

Incorporating Hysteresis in a Load Model

Dave Lorenz

December 3, 2015

This example illustrates how to set up and incorporate hysteresis into a load model. Hysteresis occurs when concentrations (and thereby loads) are different on rising and falling limbs of an event hydrograph for the same magnitude of streamflow.

This example extends the analysis of Garrett (2012) of nitrate plus nitrite loads in the Boyer River at Logan, Iowa, USGS gaging station 06609500. The original time frame for the analysis was for water years 2004 through 2008. This example extends the analysis through water year 2012. Loads will not be estimated from this model—it demonstrates only the building and evaluation phases.

```
> # Load the necessary packages and the data
> library(rloadest)
> library(dataRetrieval)
> # Get the QW data
> Boyer <- "06609500"
> BoyerQW <- importNWISqw(Boyer, "00631",
+   begin.date="2003-10-01", end.date="2012-09-30")
> # Now the Daily values data
> BoyerQ <- readNWISdv(Boyer, "00060", startDate="2003-10-01",
+   endDate="2012-09-30")
> BoyerQ <- renameNWISColumns(BoyerQ)
```

1 Compute the Hysteresis Variables and Merge the Data

There is no direct diagnostic test to determine if hysteresis is important. The best way to assess any hysteresis is to compute the hysteresis metric and plot residuals against that metric. The first section of code will replicate that effort, beginning with the "best" predefined model rather than simply replicating the model used by Garrett (2012). Garrett used a 1-day lag. This example will use that and add a 3-day lag metric. The function that computes the metric is `hysteresis` in `smwrBase`.

```
> # Compute the hysteresis metrics.
> BoyerQ <- transform(BoyerQ,
+   dq1 = hysteresis(log(Flow), 1),
+   dq3 = hysteresis(log(Flow), 3))
> # Rename the date column in QW so that the data can be merged
> names(BoyerQW)[2] <- "Date"
> # Merge the data
> BoyerData <- mergeQ(BoyerQW, FLOW=c("Flow", "dq1", "dq3"),
+   DATES="Date", Qdata=BoyerQ, Plot=F)
> # Create the initial model
> Boyer.lr <- selBestModel("NO2PlusNO3.N", BoyerData,
+   flow="Flow", dates="Date", station=Boyer)
> print(Boyer.lr)
```

*** Load Estimation ***

Station: 06609500

Constituent: NO2PlusNO3.N

Number of Observations: 101

Number of Uncensored Observations: 101

Center of Decimal Time: 2008.411

Center of ln(Q): 6.4926

Period of record: 2004-03-12 to 2012-09-10

Model Evaluation Criteria Based on AMLE Results

	model	AIC	SPCC	AICc
1	1	103.58	111.42	103.82
2	2	64.41	74.87	64.82
3	3	103.76	114.22	104.18
4	4	103.93	117.01	104.57
5	5	60.71	73.79	61.34

6	6	64.94	80.64	65.84
7	7	104.34	120.03	105.24
8	8	61.59	79.90	62.80
9	9	57.26	78.18	58.83

Model # 9 selected

Selected Load Model:

N02PlusN03.N ~ model(9)

Model coefficients:

	Estimate	Std. Error	z-score	p-value
(Intercept)	9.521540	0.05034	189.13729	0.0000
lnQ	0.916646	0.03129	29.29196	0.0000
lnQ2	-0.092313	0.01328	-6.95334	0.0000
DECTIME	-0.026090	0.01214	-2.14837	0.0278
DECTIME2	-0.015284	0.00620	-2.46536	0.0119
sin.DECTIME	0.104615	0.04892	2.13833	0.0285
cos.DECTIME	0.002354	0.04660	0.05051	0.9582

AMLE Regression Statistics

Residual variance: 0.09466

R-squared: 94.35 percent

G-squared: 290.2 on 6 degrees of freedom

P-value: <0.0001

Prob. Plot Corr. Coeff. (PPCC):

r = 0.9647

p-value = 1e-04

Serial Correlation of Residuals: 0.1054

Variance Inflation Factors:

