	80.5568025970
10/18/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6362028503	80.6362028503	80.5946951294
10/19/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294
10/20/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294
10/21/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294
10/22/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294
10/23/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294
10/24/1992		10.05	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294
10/25/1992		10.8	10.05	9.5	8.36666666667	8	8.1		80.6964559937	80.6362028503	80.5946951294

Record: 1 of 38747

The highlighted columns in the **Bugg** table above show some of the calculated moving averages to be used in the Bugg statistical model for daily discharge predictions. One extra piece of information generated on clicking *Calculate Moving Average/Bugg* is in the table **Missing Dates** shown below:



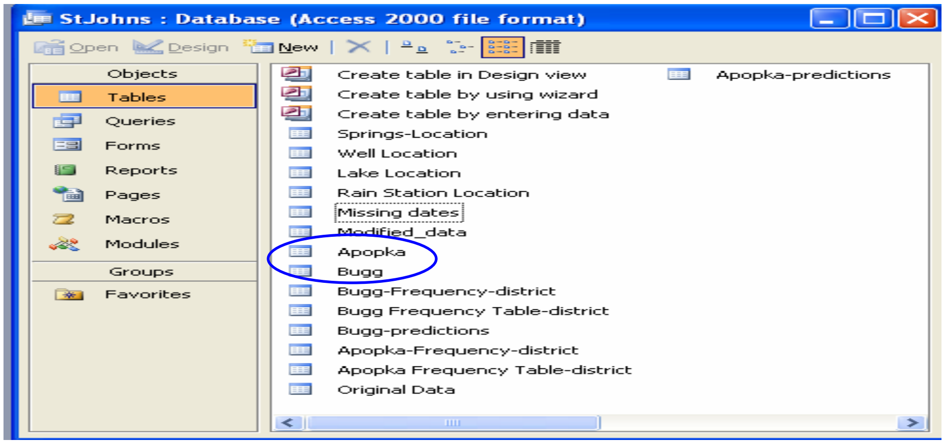
Missing dates : Table

variable	startdate	startvalue	enddate	endvalue	gap	dateint	Interpolated_val	Flag
Bugg	3/2/2002	11.9	4/13/2002	12.2	42	3/23/2002	12.05	Int
Bushnell	12/7/1944	0.66796034828	9/19/1946	2.08398017414	651	10/28/1945	1.37597026121	Int
Bushnell	12/18/1944	0.69008565806	1/28/1945	0.77789548124	41	1/8/1945	0.73399056965	Int
Bushnell	12/18/1944	0.69008565806	3/9/1945	0.86570530443	81	1/28/1945	0.77789548124	Int
Bushnell	12/18/1944	0.69008565806	5/28/1945	1.04132495080	161	3/9/1945	0.86570530443	Int
Bushnell	12/18/1944	0.69008565806	11/6/1945	1.39256424354	323	5/28/1945	1.04132495080	Int
Bushnell	12/18/1944	0.69008565806	9/25/1946	2.09504282903	646	11/6/1945	1.39256424354	Int
Bushnell	12/18/1944	0.69008565806	7/2/1948	3.5	1292	9/25/1946	2.09504282903	Int
Bushnell	12/7/1944	0.66796034828	12/28/1944	0.71221096784	21	12/18/1944	0.69008565806	Int
Bushnell	12/7/1944	0.66796034828	1/17/1945	0.75646158739	41	12/28/1944	0.71221096784	Int
Bushnell	12/7/1944	0.66796034828	2/26/1945	0.84496282651	81	1/17/1945	0.75646158739	Int
Bushnell	2/16/1945	0.81958688313	12/21/1945	1.48969016235	308	7/20/1945	1.15463852274	Int
Bushnell	12/7/1944	0.66796034828	10/28/1945	1.37597026121	325	5/19/1945	1.02196530474	Int
Bushnell	12/29/1944	0.71203811385	10/1/1946	2.10601905693	641	11/15/1945	1.40902858539	Int
Bushnell	12/7/1944	0.66796034828	7/2/1948	3.5	1303	9/19/1946	2.08398017414	Int
Bushnell	11/26/1944	0.64566082346	12/17/1944	0.69025987309	21	12/7/1944	0.66796034828	Int
Bushnell	11/26/1944	0.64566082346	1/6/1945	0.73485892273	41	12/17/1944	0.69025987309	Int
Bushnell	11/26/1944	0.64566082346	2/17/1945	0.824057022	83	1/6/1945	0.73485892273	Int
Bushnell	11/26/1944	0.64566082346	5/10/1945	1.00245322053	165	2/17/1945	0.824057022	Int
Bushnell	11/26/1944	0.64566082346	10/21/1945	1.3592456176	329	5/10/1945	1.00245322053	Int
Bushnell	11/26/1944	0.64566082346	9/14/1946	2.07283041173	657	10/21/1945	1.3592456176	Int
Bushnell	11/26/1944	0.64566082346	7/2/1948	3.5	1314	9/14/1946	2.07283041173	Int
Bushnell	12/7/1944	0.66796034828	5/19/1945	1.02196530474	163	2/26/1945	0.84496282651	Int
Bushnell	1/9/1945	0.73381906609	6/17/1945	1.07959168283	159	3/29/1945	0.90670537446	Int
Bushnell	11/2/1945	1.38353853005	7/3/1946	1.91265389754	243	3/3/1946	1.64809621379	Int
Bushnell	2/16/1945	0.81958688313	7/2/1948	3.5	1232	10/25/1946	2.15979344157	Int
Bushnell	1/28/1945	0.77704064318	3/8/1945	0.86213312308	39	2/16/1945	0.81958688313	Int
Bushnell	1/28/1945	0.77704064318	4/17/1945	0.94722560298	79	3/8/1945	0.86213312308	Int
Bushnell	1/28/1945	0.77704064318	7/4/1945	1.11741056278	157	4/17/1945	0.94722560298	Int
Bushnell	1/28/1945	0.77704064318	12/7/1945	1.45778048239	313	7/4/1945	1.11741056278	Int
Bushnell	1/28/1945	0.77704064318	10/15/1946	2.13852032159	625	12/7/1945	1.45778048239	Int
Bushnell	1/28/1945	0.77704064318	7/2/1948	3.5	1251	10/15/1946	2.13852032159	Int
Bushnell	12/18/1944	0.69008565806	1/8/1945	0.73399056965	21	12/29/1944	0.71203811385	Int
Bushnell	1/9/1945	0.73381906609	3/29/1945	0.90670537446	79	2/17/1945	0.82026222027	Int
Bushnell	12/29/1944	0.71203811385	7/2/1948	3.5	1281	10/1/1946	2.10601905693	Int
Bushnell	1/9/1945	0.73381906609	11/22/1945	1.42536429957	317	6/17/1945	1.07959168283	Int
Bushnell	1/9/1945	0.73381906609	10/6/1946	2.11690953304	635	11/22/1945	1.42536429957	Int
Bushnell	1/9/1945	0.73381906609	7/2/1948	3.5	1270	10/6/1946	2.11690953304	Int
Bushnell	12/29/1944	0.71203811385	1/19/1945	0.75560001832	21	1/9/1945	0.73381906609	Int
Bushnell	12/29/1944	0.71203811385	2/8/1945	0.7991619228	41	1/19/1945	0.75560001832	Int
Bushnell	12/29/1944	0.71203811385	3/20/1945	0.88628573174	81	2/8/1945	0.7991619228	Int
Bushnell	12/29/1944	0.71203811385	6/8/1945	1.06053334962	161	3/20/1945	0.88628573174	Int

Record: 1 of 883

The table above informs the user about interpolated values added to a particular data time-series to facilitate calculation of certain moving average variables. For example, in the first row, a linear interpolated value (12.05) is added on 3/23/2002 to fill a 42 day gap between 3/2/2002 and 4/13/2002. Values in columns *startvalue* (11.9) and *endvalue* (12.2) are the data associated with 3/2/2002 and 4/13/2002 respectively. This interpolation would then help in calculation of Bugg-6-week moving average variable.

Similarly, clicking *Calculate Moving Average/Apopka*, would fill the table **Apopka** with required moving average variables. Also, the **Missing Dates** table is updated for each spring. The following screenshot indicates the two tables being filled with moving average variables.


StJohns : Database (Access 2000 file format)

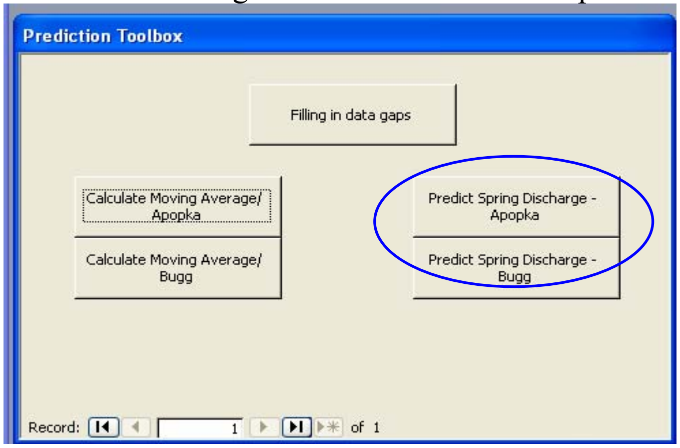
Create table in Design view
Create table by using wizard
Create table by entering data
Springs-Location
Well Location
Lake Location
Rain Station Location
Missing dates
Modified_data
Apopka
Bugg
Bugg-Frequency-district
Bugg Frequency Table-district
Bugg-predictions
Apopka-Frequency-district
Apopka Frequency Table-district
Original Data
Apopka-predictions

5. Calculate Spring discharge predictions and frequency analysis

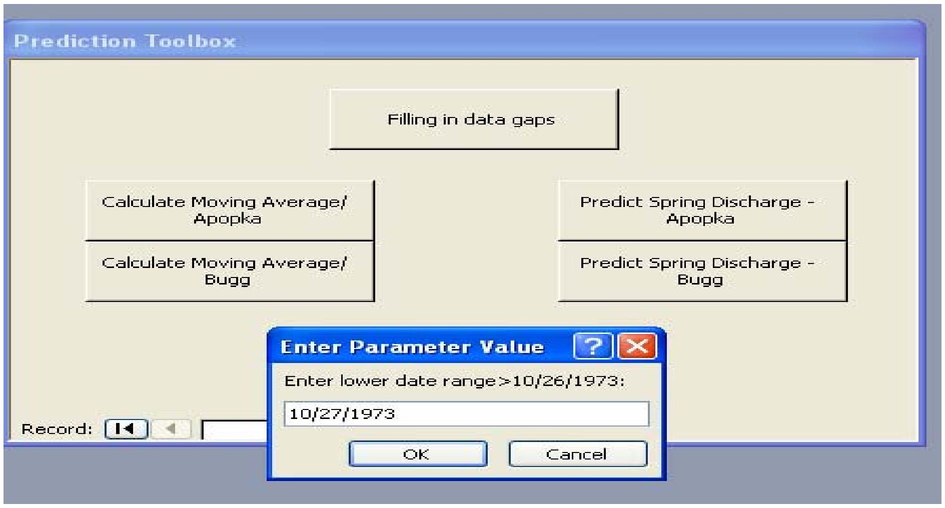
Spring discharge daily predictions are limited by a range of lower and upper date. This is due to limited date range coverage for explanatory variables in the statistical model for a particular spring. The following are the dates for the two springs for which daily discharge predictions can be computed:

Spring	Date Range for discharge predictions
Apopka	6/2/1949 to 12/31/2005
Bugg	10/27/1973 to 11/28/2005

Clicking the buttons highlighted below give daily discharge predictions and maximum and minimum frequencies for date ranges specified by the user. Note that these date ranges have to fall within the ranges mentioned above for a particular spring

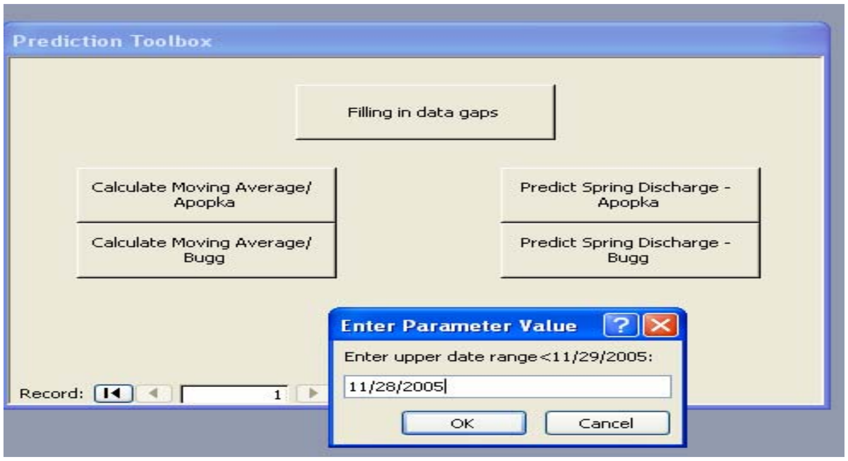

Prediction Toolbox
Filling in data gaps
Calculate Moving Average/ Apopka
Calculate Moving Average/ Bugg
Predict Spring Discharge - Apopka
Predict Spring Discharge - Bugg
Record: 1 of 1

For example, on clicking *Predict Spring Discharge - Bugg*, we see a pop-up window asking for the date from which predictions are needed. For our example enter 10/27/1973. As noted earlier, the date entered should be greater than 10/26/1973, since Bugg Spring predictions are only available since that date.


Prediction Toolbox
Filling in data gaps
Calculate Moving Average/ Apopka
Calculate Moving Average/ Bugg
Predict Spring Discharge - Apopka
Predict Spring Discharge - Bugg
Record:
Enter Parameter Value
OK
Cancel

Enter lower date range>10/26/1973:
10/27/1973

Press OK. Another window asking for the date till which predictions are needed. For our example enter 11/28/2005. Again the date entered should be less than 11/29/2005, since Bugg Spring predictions are only available till 11/28/2005.

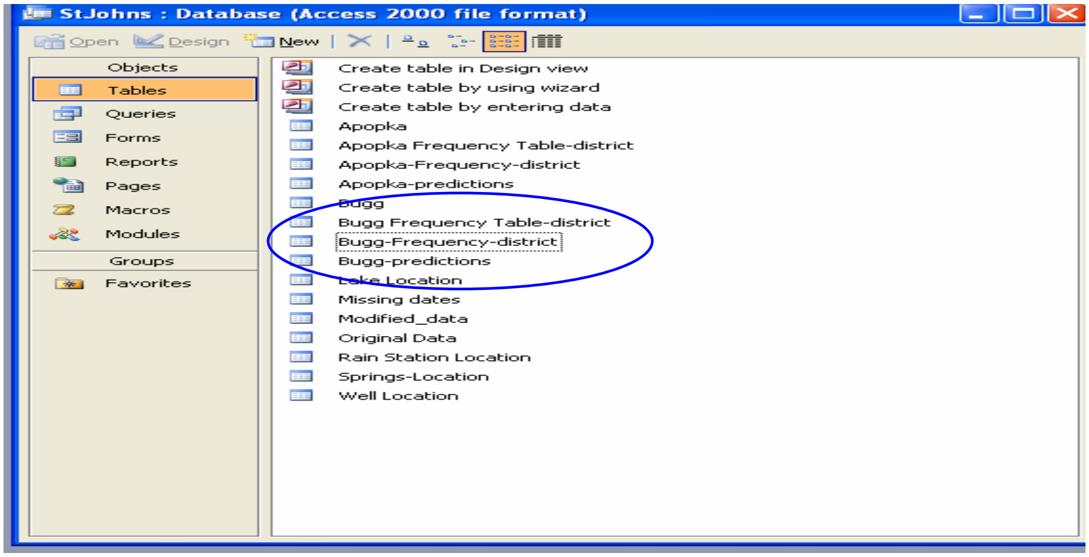


Prediction Toolbox
Filling in data gaps
Calculate Moving Average/ Apopka
Calculate Moving Average/ Bugg
Predict Spring Discharge - Apopka
Predict Spring Discharge - Bugg
Record: 1
Enter Parameter Value
OK
Cancel

Enter upper date range<11/29/2005:

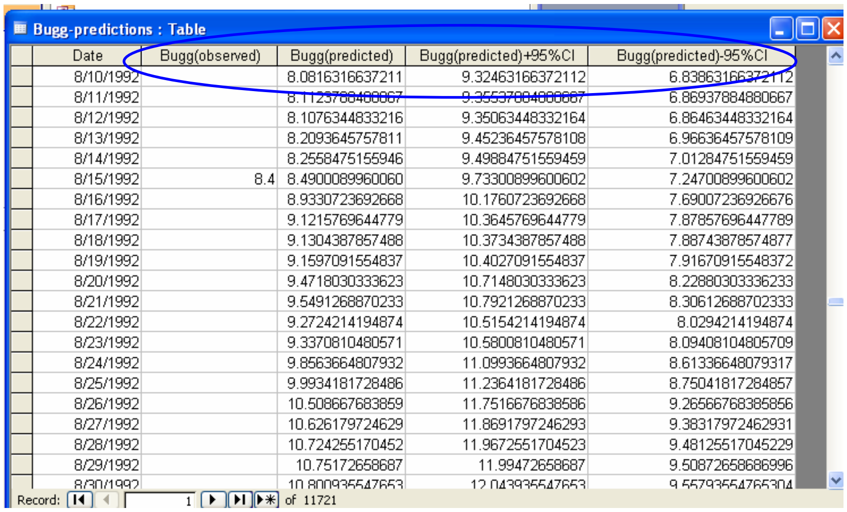
11/28/2005

On pressing OK, tables called **<u>Bugg-predictions, Bugg-Frequency-district and Bugg Frequency table-District</u>** are added to the ACCESS database as shown below:



Create table in Design view
Create table by using wizard
Create table by entering data
Apopka
Apopka Frequency Table-district
Apopka-Frequency-district
Apopka-predictions
Bugg
Bugg Frequency Table-district
Bugg-Frequency-district
Bugg-predictions
Lake Location
Missing dates
Modified_data
Original Data
Rain Station Location
Springs-Location
Well Location

Double click Bugg-predictions table to view. The screenshot on next page shows the observed Bugg discharge data and the predicted Bugg discharge data, between the lower and upper date ranges we entered.

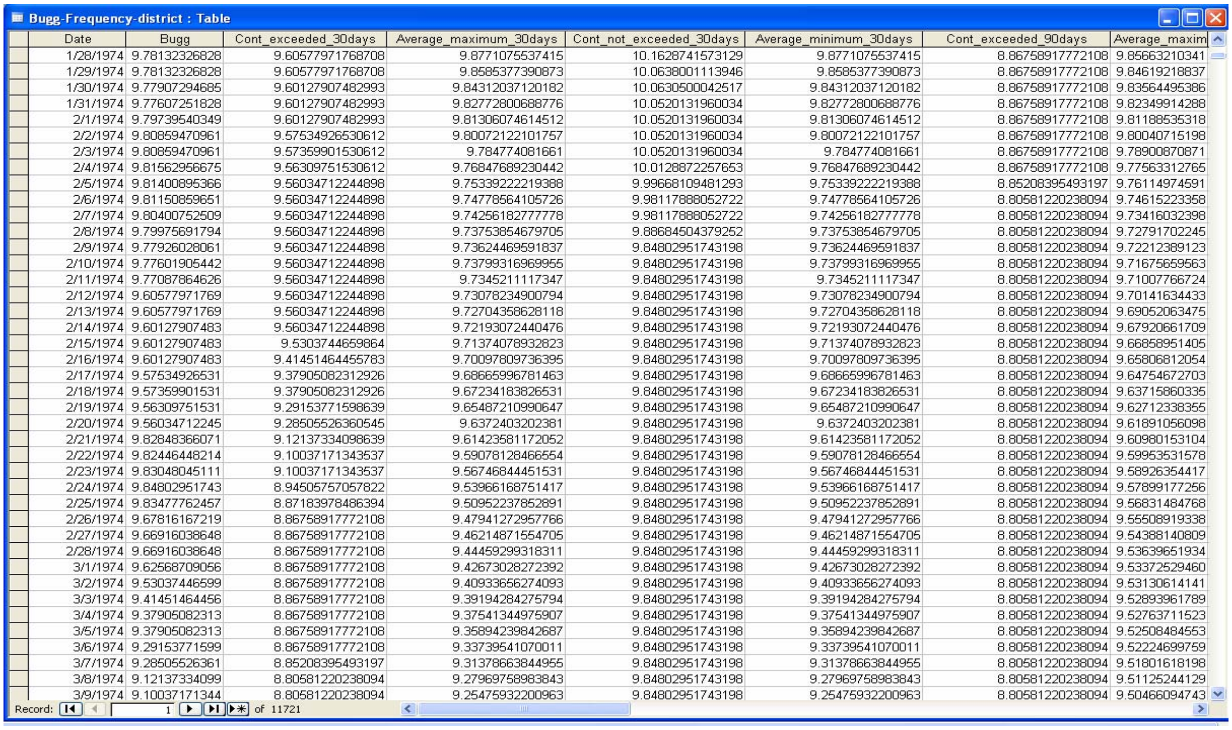


Bugg-predictions : Table

Date	Bugg(observed)	Bugg(predicted)	Bugg(predicted)+95%CI	Bugg(predicted)-95%CI
8/10/1992		8.0816316637211	9.32463166372112	6.83863166372112
8/11/1992		8.11237884880667	9.35537884880667	6.86937884880667
8/12/1992		8.1076344833216	9.35063448332164	6.86463448332164
8/13/1992		8.2093645757811	9.45236457578108	6.96636457578109
8/14/1992		8.2558475155946	9.49884751559459	7.01284751559459
8/15/1992	8.4	8.4900089960060	9.73300899600602	7.24700899600602
8/16/1992		8.9330723692668	10.1760723692668	7.69007236926676
8/17/1992		9.1215769644779	10.3645769644779	7.87857696447789
8/18/1992		9.1304387857488	10.3734387857488	7.88743878574877
8/19/1992		9.1597091554837	10.4027091554837	7.91670915548372
8/20/1992		9.4718030333623	10.7148030333623	8.22880303336233
8/21/1992		9.5491268870233	10.7921268870233	8.30612688702333
8/22/1992		9.2724214194874	10.5154214194874	8.0294214194874
8/23/1992		9.3370810480571	10.5800810480571	8.09408104805709
8/24/1992		9.8563664807932	11.0993664807932	8.61336648079317
8/25/1992		9.9934181728486	11.2364181728486	8.75041817284857
8/26/1992		10.508667683859	11.7516676838586	9.26566768385856
8/27/1992		10.626179724629	11.8691797246293	9.38317972462931
8/28/1992		10.724255170452	11.9672551704523	9.48125517045229
8/29/1992		10.75172658687	11.99472658687	9.50872658686996
8/30/1992		10.800935547653	12.043935547653	9.55793554765304

