



Techniques of Water-Resources Investigations of the United States Geological Survey

Chapter B4

REGRESSION MODELING OF GROUND-WATER FLOW

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Book 3
APPLICATIONS OF HYDRAULICS

7 Answers to Exercises

In this section answers to the exercises from the first six sections are given. For brevity, the exercises are not restated.

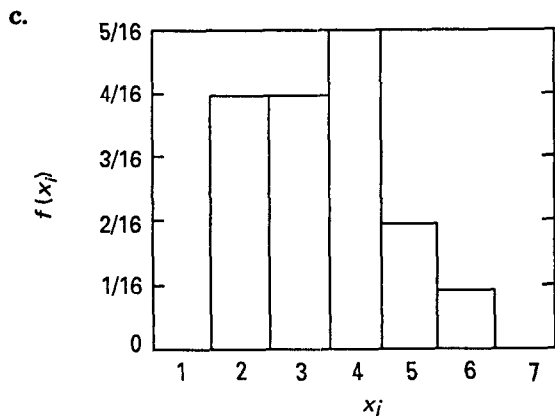
Problem 2.2-1

- a. (RR),(RW),(RB),(WW),(WR),(WB),(BB),
(BW),(BR).

b.

	R	W	B1	B2
R	RR	RW	RB1	RB2
W	WR	WW	WB1	WB2
B1	B1R	B1W	B1B1	B1B2
B2	B2R	B2W	B2B1	B2B2

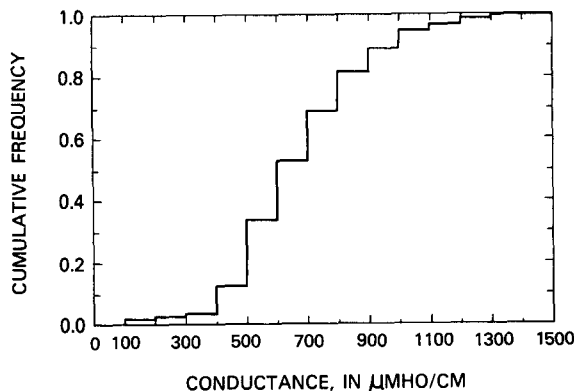
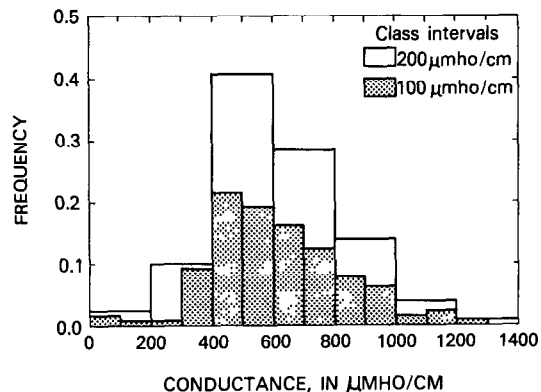
$P(RR)=1/16$ $P(WW)=1/16$ $P(BB)=1/4$
 $P(RW)=1/16$ $P(WR)=1/16$ $P(BW)=1/8$
 $P(RB)=1/8$ $P(WB)=1/8$ $P(BR)=1/8$



- d. $P(X=4)=5/16$
(RR),(WB),(BW).

Problem 2.2-2

- a. The effect of increasing the class interval size is to increase the frequency value for each class. This increase tends to make the histogram appear more peaked for larger intervals. Increasing the class interval also tends to smooth out irregularities.



- b. $P(X \leq 600) = 0.53$
 $P(X > 400) = 0.88$
 $P(400 < X \leq 600) = 0.41$
 $P(X \leq 1300) = 1.0.$