	VIF
lnQ	1.605
lnQ2	1.046
DECTIME	1.030
DECTIME2	1.307
sin.DECTIME	1.231
cos.DECTIME	1.166

Comparison of Observed and Estimated Loads

Summary Stats: Loads in kg/d

	Min	25%	50%	75%	90%	95%	Max
Est	221	3040	8470	16100	35100	51200	121000

Obs 166 3010 8230 16600 29400 42800 178000

Bias Diagnostics

Bp: -2.814 percent
PLR: 0.9719
E: 0.7913

The model selected was number 9, which includes second-order flow and time terms and the first-order seasonal terms. Reviewing the table of model evaluation criteria, model number 2 had a very small value for AIC and the second smallest for SPCC. Model number 2 would have been the equivalent starting model in Garrett (2012), including only the second-order flow terms. The printed results indicate good bias statistics, but the PPCC p-value is much less than 0.05. The next section of code illustrates plotting the residuals and hysteresis metrics. The 1-day lag appears to fit better than the 3-day lag.

```
> # residuals and hysteresis
> setSweave("graph01", 6, 8)
> AA.lo <- setLayout(num.rows=2)
> setGraph(1, AA.lo)
> AA.pl <- xyPlot(BoyerData$dQ1, residuals(Boyer.lr),
+   ytitle="Residuals", xtitle="1-day lag hysteresis",
+   xaxis.range=c(-1,3))
> addSLR(AA.pl)
> setGraph(2, AA.lo)
> AA.pl <- xyPlot(BoyerData$dQ3, residuals(Boyer.lr),
+   ytitle="Residuals", xtitle="3-day lag hysteresis",
+   xaxis.range=c(-1,3))
> addSLR(AA.pl)
> dev.off()
```

null device

1

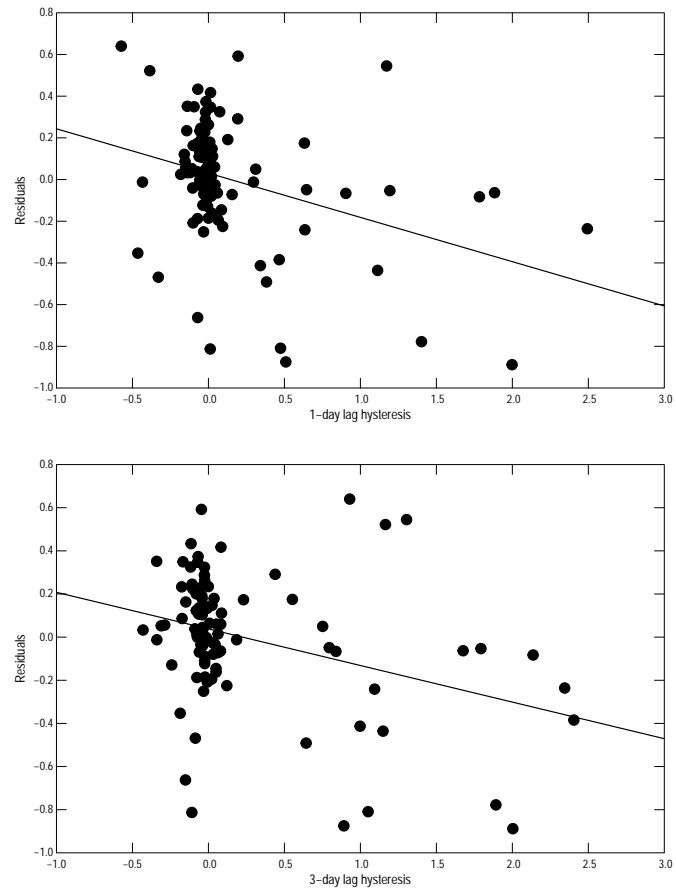


Figure 1. The residuals versus hysteresis metrics.