The highlighted columns above show Observed Bugg Discharge data, Bugg discharge predictions, Bugg discharge predictions upper (+) and lower (-) 95% confidence interval.

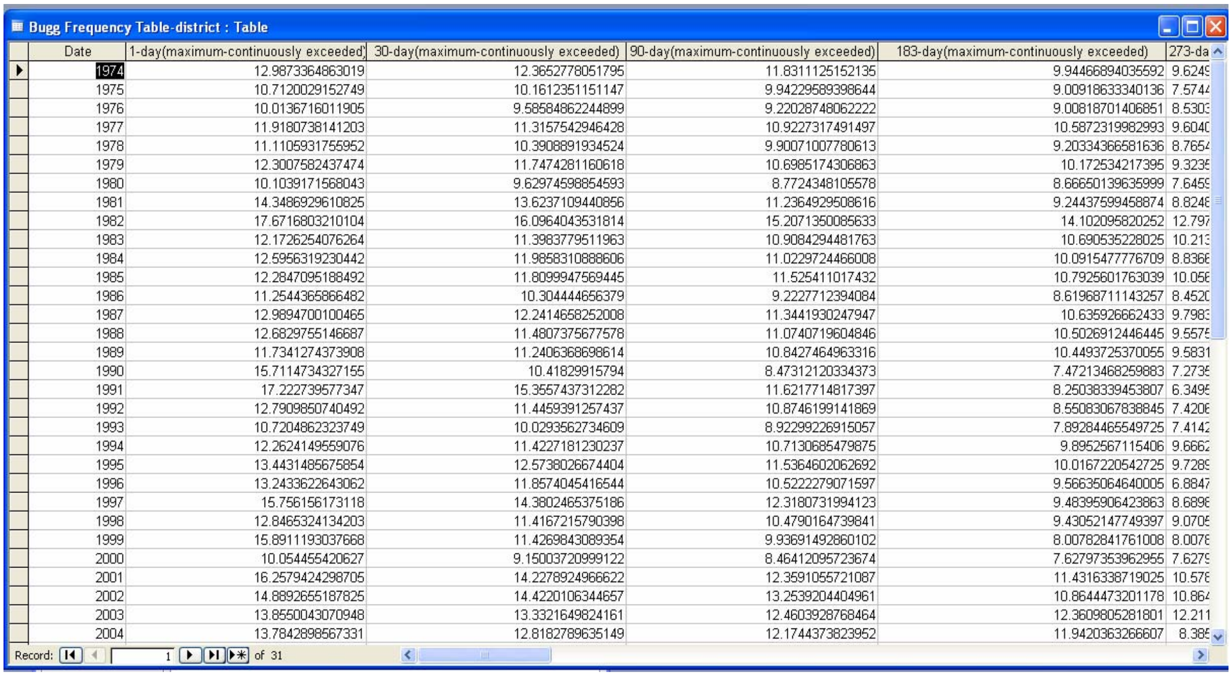
Double-click table **Bugg-Frequency-district** to view. The table has continuously-exceeded and average values for 1-day, 30-day, 90-day, 183-day, 273-day and 365-day periods for each year starting on June 1 of a year and ending on May 31 of the next year. The table also has continuously-not-exceeded and average values for 1-day, 30-day, 90-day, 183-day, 273-day and 365-day periods for each year starting on October 1 of a year and ending on September 30 of the next year. It is important to note that each year range for picking maximums and minimums is assumed to be independent of other years. The screenshot below shows some of the columns present in the table.



Bugg-Frequency-district : Table

Date	Bugg	Cont_exceeded_30days	Average_maximum_30days	Cont_not_exceeded_30days	Average_minimum_30days	Cont_exceeded_90days	Average_maxim
1/28/1974	9.78132326828	9.60577971768708	9.8771075537415	10.1628741573129	9.8771075537415	8.86758917772108	9.85663210341
1/29/1974	9.78132326828	9.60577971768708	9.8585377390873	10.0638001113946	9.8585377390873	8.86758917772108	9.84619218837
1/30/1974	9.77907294685	9.60127907482993	9.84312037120182	10.0630500042517	9.84312037120182	8.86758917772108	9.83564495386
1/31/1974	9.77607251828	9.60127907482993	9.82772800688776	10.0520131960034	9.82772800688776	8.86758917772108	9.82349914288
2/1/1974	9.79739540349	9.60127907482993	9.81306074614512	10.0520131960034	9.81306074614512	8.86758917772108	9.81188535318
2/2/1974	9.80859470961	9.57534926530612	9.80072122101757	10.0520131960034	9.80072122101757	8.86758917772108	9.80040715198
2/3/1974	9.80859470961	9.57359901530612	9.784774081661	10.0520131960034	9.784774081661	8.86758917772108	9.78900870871
2/4/1974	9.81562956675	9.56309751530612	9.76847689230442	10.0128872257653	9.76847689230442	8.86758917772108	9.77563312765
2/5/1974	9.81400895366	9.56034712244898	9.75339222219388	9.99668109481293	9.75339222219388	8.85208395493197	9.76114974591
2/6/1974	9.81150859651	9.56034712244898	9.74778564105726	9.98117888052722	9.74778564105726	8.80581220238094	9.74615223358
2/7/1974	9.80400752509	9.56034712244898	9.74256182777778	9.98117888052722	9.74256182777778	8.80581220238094	9.73416032398
2/8/1974	9.79975691794	9.56034712244898	9.73753854679705	9.88684504379252	9.73753854679705	8.80581220238094	9.72791702245
2/9/1974	9.77926028061	9.56034712244898	9.73624469591837	9.84802951743198	9.73624469591837	8.80581220238094	9.72212389123
2/10/1974	9.77601905442	9.56034712244898	9.73799316969955	9.84802951743198	9.73799316969955	8.80581220238094	9.71675659563
2/11/1974	9.77087864626	9.56034712244898	9.7345211117347	9.84802951743198	9.7345211117347	8.80581220238094	9.71007766724
2/12/1974	9.60577971769	9.56034712244898	9.73078234900794	9.84802951743198	9.73078234900794	8.80581220238094	9.70141634433
2/13/1974	9.60577971769	9.56034712244898	9.72704358628118	9.84802951743198	9.72704358628118	8.80581220238094	9.69052063475
2/14/1974	9.60127907483	9.56034712244898	9.72193072440476	9.84802951743198	9.72193072440476	8.80581220238094	9.67920661709
2/15/1974	9.60127907483	9.5303744659864	9.71374078932823	9.84802951743198	9.71374078932823	8.80581220238094	9.66858951405
2/16/1974	9.60127907483	9.41451464455783	9.70097809736395	9.84802951743198	9.70097809736395	8.80581220238094	9.65806812054
2/17/1974	9.57534926531	9.37905082312926	9.68665996781463	9.84802951743198	9.68665996781463	8.80581220238094	9.64754672703
2/18/1974	9.57359901531	9.37905082312926	9.67234183826531	9.84802951743198	9.67234183826531	8.80581220238094	9.63715860335
2/19/1974	9.56309751531	9.29153771598639	9.65487210990647	9.84802951743198	9.65487210990647	8.80581220238094	9.62712338355
2/20/1974	9.56034712245	9.28505526360545	9.6372403202381	9.84802951743198	9.6372403202381	8.80581220238094	9.61891056098
2/21/1974	9.82848366071	9.12137334098639	9.61423581172052	9.84802951743198	9.61423581172052	8.80581220238094	9.60980153104
2/22/1974	9.82446448214	9.10037171343537	9.59078128466554	9.84802951743198	9.59078128466554	8.80581220238094	9.59953531578
2/23/1974	9.83048045111	9.10037171343537	9.56746844451531	9.84802951743198	9.56746844451531	8.80581220238094	9.58926354417
2/24/1974	9.84802951743	8.94505757057822	9.53966168751417	9.84802951743198	9.53966168751417	8.80581220238094	9.57899177256
2/25/1974	9.83477762457	8.87183978486394	9.50952237852891	9.84802951743198	9.50952237852891	8.80581220238094	9.56831484768
2/26/1974	9.67816167219	8.86758917772108	9.47941272957766	9.84802951743198	9.47941272957766	8.80581220238094	9.55508919338
2/27/1974	9.66916038648	8.86758917772108	9.46214871554705	9.84802951743198	9.46214871554705	8.80581220238094	9.54388140809
2/28/1974	9.66916038648	8.86758917772108	9.44459299318311	9.84802951743198	9.44459299318311	8.80581220238094	9.53639651934
3/1/1974	9.62568709056	8.86758917772108	9.42673028272392	9.84802951743198	9.42673028272392	8.80581220238094	9.53372529460
3/2/1974	9.53037446599	8.86758917772108	9.40933656274093	9.84802951743198	9.40933656274093	8.80581220238094	9.53130614141
3/3/1974	9.41451464456	8.86758917772108	9.39194284275794	9.84802951743198	9.39194284275794	8.80581220238094	9.52893961789
3/4/1974	9.37905082313	8.86758917772108	9.37541344975907	9.84802951743198	9.37541344975907	8.80581220238094	9.52763711523
3/5/1974	9.37905082313	8.86758917772108	9.35894239842687	9.84802951743198	9.35894239842687	8.80581220238094	9.52508484553
3/6/1974	9.29153771599	8.86758917772108	9.33739541070011	9.84802951743198	9.33739541070011	8.80581220238094	9.52224699759
3/7/1974	9.28505526361	8.85208395493197	9.31378663844955	9.84802951743198	9.31378663844955	8.80581220238094	9.51801618198
3/8/1974	9.12137334099	8.80581220238094	9.27969758983843	9.84802951743198	9.27969758983843	8.80581220238094	9.51125244129
3/9/1974	9.10037171344	8.80581220238094	9.25475932200963	9.84802951743198	9.25475932200963	8.80581220238094	9.50466094743