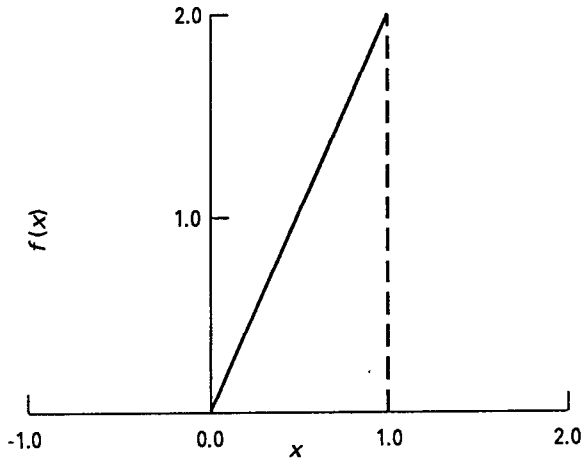
Problem 2.3-1

- a. $\bar{x} = \sum_{(all\ i)} \bar{x}_i f_i^* = (2 \times 50 + 1 \times 150 + 1 \times 250 + 12 \times 350 + 28 \times 450 + 25 \times 550 + 21 \times 650 + 16 \times 750 + 10 \times 850 + 8 \times 950 + 2 \times 1050 + 3 \times 1150 + 1 \times 1250) / 130$
 $= 612.$
- b. By replacing the integration in equation 2.3-3 with a summation, it is seen that the population mean μ_X for this random variable is represented by

$$\begin{aligned} \mu_X &= \sum_{i=2}^6 i f_i \\ &= (2 \times 1/4 + 3 \times 1/4 + 4 \times 5/16 + 5 \times 1/8 + 6 \times 1/16) \\ &= 3 \frac{1}{2} . \end{aligned}$$

Problem 2.3-2

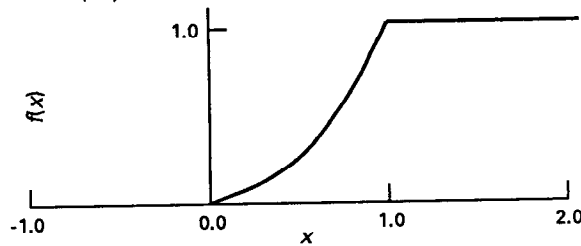
- a. Triangular density problem.
(i)



(ii)

$$F(x) = \int_{-\infty}^x f(s) ds = \begin{cases} 1 & ,x > 1 \\ 2 \int_0^x s ds = x^2 & ,0 \leq x \leq 1 \\ 0 & ,x < 0 \end{cases}$$

(iii)



$$E[X] = \int_{-\infty}^{\infty} s f(s) ds = 2 \int_0^1 s^2 ds = \frac{2}{3}$$

$$E[X^2] = \int_{-\infty}^{\infty} s^2 f(s) ds = 2 \int_0^1 s^3 ds = \frac{1}{2}$$

$$\sigma_X^2 = E[X^2] - (E[X])^2 = \frac{1}{2} - \frac{4}{9} = \frac{1}{18}$$

- b. $\bar{x} = 1.25 \times 0.051 + 1.75 \times 0.103 + 2.25 \times 0.103$
 $+ 2.75 \times 0.154 + 3.25 \times 0.154 + 3.75 \times 0.128$
 $+ 4.25 \times 0.128 + 4.75 \times 0.090 + 5.25 \times 0.026$
 $+ 5.75 \times 0.064 = 3.36.$

$$s_x^{*2} = \sum_{i=1}^{10} (\bar{x}_i - \bar{x})^2 f_i^*$$

$$\begin{aligned} &= (-2.11)^2 \times 0.051 + (-1.61)^2 \times 0.103 \\ &+ (-1.11)^2 \times 0.103 + (-0.61)^2 \times 0.154 \\ &+ (-0.11)^2 \times 0.154 + (0.39)^2 \times 0.128 \\ &+ (0.89)^2 \times 0.128 + (1.39)^2 \times 0.090 \\ &+ (1.89)^2 \times 0.026 + (2.39)^2 \times 0.064 = 1.43. \end{aligned}$$

Problem 2.4-1

- a. $P(X=3 \text{ and } Y=2) = P(X=3)P(Y=2) = 1/36.$
 b. $P(X+Y=5) = 1/9.$
 c. $P(Y=2|X=3) = 1/6.$
 d. $P(X+Y=5|X=3) = 1/6.$
 e. $P(X+Y \leq 5|X=3) = 1/3.$