2 Construct and Validate the Hysteresis Model

The model...

```
> # Construct the model
> Boyer.lr <- loadReg(NO2PlusNO3.N ~ quadratic(log(Flow)) +
+   quadratic(dectime(Date)) + fourier(Date) + dQ1, data=BoyerData,
+   flow="Flow", dates="Date", station=Boyer)
> print(Boyer.lr)
```

*** Load Estimation ***

Station: 06609500
Constituent: NO2PlusNO3.N

Number of Observations: 101
Number of Uncensored Observations: 101
Center of Decimal Time: 2008.411
Center of ln(Q): 6.4926
Period of record: 2004-03-12 to 2012-09-10

Selected Load Model:

NO2PlusNO3.N ~ quadratic(log(Flow)) + quadratic(dectime(Date)) +
fourier(Date) + dQ1

Model coefficients:

	Estimate	Std. Error	z-score	p-value
(Intercept)	9.544866	0.045678	208.9610	0.0000
quadratic(log(Flow))(6.49264)1	0.994701	0.032673	30.4438	0.0000
quadratic(log(Flow))(6.49264)2	-0.078945	0.012303	-6.4167	0.0000
quadratic(dectime(Date))(2008.41)1	-0.037260	0.011208	-3.3243	0.0008
quadratic(dectime(Date))(2008.41)2	-0.009752	0.005713	-1.7070	0.0775
fourier(Date)sin(k=1)	0.094321	0.044187	2.1346	0.0280
fourier(Date)cos(k=1)	0.024502	0.042293	0.5793	0.5464
dQ1	-0.320909	0.067635	-4.7447	0.0000

AMLE Regression Statistics

Residual variance: 0.07703

R-squared: 95.45 percent

G-squared: 312 on 7 degrees of freedom

P-value: <0.0001

Prob. Plot Corr. Coeff. (PPCC):

r = 0.9652

```

p-value = 1e-04
Serial Correlation of Residuals: 0.0863

```

Variance Inflation Factors:

	VIF
quadratic(log(Flow))(6.49264)1	2.150
quadratic(log(Flow))(6.49264)2	1.104
quadratic(dectime(Date))(2008.41)1	1.078
quadratic(dectime(Date))(2008.41)2	1.364
fourier(Date)sin(k=1)	1.234
fourier(Date)cos(k=1)	1.181
dQ1	1.510

Comparison of Observed and Estimated Loads

```

-----
Summary Stats: Loads in kg/d
-----
      Min  25%  50%   75%   90%   95%   Max
Est 215 3000 8400 16400 30700 45700 181000
Obs 166 3010 8230 16600 29400 42800 178000

```

Bias Diagnostics

```

-----
Bp: 0.2218 percent
PLR: 1.002
E: 0.9312

```

The printed output shows an improved model, but the PPCC test still indicates lack of normality. A review of the linearity of the explanatory variables indicates the need for second-order seasonal terms (figure 1). The sine term is also nonlinear, but not shown. The second order linear time term will be dropped because it is not significant at the 0.05 level.

```

> # Plot the overall fit, choose "fourier(Date)cos(k=1)"
> setSweave("graph02", 6, 6)
> plot(Boyer.lr, which="fourier(Date)cos(k=1)", set.up=FALSE)
> dev.off()

```

```

null device
      1

```

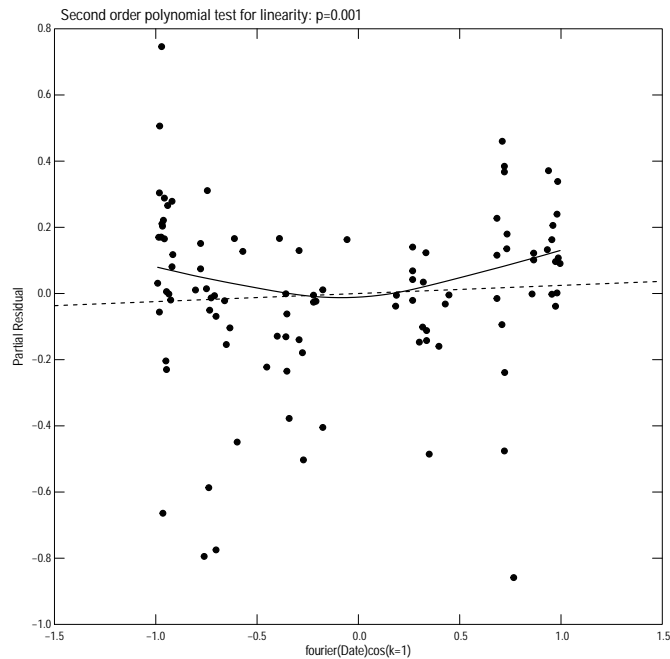


Figure 2. The diagnostic plot for the linearity of a seasonal term.