Double-click table **Bugg Frequency Table-district** to view. The table contains the maximums from 1-day, 30-day, 90-day, 183-day, 273-day and 365-day continuously-exceeded and average time-series for each year. The table also contains the minimums from 1-day, 30-day, 90-day, 183-day, 273-day and 365-day continuously-not-exceeded and average time-series for each year. The screenshot below shows a few columns from the table

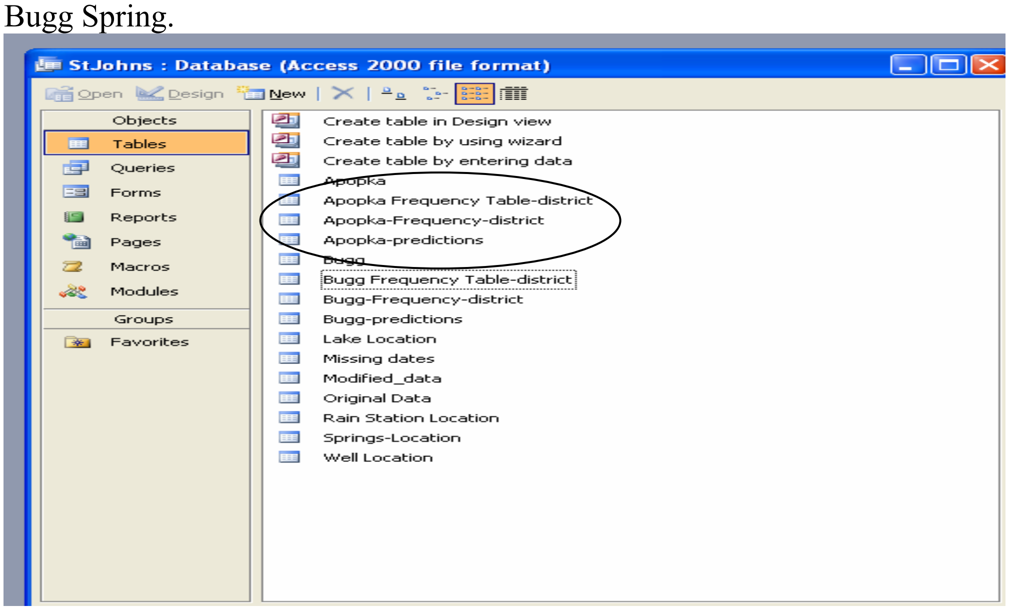


Bugg Frequency Table-district : Table

Date	1-day(maximum-continuously exceeded)	30-day(maximum-continuously exceeded)	90-day(maximum-continuously exceeded)	183-day(maximum-continuously exceeded)	273-da
1974	12.9873364863019	12.3652778051795	11.8311125152135	9.94466894035592	9.624
1975	10.7120029152749	10.1612351151147	9.94229589398644	9.00918633340136	7.574
1976	10.0136716011905	9.58584862244899	9.22028748062222	9.00818701406851	8.530
1977	11.9180738141203	11.3157542946428	10.9227317491497	10.5872319982993	9.604
1978	11.1105931755952	10.3908891934524	9.90071007780613	9.20334366581636	8.765
1979	12.3007582437474	11.7474281160618	10.6985174306863	10.172534217395	9.323
1980	10.1039171568043	9.62974598854593	8.7724348105578	8.66650139635999	7.645
1981	14.3486929610825	13.6237109440856	11.2364929508616	9.24437599458874	8.824
1982	17.6716803210104	16.0964043531814	15.2071350085633	14.102095820252	12.797
1983	12.1726254076264	11.3983779511963	10.9084294481763	10.690535228025	10.21
1984	12.5956319230442	11.9858310888606	11.0229724466008	10.0915477776709	8.836
1985	12.2847095188492	11.8099947569445	11.525411017432	10.7925601763039	10.05
1986	11.2544365866482	10.304444656379	9.2227712394084	8.61968711143257	8.452
1987	12.9894700100465	12.2414658252008	11.3441930247947	10.635926662433	9.798
1988	12.6829755146687	11.4807375677578	11.0740719604846	10.5026912446445	9.557
1989	11.7341274373908	11.2406368698614	10.8427464963316	10.4493725370055	9.5831
1990	15.7114734327155	10.41829915794	8.47312120334373	7.47213468259883	7.273
1991	17.222739577347	15.3557437312282	11.6217714817397	8.25038339453807	6.349
1992	12.7909850740492	11.4459391257437	10.8746199141869	8.55083067838845	7.420
1993	10.7204862323749	10.0293562734609	8.92299226915057	7.89284465549725	7.414
1994	12.2624149559076	11.4227181230237	10.7130685479875	9.8952567115406	9.666
1995	13.4431485675854	12.5738026674404	11.5364602062692	10.0167220542725	9.728
1996	13.2433622643062	11.8574045416544	10.5222279071597	9.56635064640005	6.8847
1997	15.756156173118	14.3802465375186	12.3180731994123	9.48395906423863	8.689
1998	12.8465324134203	11.4167215790398	10.4790164739841	9.43052147749397	9.070
1999	15.8911193037668	11.4269843089354	9.93691492860102	8.00782841761008	8.007
2000	10.054455420627	9.15003720999122	8.46412095723674	7.62797353962955	7.627
2001	16.2579424298705	14.2278924966622	12.3591055721087	11.4316338719025	10.57
2002	14.8892655187825	14.4220106344657	13.2539204404961	10.8644473201178	10.864
2003	13.8550043070948	13.3321649824161	12.4603928768464	12.3609805281801	12.211
2004	13.7842898567331	12.8182789635149	12.1744373823952	11.9420363266607	8.385

Record: 1 of 31

Similarly predictions and, maximum and minimum frequencies, for Apopka Spring can be obtained for any specified upper and lower date ranges. Tables **Apopka-predictions, Apopka-Frequency-District, Apopka Frequency Table-district** (shown below) are added to the database on clicking *Predict Spring Discharge – Apopka* and following all the above steps as for Bugg Spring.



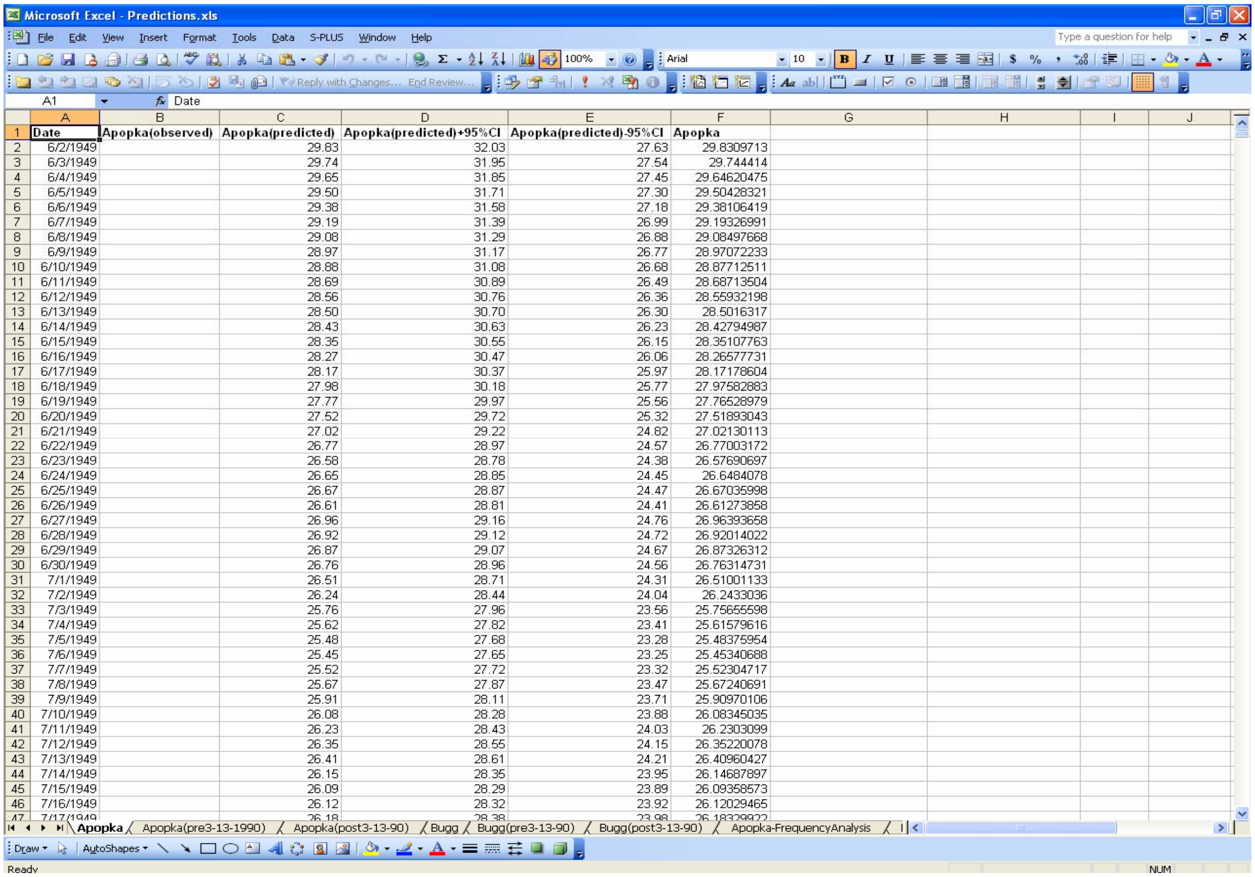
StJohns : Database (Access 2000 file format)

- Create table in Design view
- Create table by using wizard
- Create table by entering data
- Apopka
- Apopka Frequency Table-district
- Apopka-Frequency-district
- Apopka-predictions
- Bugg
- Bugg Frequency Table-district
- Bugg-Frequency-district
- Bugg-predictions
- Lake Location
- Missing dates
- Modified_data
- Original Data
- Rain Station Location
- Springs-Location
- Well Location