Problem 2.4-2

a. $E[Y] = a_1 \mu_{X_1} + a_2 \mu_{X_2} + a_3 \mu_{X_3}$

$$\begin{aligned} \text{Var}[Y] &= E\{[Y - E(Y)]^2\} = E\{[a_1(X_1 - \mu_{X_1}) \\ &+ a_2(X_2 - \mu_{X_2}) + a_3(X_3 - \mu_{X_3})]^2\} \\ &= E[a_1^2(X_1 - \mu_{X_1})^2 + a_2^2(X_2 - \mu_{X_2})^2 \\ &+ a_3^2(X_3 - \mu_{X_3})^2 \\ &+ 2a_1a_2(X_1 - \mu_{X_1})(X_2 - \mu_{X_2}) \\ &+ 2a_1a_3(X_1 - \mu_{X_1})(X_3 - \mu_{X_3}) \\ &+ 2a_2a_3(X_2 - \mu_{X_2})(X_3 - \mu_{X_3})] \\ &= a_1^2 \sigma_{X_1}^2 + a_2^2 \sigma_{X_2}^2 + a_3^2 \sigma_{X_3}^2 \\ &+ 2a_1a_2 \sigma_{X_1 X_2} + 2a_1a_3 \sigma_{X_1 X_3} \\ &+ 2a_2a_3 \sigma_{X_2 X_3} \end{aligned}$$

because $\sigma_{X_i}^2 = E[(X_i - \mu_{X_i})^2]$ and $\sigma_{X_i X_j} = E[(X_i - \mu_{X_i})(X_j - \mu_{X_j})]$.

b. $\underline{a} \text{Var}[X] \underline{a}^T = \underline{a} E[(X - E[X])(X - E[X])^T] \underline{a}^T$
 $= \underline{a} E[XX^T - XE[X]^T - E[X]X^T]$
 $+ E[X]E[X]^T \underline{a}^T$
 $= \underline{a} (E[XX^T] - E[X]E[X]^T) \underline{a}^T$
 $= E[\underline{a}XX^T \underline{a}^T] - E[\underline{a}X]E[X^T \underline{a}^T]$
 $= \text{Var}[\underline{a}X]$

c. $\text{Var}[Y] = \begin{bmatrix} \sigma_{Y_1}^2 & \sigma_{Y_1 Y_2} & \cdots & \sigma_{Y_1 Y_p} \\ & \sigma_{Y_2}^2 & \cdots & \sigma_{Y_2 Y_p} \\ & & \text{symmetry} & \vdots \\ & & & \sigma_{Y_p}^2 \end{bmatrix}$

$$\begin{aligned} \sigma_{Y_i}^2 &= \text{Var}[Y_i] = \text{Var}[a_i X] = a_i \text{Var}[X] a_i^T \\ \sigma_{Y_i Y_j} &= E[Y_i Y_j] - E[Y_i] E[Y_j] \\ &= E[a_i X X^T a_j^T] - E[a_i X] E[X^T a_j^T] \\ &= a_i (E[XX^T] - E[X] E[X^T]) a_j^T \\ &= a_i \text{Var}[X] a_j^T \end{aligned}$$

$$\begin{aligned} \text{Var}[Y] &= \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} \text{Var}[X] [a_1^T, a_2^T, \dots, a_p^T] \\ &= \underline{A} \text{Var}[X] \underline{A}^T \end{aligned}$$

Problem 2.5-1

a. $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i = 610$

The results differ very little, indicating the validity of approximation in equation 2.3-1. The repeat values probably result from measurement errors, indicating that a value of the random variable could not be determined more precisely than one $\mu\text{mho/cm}$.

b. $\bar{x} = 3.36 \quad s_X^2 = 1.43$
 $\bar{t}_g = 10^{\bar{x}} = 2,290 \text{ gal/d/ft}$
 $d_g = 10^{(\bar{x} \pm s_X)} = \bar{t}_g \times 10^{\pm s_X}$
 $= (146, 35900) \text{ gal/d/ft}$

The large dispersion strongly suggests that \bar{t}_g may not represent the true geometric mean, since there is significant scatter in T in the vicinity of \bar{t}_g .