Construct the revised model that drops the second order time term and adds the second order seasonal terms. The diagnostic plots follow.

```
> # Construct the revised model
> Boyer.lr <- loadReg(N02PlusN03.N ~ quadratic(log(Flow)) +
+   dectime(Date) + fourier(Date, 2) + dQ1, data=BoyerData,
+   flow="Flow", dates="Date", station=Boyer)
> print(Boyer.lr)
```

*** Load Estimation ***

Station: 06609500

Constituent: N02PlusN03.N

Number of Observations: 101

Number of Uncensored Observations: 101

Center of Decimal Time: 2008.411

Center of ln(Q): 6.4926

Period of record: 2004-03-12 to 2012-09-10

Selected Load Model:

N02PlusN03.N ~ quadratic(log(Flow)) + dectime(Date) + fourier(Date,
2) + dQ1

Model coefficients:

	Estimate	Std. Error	z-score	p-value
(Intercept)	87.67707	21.30032	4.116	0.0000
quadratic(log(Flow))(6.49264)1	1.00857	0.02737	36.852	0.0000
quadratic(log(Flow))(6.49264)2	-0.08290	0.01164	-7.119	0.0000
dectime(Date)	-0.03893	0.01060	-3.671	0.0002
fourier(Date, 2)sin(k=1)	0.08243	0.04082	2.019	0.0363
fourier(Date, 2)cos(k=1)	0.05420	0.03893	1.392	0.1467
fourier(Date, 2)sin(k=2)	-0.06357	0.03709	-1.714	0.0748
fourier(Date, 2)cos(k=2)	0.12666	0.03861	3.280	0.0008
dQ1	-0.34424	0.06305	-5.460	0.0000

AMLE Regression Statistics

Residual variance: 0.06958

R-squared: 95.93 percent

G-squared: 323.4 on 8 degrees of freedom

P-value: <0.0001

Prob. Plot Corr. Coeff. (PPCC):

r = 0.9656

p-value = 2e-04

Serial Correlation of Residuals: 0.0449

Variance Inflation Factors:

	VIF
quadratic(log(Flow))(6.49264)1	1.670
quadratic(log(Flow))(6.49264)2	1.095
dectime(Date)	1.068
fourier(Date, 2)sin(k=1)	1.165
fourier(Date, 2)cos(k=1)	1.107
fourier(Date, 2)sin(k=2)	1.038
fourier(Date, 2)cos(k=2)	1.033
dQ1	1.453

Comparison of Observed and Estimated Loads

Summary Stats: Loads in kg/d

	Min	25%	50%	75%	90%	95%	Max
Est	195	3420	8460	15900	33900	46200	193000

Obs 166 3010 8230 16600 29400 42800 178000

Bias Diagnostics

Bp: 0.2405 percent
PLR: 1.002
E: 0.9379

A complete review of the partial residual graphs is not included in this example. Only the partial residual for `fourier(Date)cos(k=1)` is shown to show that the linearity has improved. No partial residual plot indicates a serious lack of linearity.

```
> # Plot the residual Q-normal graph.  
> setSweave("graph03", 6, 6)  
> plot(Boyer.lr, which = "fourier(Date, 2)cos(k=1)", set.up=FALSE)  
> dev.off()
```