6. Viewing prediction plots and maximum and minimum frequencies

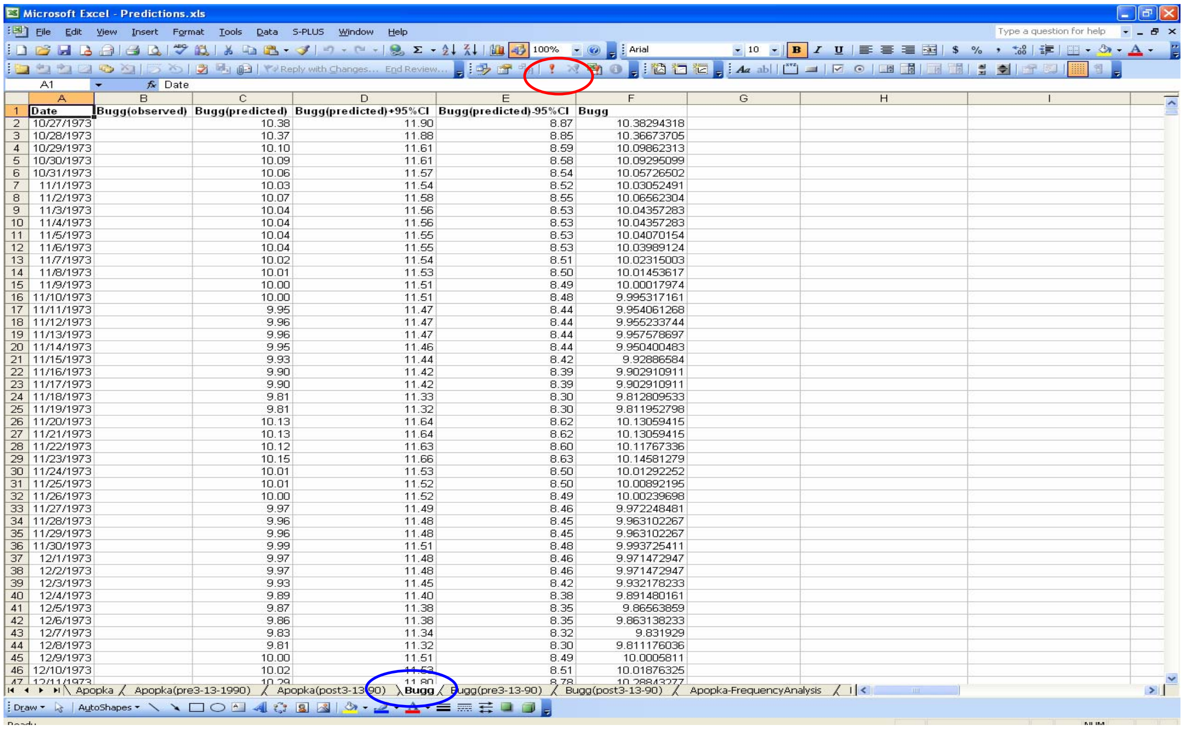
Plots of observed and predicted daily discharge data can be viewed in the EXCEL file **predictions.xls** which is linked to the prediction tables in ACCESS. The file already has been run to include daily predictions and frequencies for Apopka and Bugg springs for the complete date ranges associated with the two springs.

For our example, open **predictions.xls**. The screenshot below shows this file. By default, the *Apopka* worksheet opens up, which contains the predictions for the complete range for which daily discharge values can be computed for Apopka (6/2/1949 to 12/31/2005)



	A	B	C	D	E	F
1	Date	Apopka(observed)	Apopka(predicted)	Apopka(predicted)+95%CI	Apopka(predicted)-95%CI	Apopka
2	6/2/1949		29.83	32.03	27.63	29.8309713
3	6/3/1949		29.74	31.95	27.54	29.744414
4	6/4/1949		29.65	31.85	27.45	29.64620475
5	6/5/1949		29.50	31.71	27.30	29.50428321
6	6/6/1949		29.38	31.58	27.18	29.38106419
7	6/7/1949		29.19	31.39	26.99	29.19326991
8	6/8/1949		29.08	31.29	26.88	29.08497668
9	6/9/1949		28.97	31.17	26.77	28.97072233
10	6/10/1949		28.88	31.08	26.68	28.87712511
11	6/11/1949		28.69	30.89	26.49	28.68713504
12	6/12/1949		28.56	30.76	26.36	28.55932198
13	6/13/1949		28.50	30.70	26.30	28.5016317
14	6/14/1949		28.43	30.63	26.23	28.42794987
15	6/15/1949		28.35	30.55	26.15	28.35107763
16	6/16/1949		28.27	30.47	26.06	28.26577731
17	6/17/1949		28.17	30.37	25.97	28.17178604
18	6/18/1949		27.98	30.18	25.77	27.97582883
19	6/19/1949		27.77	29.97	25.56	27.76528979
20	6/20/1949		27.52	29.72	25.32	27.51893043
21	6/21/1949		27.02	29.22	24.82	27.02130113
22	6/22/1949		26.77	28.97	24.57	26.77003172
23	6/23/1949		26.58	28.78	24.38	26.57690697
24	6/24/1949		26.65	28.85	24.45	26.6484078
25	6/25/1949		26.67	28.87	24.47	26.67035998
26	6/26/1949		26.61	28.81	24.41	26.61273858
27	6/27/1949		26.96	29.16	24.76	26.96393658
28	6/28/1949		26.92	29.12	24.72	26.92014022
29	6/29/1949		26.87	29.07	24.67	26.87326312
30	6/30/1949		26.76	28.96	24.56	26.76314731
31	7/1/1949		26.51	28.71	24.31	26.51001133
32	7/2/1949		26.24	28.44	24.04	26.2433036
33	7/3/1949		25.76	27.96	23.56	25.75655598
34	7/4/1949		25.62	27.82	23.41	25.61579616
35	7/5/1949		25.48	27.68	23.28	25.48375954
36	7/6/1949		25.45	27.65	23.25	25.45340688
37	7/7/1949		25.52	27.72	23.32	25.52304717
38	7/8/1949		25.67	27.87	23.47	25.67240691
39	7/9/1949		25.91	28.11	23.71	25.90970106
40	7/10/1949		26.08	28.28	23.88	26.08345035
41	7/11/1949		26.23	28.43	24.03	26.2303099
42	7/12/1949		26.35	28.55	24.15	26.35220078
43	7/13/1949		26.41	28.61	24.21	26.40960427
44	7/14/1949		26.15	28.35	23.95	26.14687897
45	7/15/1949		26.09	28.29	23.89	26.09358573
46	7/16/1949		26.12	28.32	23.92	26.12029465
47	7/17/1949		26.18	28.38	23.98	26.18329922

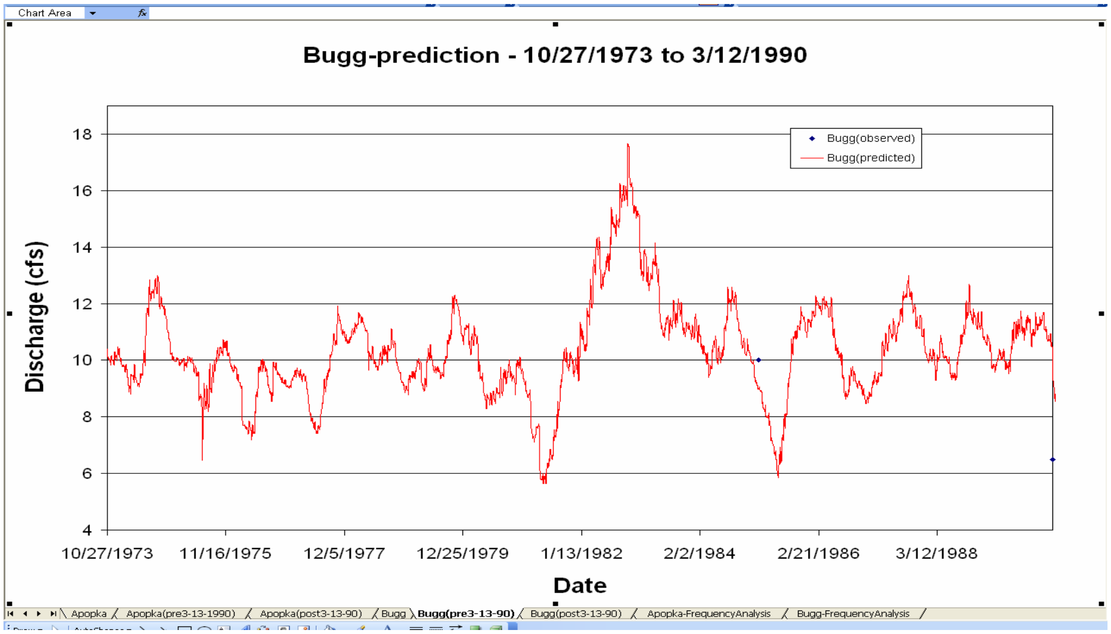
Click worksheet *Bugg* as shown below. We see the daily predictions for Bugg:



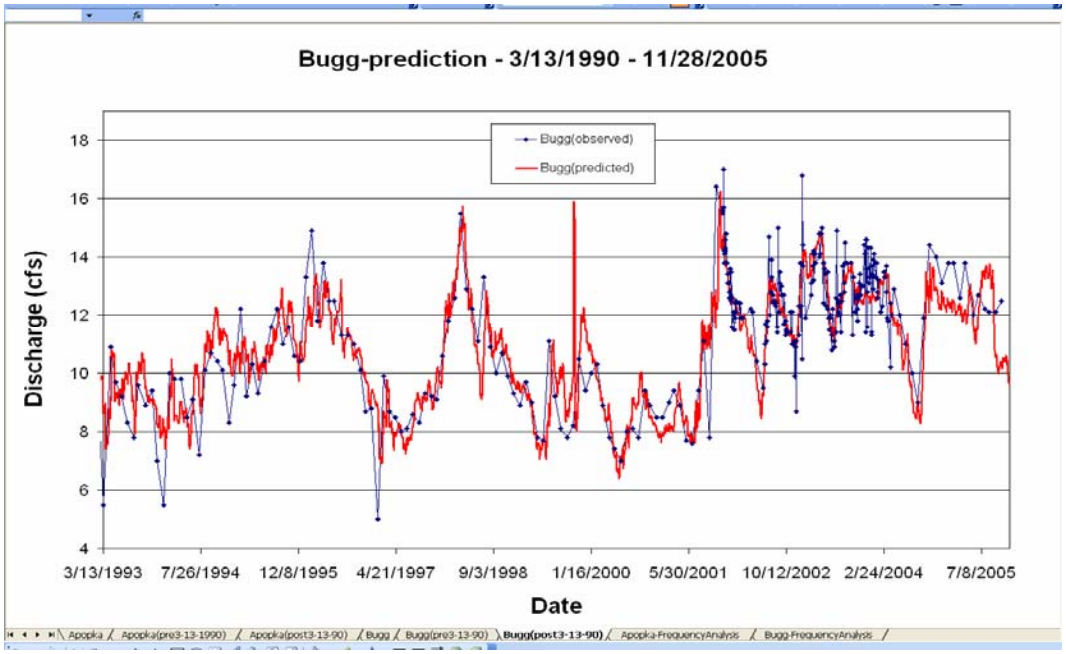
	A	B	C	D	E	F
1	Date	Bugg(observed)	Bugg(predicted)	Bugg(predicted)+95%CI	Bugg(predicted)-95%CI	Bugg
2	10/27/1973		10.38	11.90	8.87	10.38294318
3	10/28/1973		10.37	11.88	8.85	10.36673705
4	10/29/1973		10.10	11.61	8.59	10.09862313
5	10/30/1973		10.09	11.61	8.58	10.09295099
6	10/31/1973		10.06	11.57	8.54	10.05726502
7	11/1/1973		10.03	11.54	8.52	10.03052491
8	11/2/1973		10.07	11.58	8.55	10.06562304
9	11/3/1973		10.04	11.56	8.53	10.04357283
10	11/4/1973		10.04	11.56	8.53	10.04357283
11	11/5/1973		10.04	11.55	8.53	10.04070154
12	11/6/1973		10.04	11.55	8.53	10.03989124
13	11/7/1973		10.02	11.54	8.51	10.02315003
14	11/8/1973		10.01	11.53	8.50	10.01453617
15	11/9/1973		10.00	11.51	8.49	10.00017974
16	11/10/1973		10.00	11.51	8.48	9.995317161
17	11/11/1973		9.95	11.47	8.44	9.954061268
18	11/12/1973		9.96	11.47	8.44	9.955233744
19	11/13/1973		9.96	11.47	8.44	9.957578697
20	11/14/1973		9.95	11.46	8.44	9.950400483
21	11/15/1973		9.93	11.44	8.42	9.92886584
22	11/16/1973		9.90	11.42	8.39	9.902910911
23	11/17/1973		9.90	11.42	8.39	9.902910911
24	11/18/1973		9.81	11.33	8.30	9.812809533
25	11/19/1973		9.81	11.32	8.30	9.811952798
26	11/20/1973		10.13	11.64	8.62	10.13059415
27	11/21/1973		10.13	11.64	8.62	10.13059415
28	11/22/1973		10.12	11.63	8.60	10.11767336
29	11/23/1973		10.15	11.66	8.63	10.14581279
30	11/24/1973		10.01	11.53	8.50	10.01292252
31	11/25/1973		10.01	11.52	8.50	10.00892195
32	11/26/1973		10.00	11.52	8.49	10.00239698
33	11/27/1973		9.97	11.49	8.46	9.972248481
34	11/28/1973		9.96	11.48	8.45	9.963102267
35	11/29/1973		9.96	11.48	8.45	9.963102267
36	11/30/1973		9.99	11.51	8.48	9.993725411
37	12/1/1973		9.97	11.48	8.46	9.971472947
38	12/2/1973		9.97	11.48	8.46	9.971472947
39	12/3/1973		9.93	11.45	8.42	9.932178233
40	12/4/1973		9.89	11.40	8.38	9.891480161
41	12/5/1973		9.87	11.38	8.35	9.86563859
42	12/6/1973		9.86	11.38	8.35	9.863138233
43	12/7/1973		9.83	11.34	8.32	9.831929
44	12/8/1973		9.81	11.32	8.30	9.811176036
45	12/9/1973		10.00	11.51	8.49	10.0005811
46	12/10/1973		10.02	11.53	8.51	10.01876325
47	12/11/1973		10.29	11.80	8.78	10.28843277

The next step is pressing the red exclamation button to refresh the predictions for the date range which the user requested for this example, i.e. 10/27/1973 to 11/28/2005. The exclamation mark is highlighted by a red ellipse in the above figure.

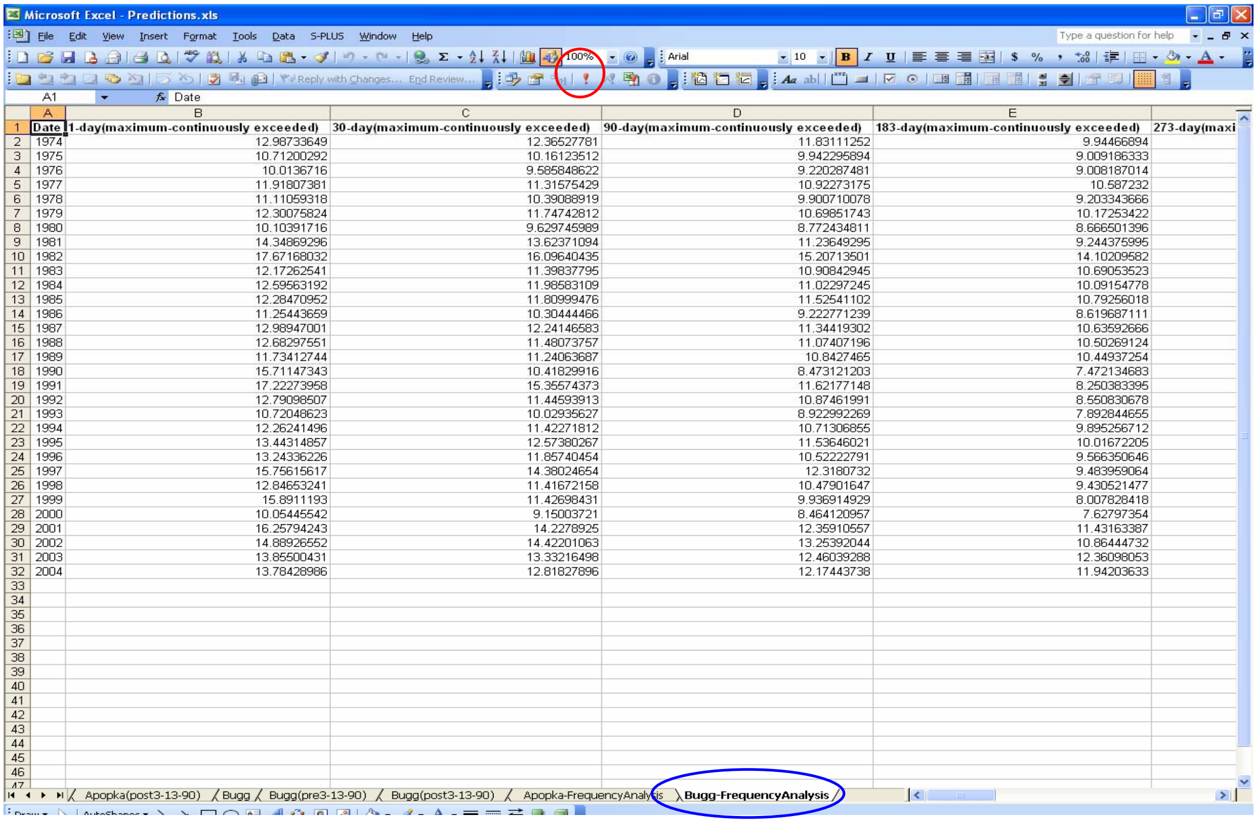
To view the plots for the above data, click on worksheet *Bugg (pre3-13-90)* for predictions before 3/13/1990 and worksheet *Bugg (post3-13-90)* for predictions from 3/13/1990. The worksheets have been highlighted in the figure above. The screenshot below shows worksheet *Bugg (pre3-13-90)*:



Also, the screenshot below shows worksheet *Bugg (post3-13-990)*:



The procedure to view maximum and minimum frequencies is similar to viewing predictions. Click worksheet *Bugg-FrequencyAnalysis* as shown below. We see the maximum and minimum frequencies for Bugg for the year range 1974-2004



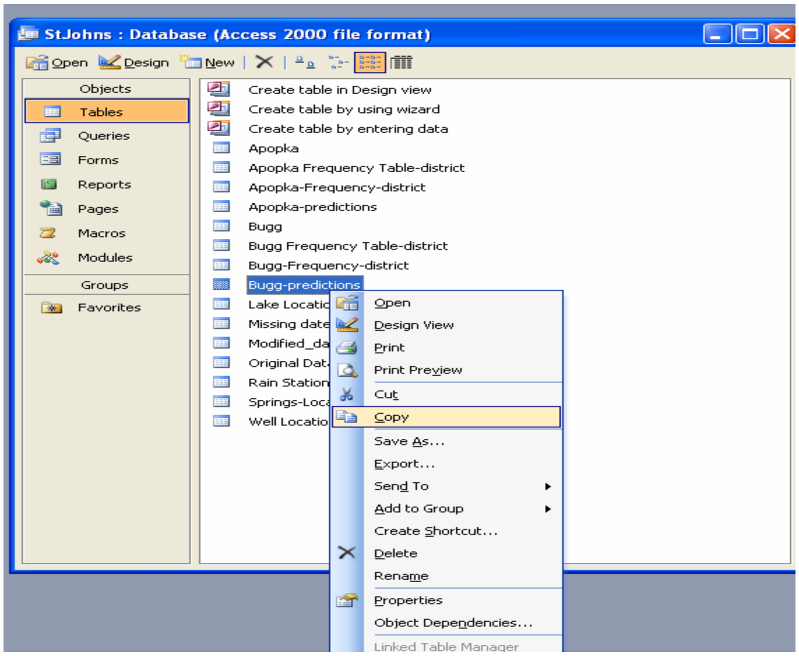
Date	1-day(maximum-continuously exceeded)	30-day(maximum-continuously exceeded)	90-day(maximum-continuously exceeded)	183-day(maximum-continuously exceeded)	273-day(maxi
1974	12.98733649	12.36527781	11.83111252	9.94466894	
1975	10.71200292	10.16123512	9.942295894	9.009186333	
1976	10.0136716	9.585848622	9.220287481	9.008187014	
1977	11.91807381	11.31575429	10.92273175	10.587232	
1978	11.11059318	10.39088919	9.900710078	9.203343666	
1979	12.30075824	11.74742812	10.69851743	10.17253422	
1980	10.10391716	9.629745989	8.772434811	8.666501396	
1981	14.34869296	13.62371094	11.23649295	9.244375995	
1982	17.67168032	16.09640435	15.20713501	14.10209582	
1983	12.17262541	11.39837795	10.90842945	10.69053523	
1984	12.59563192	11.98583109	11.02297245	10.09154778	
1985	12.28470952	11.80999476	11.52541102	10.79256018	
1986	11.25443659	10.30444466	9.222771239	8.619687111	
1987	12.98947001	12.24146583	11.34419302	10.63592666	
1988	12.68297551	11.48073757	11.07407196	10.50269124	
1989	11.73412744	11.24063687	10.8427465	10.44937254	
1990	15.71147343	10.41829916	8.473121203	7.472134683	
1991	17.22273958	15.35574373	11.62177148	8.250383395	
1992	12.79098507	11.44593913	10.87461991	8.550830678	
1993	10.72048623	10.02935627	8.922992269	7.892844655	
1994	12.26241496	11.42271812	10.71306855	9.895256712	
1995	13.44314857	12.57380267	11.53646021	10.01672205	
1996	13.24336226	11.85740454	10.52222791	9.566350646	
1997	15.75615617	14.38024654	12.3180732	9.483959064	
1998	12.84653241	11.41672158	10.47901647	9.430521477	
1999	15.8911193	11.42698431	9.936914929	8.007828418	
2000	10.05445542	9.15003721	8.464120957	7.62797354	
2001	16.25794243	14.2278925	12.35910557	11.43163387	
2002	14.88926552	14.42201063	13.25392044	10.86444732	
2003	13.85500431	13.33216498	12.46039288	12.36098053	
2004	13.78428986	12.81827896	12.17443738	11.94203633	