Problem 2.5-2

Let X be the specific conductance random variable and Y be the dissolved solids random variable. Then

$\sum x_i = 14,999$	$\sum y_i = 9,140$
$\sum x_i^2 = 11,743,379$	$\sum y_i^2 = 4,316,966$
$\sum x_i y_i = 7,095,973$	$n = 23$
$\bar{x} = 652$	$\bar{y} = 397$
$s_X^2 = 89,200$	$s_Y^2 = 31,300$
$s_X = 299$	$s_Y = 176$

$r_{XY} = 0.98$

Problem 2.6-1

$\bar{x} = 3 \times 10^{-4} \quad s_X^2 = 6.6 \times 10^{-5}$
 $P(\bar{X}^2 / (S_X^2/n) \leq F_\alpha(1, n-1))$
 $= P(-\sqrt{F_\alpha(1, n-1)} \leq \bar{X} / (S_X / \sqrt{n}) \leq \sqrt{F_\alpha(1, n-1)})$
 $= P(-2.26 \leq \bar{X} / (S_X / \sqrt{n}) \leq 2.26) = 0.95$
 $\bar{x} / (s_X / \sqrt{n}) = 0.12$

The value of the statistic is well within the interval $(-2.26 < 0.12 < 2.26)$. This result is expected, if the titration experiment is valid, as 95 percent of all values of the statistic $\bar{X} / (S_X / \sqrt{n})$, calculated from repeated random sampling, would be expected to fall in this interval. If the value had fallen outside the interval, one should feel uneasy because this should occur only 5 percent of the time. One would then be obligated to question whether the assumption $\mu_X = 0$ inherent to the titration test is valid.

Problem 2.8-1

a. $\bar{x} = 10 \quad s_X^2 = 0.08 \quad n = 7$

$$\begin{aligned} P\left(\frac{(\bar{X} - \mu_X)^2}{S_X^2/n} \leq F_\alpha(1, 6)\right) \\ = P\left(-\sqrt{F_\alpha(1, 6)} \leq \frac{\bar{X} - \mu_X}{S_X / \sqrt{n}} \leq \sqrt{F_\alpha(1, 6)}\right) \end{aligned}$$

Therefore, an interval can be constructed from

$$-\sqrt{F_\alpha(1, 6)} \leq \frac{\bar{x} - \mu_X}{s_X / \sqrt{n}} \leq \sqrt{F_\alpha(1, 6)}$$

where $F_\alpha(1, 6) = 5.99$. Thus

$$-s_X \sqrt{\frac{F_\alpha(1, 6)}{n}} \leq (\bar{x} - \mu_X) \leq s_X \sqrt{\frac{F_\alpha(1, 6)}{n}}$$

or

$$\bar{x} + s_X \sqrt{\frac{F_\alpha(1, 6)}{n}} \geq \mu_X \geq \bar{x} - s_X \sqrt{\frac{F_\alpha(1, 6)}{n}}$$

and

$10.26 \geq \mu_X \geq 9.74$

- b. As 95 percent of all intervals so constructed will contain μ_X , there is a 0.95 probability that this interval contains μ_X .

Problem 2.9-1

- a. $H_0: \mu_X = 0$
 $H_1: \mu_X \neq 0$.
- b. From equation 2.6-21, the statement $P(\text{reject } H_0/H_0 \text{ true}) = \alpha$ becomes

$$P\left(\frac{S_1/\sigma_1^2}{S_2^2/\sigma_2^2} > a \mid \frac{\sigma_1^2}{\sigma_2^2} = 1\right) = P(S_1^2/S_2^2 > c) = 0.05$$

where S_1^2/S_2^2 is an $F(24,15)$ random variable. Because the critical region is defined by values of $F(24,15)$ greater than or equal to c , c must be equal to $F_{0.05}(24,15)$ (see equation 2.6-15). Thus, $c=2.29$ and, because $s_1^2/s_2^2=1.31$, we accept H_0 at 0.05 significance level.

- c. Hypothesis to be tested for rejection:

$$H_0: \mu_X = 9.8$$

Alternate hypothesis:

$$H_1: \mu_X \neq 9.8$$

From equation 2.9-7,

$$\begin{aligned} & P\left(\frac{\bar{X} - \mu_0}{S_X/\sqrt{n}} < -\sqrt{F_\alpha(\nu_1, \nu_2)}\right) \\ & + P\left(\frac{\bar{X} - \mu_0}{S_X/\sqrt{n}} > \sqrt{F_\alpha(\nu_1, \nu_2)}\right) \\ & = P\left(\left|\frac{\bar{X} - \mu_0}{S_X/\sqrt{n}}\right|^2 > F_\alpha(1, n-1)\right) = \alpha \end{aligned}$$

Thus, the critical value for the statistic $(\bar{X} - \mu_0)^2 / (S_X^2/n)$ is $F_\alpha(1, n-1)$, which, at the 0.05 significance level, has a value of 5.99. Because the statistic for the random sample in question takes on the value 3.50, we are forced to accept the possibility that $\mu_X = 0$: We cannot safely reject H_0 at the 0.05 significance level.