null device
1

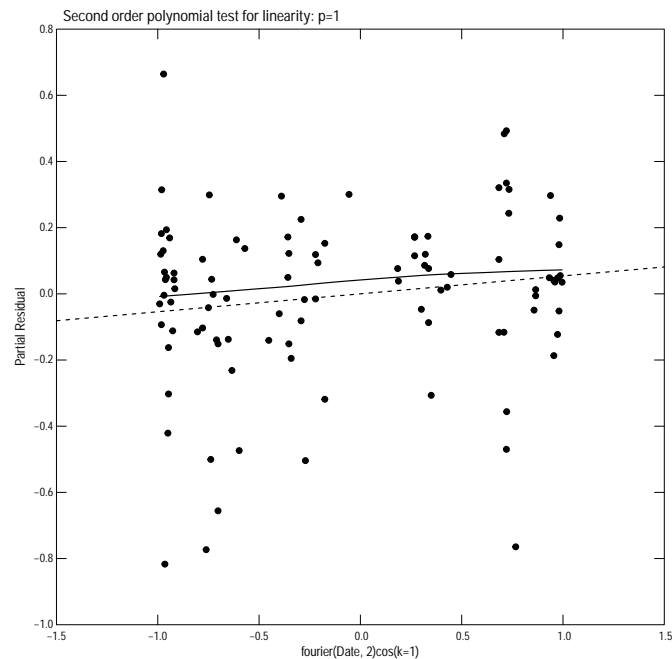


Figure 3. The partial residual for `fourier(Date, 2)cos(k=1)` graph.

The correlogram indicates a much better seasonal fit and no long-term lack of fit.

```
> # Plot the overall fit, choose plot number 2.  
> setSweave("graph04", 6, 6)  
> plot(Boyer.lr, which = 4, set.up=FALSE)  
> dev.off()
```

```
null device  
1
```

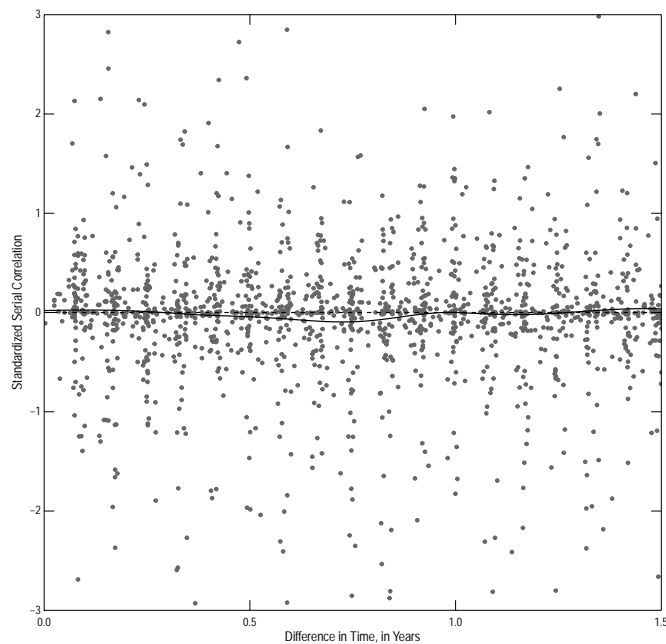


Figure 4. The correlogram for the revised model.

For this model, the S-L plot is shown. It shows a slight decrease in heteroscedasticity as the fitted values increase. The decrease is small and likely drive by the 3 largest fitted values and there is very little visual decrease in scatter as the fitted values increase.

```
> # Plot the S-L graph.  
> setSweave("graph05", 6, 6)
```

```
> plot(Boyer.lr, which = 3, set.up=FALSE)
> dev.off()
```

```
null device
      1
```

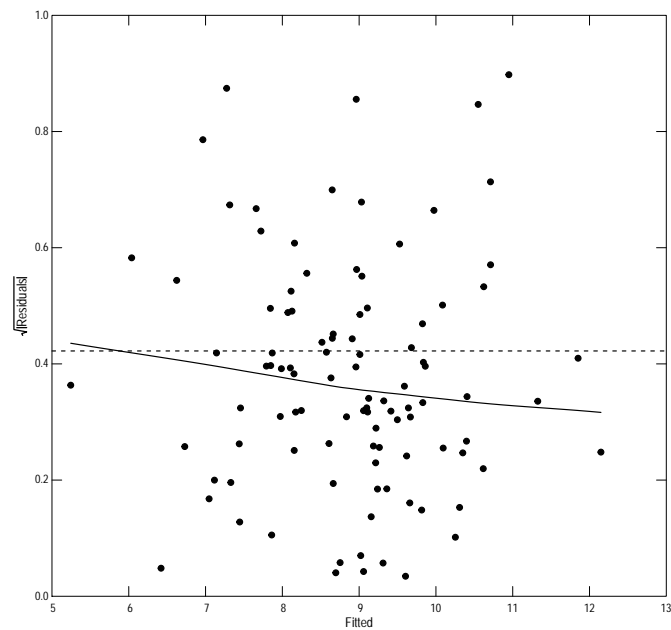


Figure 5. The S-L graph for the revised model.