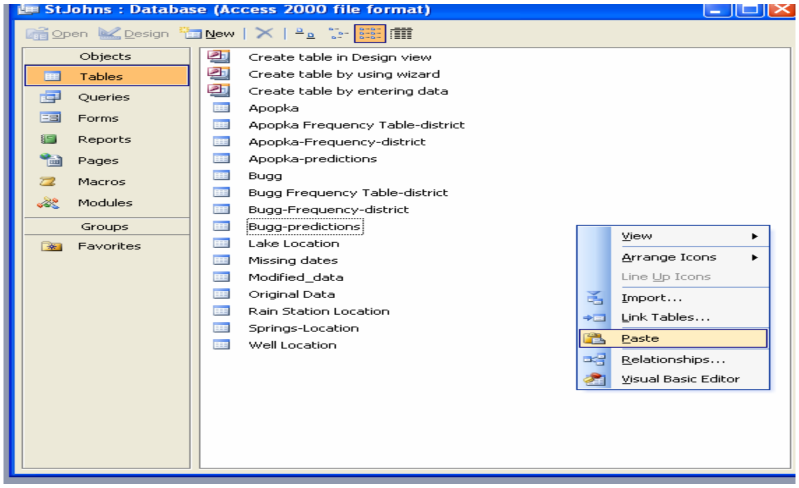
The next step is pressing the red exclamation button to refresh the frequencies for the date range which the user requested for this example, i.e. 10/27/1973 to 11/28/2005. The exclamation mark is highlighted by a red ellipse in the above figure.

The table above only shows the maximum and minimum frequencies for the years they can be computed.

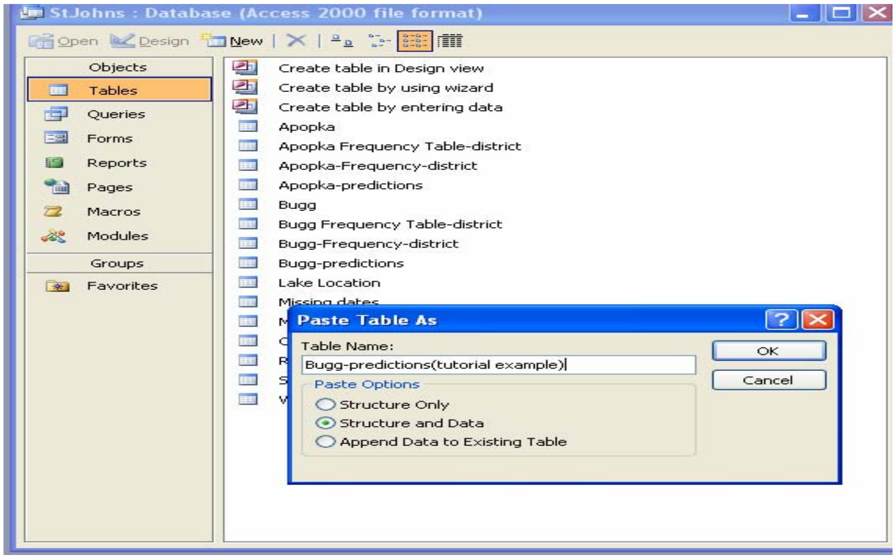
7. <u>Saving results for different cases</u>

To save the daily discharge predictions and frequencies for a particular set of well or spring data in **<u>Original Data</u>** table, make another copy of the prediction tables in ACCESS and give them a different name. This step is crucial since for a new set of data, the prediction and frequency tables are overwritten. In our example for instance, copy the Bugg-predictions table as shown below:





ACCESS prompts for a new name as shown below:

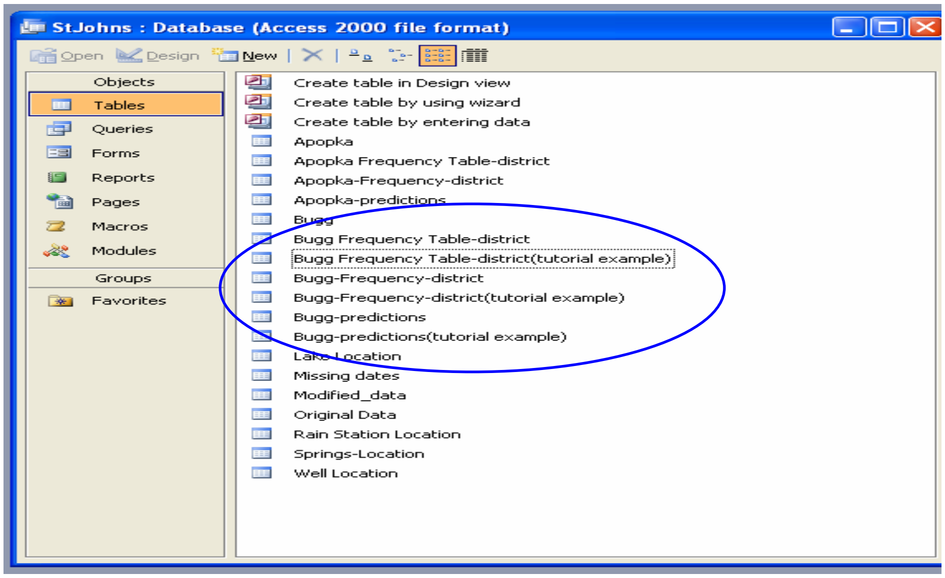


Create table in Design view
Create table by using wizard
Create table by entering data
Apopka
Apopka Frequency Table-district
Apopka-Frequency-district
Apopka-predictions
Bugg
Bugg Frequency Table-district
Bugg-Frequency-district
Bugg-predictions
Lake Location
Missing dates

Table Name: Bugg-predictions(tutorial example)

Paste Options
○ Structure Only
● Structure and Data
○ Append Data to Existing Table

Enter a table name and press OK. The prediction table for our example is created. Similarly create new tables for the Bugg-frequency-district and Bugg Frequency Table-district. The highlighted tables in the screenshot are the new tables created.



Create table in Design view
Create table by using wizard
Create table by entering data
Apopka
Apopka Frequency Table-district
Apopka-Frequency-district
Apopka-predictions
Bugg
Bugg Frequency Table-district
Bugg Frequency Table-district(tutorial example)
Bugg-Frequency-district
Bugg-Frequency-district(tutorial example)
Bugg-predictions
Bugg-predictions(tutorial example)
Lake Location
Missing dates
Modified_data
Original Data
Rain Station Location
Springs-Location
Well Location

It is also necessary to save the predictions and frequencies in **predictions.xls** in a different file before the prediction worksheets in EXCEL are refreshed to get predictions for a different case.

APPENDIX B
Resolution of Peer Review Comments

APPENDIX B: Resolution of Peer Review Comments.

Appendix B contains the comments provided by peer review of the first report in this Statistical Modeling of Spring Discharge series and the author's resolution of these comments. This peer review and the subsequent resolution pertain to application of statistical methodology and are, therefore, included in this report as well. The report modifications included some comments on potential use of the presented models as well as a clear statement of the models objectives.

NEWFIELDS

Memorandum

TO: Bob Epting, St. Johns River Water Management District

FROM: Shahrokh Rouhani, Ph.D., P.E., NewFields

SUBJECT: Peer review of “Statistical Modeling of Spring Discharge at Ponce de Leon, Green and Gemini Springs in Volusia County Florida” by Intera (2005) and “Statistical Modeling of Spring Discharge at Apopka and Bugg springs in Lake County Florida” by Intera (2006)

DATE: July 16, 2006

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INTRODUCTION

St. Johns River Water Management District (District) is engaged in ongoing Minimum Flows and Levels (MFLs) and Water Supply Development projects. Such projects require daily discharge time series at a number of springs of interest. Most of these springs suffer from sporadic discharge measurements. Intera (2005 and 2006) utilizes multiple regression models to estimate (hindcast) daily discharges at a number of springs of interest based on a variety of available nearby moving averages of measured spring discharges, groundwater levels, lake levels, and precipitation rates. The estimated daily discharge time series at each spring are then used to generate frequency, duration, discharge curves.

GENERAL COMMENT

In general, I must note that the reports are well written, and easy to follow. Furthermore, from a conceptual point of view, multiple regression of nearby hydrologic data to fill the gaps in times series of daily spring discharges is quite acceptable. The resulting estimated time series and frequency curves also display reasonable patterns consistent with existing, albeit limited, discharge measurements at the investigated springs. However, the review of the reports raises a number of fundamental questions that may warrant further considerations by the authors. These mainly statistical questions are the focus of this memorandum.

SPECIFIC COMMENTS

1. The above reports use multiple regression models that relate moving averages (MA) of nearby hydrologic data to estimate daily spring discharges. Intera (2005) presents the general form of such a model as

   [Spring discharge] = ***f*** {[same spring MA] + [water level MA]
   + [precipitation MA] + [adjacent spring MA] }

   The authors state that "the use of moving-average-based independent variables is necessitated by the fact that most independent variables are not measured on a daily basis." Although, statistical methods, including multiple regression analysis, are not bound by hydrological principals, it is always desirable to use independent variables that are hydrologically consistent with the dependent variable.

   The independent variable in the above reports is daily spring discharge, i.e. a non-integrated or *differentiated* flow variable. Daily precipitation is also a flow variable, while water levels (either groundwater or lake levels) are storage variables. Within the context of mass balance, the net sum of flows is equal to the rate of change of storage variables. In other words, in a linear model, daily spring discharge is expected to be related to (a) daily values of other flow variables (e.g. precipitation or nearby spring discharges), and (b) daily rates of changes in storage variables (e.g. water levels). This implies that under ideal conditions, non-integrated flow variables and differentiated storage variables should be used in a regression model.

   While I recognize that absence of continuous data may make some of the above differentiations impossible, I am still puzzled about the fact that all dependent variables are uniformly integrated. Integration is the exact opposite of what mass balance suggests. In fact, in cases that continuous daily time series of storage variables (e.g. groundwater or lake levels) are available; their difference values should be explored as an alternative to the current moving averages. For this purpose, continuous or augmented groundwater level time series, such as L-0054 and L-0703, along with other complete daily time series appear to be suitable candidates. I encourage the authors to consider this alternative approach, which is more consistent with the mass balance concept.