The Q-normal graph shows a non-normal distribution, but without distinctive skewness or kurtosis.

```
> # Plot the residual Q-normal graph.
> setSweave("graph06", 6, 6)
> plot(Boyer.lr, which = 5, set.up=FALSE)
> dev.off()
```

```
null device
      1
```

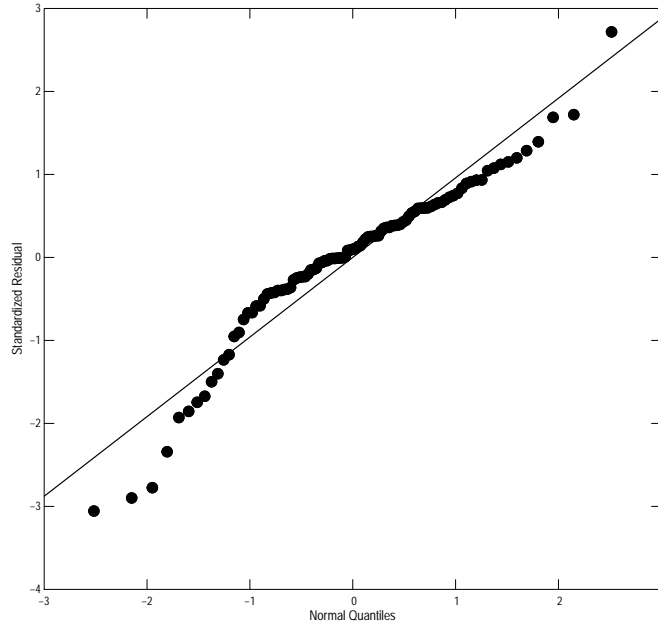


Figure 6. The residual Q-normal graph.

The non-normality of the residuals poses at least three potential problems: (1) lack of confidence in the confidence limits for regression parameter estimates, (2) bias in the back-transformation corrections for the mean load, and (3) lack of confidence in the confidence intervals of the load estimate. For the first potential problem, the confidence intervals of the parameter estimates and their significance are not critical to load estimation and the non-normality is not so large that this is a major concern (Greene, 2012). Several factors must be considered to address the second potential problem—the magnitude of the bias correction and the measured bias. The actual bias correction factor (BCF) used is AMLE, which cannot be directly computed, but can be estimated by using the MLE BCF. The MLE BCF for this model is $\exp(0.06958/2) = 1.0354$. For non-normal data, Duan’s smoothing BCF is often used (Helsel and Hirsch, 2002); the value for that BCF is $\text{mean}(\exp(\text{residuals}(\text{Boyer.lm}))) = 1.0302$. The BCFs are very similar, which suggests that the bias from the back transform could be small. That is confirmed by the very small value for the percent bias in the printed report (0.2405). The third potential problem and no way to address it other than by using bootstrapping methods. Any reported confidence intervals on loads or fluxes should be treated as approximate.

References

- [1] Garrett, J.D., 2012, Concentrations, loads, and yields of select constituents from major tributaries of the Mississippi and Missouri Rivers in Iowa, water years 2004-2008: U.S. Geological Survey Scientific Investigations Report 2012-5240, 61 p.
- [2] Greene, W.H., 2012, Econometric analysis, seventh edition: Upper Saddle River, New. Jersey, Prentice Hall, 1198 p.
- [3] Helsel, D.R., and Hirsch, R.M., 2002, Statistical methods in water resources: U.S. Geological Survey Techniques of Water-Resources Investigations, book 4, chap. A3, 522 p.