2. Intera (2006) notes the issue of multicolinearity, but suggests that computation of partial correlation coefficients (PCC) and stepwise analysis somehow solves this problem. While the use of PCC and stepwise analysis are commendable, they do not address the issue of multicolinearity.

   Multiple regression analysis is based on the fundamental assumption that the variables on the right hand side of the equation are statistically independent, i.e. uncorrelated. Multicolinearity exists when independent variables are highly correlated. Unfortunately, the reports do not contain any systematic information on cross correlations among independent variables. However, statements made in Intera (2006) concerning high correlations among certain groundwater levels (which were used to justify the filling of data gaps in some of the monitoring wells) clearly indicate that at least some of the independent variables are highly correlated. This is especially true for moving averages of the same variables, which are used concurrently as independent variables in the same model. So one can assume that some, if not all of the models used in Intera (2005 and 2006), suffer from multicolinearity.

   A high degree of multicolinearity produces unacceptable uncertainty (large variance) in regression coefficient estimates. Specifically, the coefficients can change drastically depending on which terms are in or out of the model and also the order they are placed in the model. In fact, a typical consequence of multicolinearity is a high regression coefficient, when a number of independent variables have regression coefficients that are deemed as insignificant. For example, Table 8 in Intera (2006) indicates that of the 13 independent variables used to estimate Apopka (post-1990) five variables have statistically insignificant coefficient (i.e. their p values are greater than or equal to 0.05), while R^2 of the same model is nearly 0.80. In other words, the regression results indicate that the collection of selected independent variables has explanatory power but we cannot tell which variable or to what degree the individual variable is explaining the variations of the dependent variable. Generally, such 'black-box' models are viewed as undesirable.

   I encourage the authors to consider computing the variance inflation factor (VIF) of each independent variable. VIF associated with the i^{th} independent variable is equal to

$\frac{1}{1-R_i^2}$ where R_i is the regression coefficient of the ith independent variable on all of the other independent variables. A rule of thumb is to treat any VIF in excess of 10 as evidence of multicolinearity. Elimination of collinear independent variables should continue until all VIF are below 10. This approach along with the stepwise analysis would lead to much more defensible models. Other remedies are also discussed in Gujarati (*Basic Econometrics*, 4th Edition, McGraw Hill, 2002, Chapter 10).

3. The results of predicted versus observed time series are visually satisfactory (e.g. Figure 18 in Intera, 2006); however, their corresponding observed versus predicted plots (e.g. Figure 12 in Intera 2006) display poor fits. An explanation of this visual discrepancy would be helpful. I also noticed that the updated frequency curves for Apopka and Bugg springs are much closer to the pattern exhibited by the observed data. However, the addendum dated July 11, 2006 does not describe the reason for this improvement.

4. To compare observed versus predicted discharges, the authors should also consider the comparison of their variances. Results like Figure 12 (Intera, 2006) imply that the predicted values are much less variable that measured discharges. Although, such results are not unexpected (estimated values are generally smoother than actual data), the impacts of such smoothings on the frequency curves must be discussed. Specifically, are extreme discharges adequately estimated?

   Consider the updated frequency curve for Bugg Spring (Intera addendum dated 7/11/06). While observed discharges in the central portion of the curve match their estimated values, extreme values deviate systematically, i.e. biased results. Similar patterns are present in almost all the generated frequency curves. The authors should address this issue, and if deemed significant, appropriate remedies should be considered.

TECHNICAL MEMORANDUM

PREPARED FOR:	Bob Epting, St. Johns River Water Management District
PREPARED BY:	Alaa Aly and Srikanta Mishra, INTERA Incorporated
SUBJECT:	Resolution of peer review comments of “Statistical Modeling of Spring Discharge at Ponce de Leon, Green and Gemini Springs in Volusia County Florida” by Intera (2005) and “Statistical Modeling of Spring Discharge at Apopka and Bugg springs in Lake County Florida” by Shahrokh Rouhani, NewFields
DATE:	June 19, 2007

INTRODUCTION

St. Johns River Water Management District (District) is engaged in ongoing Minimum Flows and Levels (MFLs) and Water Supply Development projects. Such projects require daily discharge time series at a number of springs of interest. Most of these springs suffer from sporadic discharge measurements. Intera (2005 and 2006) utilizes multiple regression models to estimate (hindcast) daily discharges at a number of springs of interest based on a variety of available nearby moving averages of measured spring discharges, groundwater levels, lake levels, and precipitation rates. The estimated daily discharge time series at each spring are then used to generate frequency, duration, discharge curves.

GENERAL COMMENT

We appreciate the comments from Dr. Rouhani about the validity of the approach and the clarity of the presentation in the report. The following sections address the specific comments in the peer review memorandum.

SPECIFIC COMMENTS

1. …… Within the context of mass balance, the net sum of flows is equal to the rate of change of storage variables. ……. This implies that under ideal conditions, non-integrated flow variables and differentiated storage variables should be used in a regression model. While I recognize that absence of continuous data may make some of the above differentiations impossible, I am still puzzled about the fact that all dependent variables are uniformly integrated. Integration is the exact opposite of what mass balance suggests. ……. I encourage the authors to consider this alternative approach, which is more consistent with the mass balance concept.

While mass balance would suggest exactly what the reviewer points out, the presented models are statistical, not physical. Therefore, they are not intended to be used as mass balance models. The models are based on exploitation of the statistical correlation between the explanatory and response variables. For example, spring discharge is correlated with aquifer water levels, perhaps with a lead time. This correlation explains some of the variability in the observed spring discharge rates. Further, the correlation is improved using the average water level values rather than the individual measurements which always have higher variances. However, as the reviewer notes, spring discharge can also be expected to be correlated to the change in water levels over time. These changes are a function of the "net" change of fluxes to and from the aquifer. In the absence of other significant fluxes such as recharge and pumping, these changes will be closely correlated to the observed spring discharge rates. Unobserved (e.g., pumping) and unobservable (e.g., aquifer recharge) fluxes will complicate this correlation. Further, as noted, this difference is typically very difficult to obtain from real data as data gaps can be a major obstacle for such calculation.

2. Intera (2006) notes the issue of multicolinearity, but suggests that computation of partial correlation coefficients (PCC) and stepwise analysis somehow solves this problem. …… Multiple regression analysis is based on the fundamental assumption that the variables on the right hand side of the equation are statistically independent, i.e. uncorrelated. ….. However, statements made in Intera (2006) concerning high correlations among certain groundwater levels (which were used to justify the filling of data gaps in some of the monitoring wells) clearly indicate that at least some of the independent variables are highly correlated. ...... So one can assume that some, if not all of the models used in Intera (2005 and 2006), suffer from multicolinearity. ….. I encourage the authors to consider computing the variance inflation factor (VIF) of each independent variable.

First, multicolinearity is mainly a problem for the uniqueness and variances for the regression coefficients. That is, when correlated variables are used as explanatory variables, the fitted regression coefficients will not be meaningful and might have very high variances. However, the predicted values from such regression model are still acceptable with the only issue that needs to be addressed is whether adding the correlated variable(s) have resulted in unnecessary inflation of the prediction variance. This variance inflation resulting from adding more variables to the regression equation is exactly what is considered in the stepwise regression algorithm. As detailed below, a variable is only added to the regression equation if it will improve the prediction capability of the final regression equation without adding significantly to the prediction variance. Our experience in applying stepwise regression to outputs of probabilistic risk assessment models confirms this. We have also computed variance inflation factors for the discharge models for Rock and Wekiva springs, and these also indicate that the stepwise regression process has minimized multicolinearity issues. The following description of stepwise regression provides the background information for the procedure showing how multicolinearity is formally dealt with.

In the utilized stepwise approach, a sequence of regression models is constructed starting with the input variable that explains the largest amount of variance in the output, i.e., the variable that has the highest Pearson correlation coefficient with the output. At each successive step in the regression modeling process, the variable that explains the largest fraction of unexplained variance from the previous step is included. This is the variable with the largest absolute value of the partial correlation coefficient. The model generated at every step is tested to ensure that the each of the regression coefficients is significantly different from zero. The test is implemented in two stages. First, a variable selected for entry via the PCC criterion is tested for its significance before it is admitted into the model. Second, after the model is built at that step, each of the variables in the model is tested for significance. If some variables are found to be insignificant, then the "most insignificant" variable is dropped and the model is built again. The sequential dropping of the variables judged to be not significant and rebuilding the model continues until all the variables in the model become significant at the prescribed levels. The significance levels are prescribed separately for the entering and departing variables to avoid possible looping where the same variable can enter and depart from the model with the significance level for the departing variables generally set larger than that for the entering variable. Note that the need for dropping a variable generally arises only in the cases when the input variables are strongly correlated (strong multicolinearity). This step ensures that no significant multicolinearity will be present in the final multiple regression model. The stepwise regression process continues until the input-output model contains all of the input variables that explain statistically significant amounts of variance in the output (i.e., no more variables are found with a statistically significant regression coefficient).

3. The results of predicted versus observed time series are visually satisfactory (e.g. Figure 18 in Intera, 2006); however, their corresponding observed versus predicted plots (e.g. Figure 12 in Intera 2006) display poor fits. An explanation of this visual discrepancy would be helpful. I also noticed that the updated frequency curves for Apopka and Bugg springs are much closer to the pattern exhibited by the observed data. However, the addendum dated July 11, 2006 does not describe the reason for this improvement.

Figure 18 shows that the general pattern displayed by the observed discharge hydrograph for Bugg Spring. While there is significant visual scatter shown in Figure 12, this figure also shows that the vast majority of the predicted discharge values are in agreement with the observed values. Figure 12 also shows that there in no general bias in any direction for the entire range of observed discharge values, a further affirmation for the validity of predictive model. The explanations missing from the July 11, 2006 addendum have been added to the final report.

4. To compare observed versus predicted discharges, the authors should also consider the comparison of their variances. Results like Figure 12 (Intera, 2006) imply that the predicted values are much less variable that measured discharges. Although, such results are not unexpected (estimated values are generally smoother than actual data), the impacts of such smoothings on the frequency curves must be discussed. Specifically, are extreme discharges adequately estimated?

Consider the updated frequency curve for Bugg Spring (Intera addendum dated 7/11/06). While observed discharges in the central portion of the curve match their estimated values, extreme values deviate systematically, i.e. biased results. Similar patterns are present in almost all the generated frequency curves. The authors should address this issue, and if deemed significant, appropriate remedies should be considered.

While it is not anticipated that extreme discharge values will be predicted accurately, it is important that no consistent bias is displayed by the predictive models. Figure 12 clearly shows that predicted values are not biased at either end of the observed discharge values because high and low values are equally spread around the regression line. Further, additional analyses are added to the report to examine the differences between the variances of the observed and regression-model-generated spring discharge values.