Problem 3.1-1

Upon substitution of equation 4 into equation 3, one obtains

$$h = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

For n observations

$$\underline{Y} = \underline{X}\underline{\beta} + \underline{\epsilon}$$

where $\underline{Y} - \underline{h} = \underline{\epsilon}$,

$$\underline{Y} = \begin{bmatrix} Y_1 \\ \vdots \\ Y_{n_s} \end{bmatrix} \quad \underline{h} = \begin{bmatrix} h_1 \\ \vdots \\ h_{n_s} \end{bmatrix} \quad \underline{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_3 \end{bmatrix} \quad \underline{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_{n_s} \end{bmatrix}$$

and

$$\underline{X} = \begin{bmatrix} X_{11} & X_{12} & X_{13} \\ \vdots & \vdots & \vdots \\ X_{n_s,1} & X_{n_s,2} & X_{n_s,3} \end{bmatrix}$$

In the regression model:

\underline{Y} = observed dependent variable vector;
 \underline{h} = computed dependent variable vector;
 s = independent variable (distance along stream tube);

\underline{X} = sensitivities; and
 $\underline{\beta}$ = parameters.

a. $S(\underline{b}) = [\underline{Y} - \underline{X}\underline{b}]^T [\underline{Y} - \underline{X}\underline{b}]$

where

$$\underline{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

That is,

$$\begin{aligned} S(\underline{b}) = & \left[Y_1 - (b_1 X_{11} + b_2 X_{12} + b_3 X_{13}) \right]^2 \\ & + \left[Y_2 - (b_1 X_{21} + b_2 X_{22} + b_3 X_{23}) \right]^2 \\ & + \dots \\ & + \left[Y_{n_s} - (b_1 X_{n_s,1} + b_2 X_{n_s,2} + b_3 X_{n_s,3}) \right]^2 \end{aligned}$$

b. $S(\underline{b}) = [\underline{Y} - \underline{X}\underline{b}]^T \underline{\omega} [\underline{Y} - \underline{X}\underline{b}]$

where $\underline{\omega} = \underline{V}^{-1}$ and

$$\underline{V} = \begin{bmatrix} \sigma_1^2/\sigma^2 & & & 0 \\ & \sigma_2^2/\sigma^2 & & \\ & & \dots & \\ 0 & & & \sigma_{n_s}^2/\sigma^2 \end{bmatrix}$$

so that

$$\underline{V}^{-1} = \begin{bmatrix} \sigma_1^{-2} & & & 0 \\ & \sigma_2^{-2} & & \\ & & \dots & \\ 0 & & & \sigma_{n_s}^{-2} \end{bmatrix} \sigma^2$$

That is,

$$S(\underline{b}) = \sigma^2 \left\{ \left[\frac{1}{\sigma_1} (Y_1 - (b_1 X_{11} + b_2 X_{12} + b_3 X_{13})) \right]^2 + \left[\frac{1}{\sigma_2} (Y_2 - (b_1 X_{21} + b_2 X_{22} + b_3 X_{23})) \right]^2 + \dots + \left[\frac{1}{\sigma_{n_s}} (Y_{n_s} - (b_1 X_{n_s,1} + b_2 X_{n_s,2} + b_3 X_{n_s,3})) \right]^2 \right\}$$

c. $S(\underline{b}) = [\underline{Y} - \underline{X}\underline{b}]^T \underline{\omega} [\underline{Y} - \underline{X}\underline{b}]$

where

$$\underline{Y} - \underline{X}\underline{b} = \begin{bmatrix} Y_1 - (b_1 X_{11} + b_2 X_{12} + b_3 X_{13}) \\ \vdots \\ Y_{n_s} - (b_1 X_{n_s,1} + b_2 X_{n_s,2} + b_3 X_{n_s,3}) \\ h_b \\ -b_2 \end{bmatrix}$$

and $\underline{\omega} = \underline{V}^{-1}$, so that

$$\underline{V} = \begin{bmatrix} 1 & & & 0 \\ & \dots & & \\ 0 & & & \sigma_{h_b}^2/\sigma^2 \end{bmatrix}$$

and

$$\underline{V}^{-1} = \begin{bmatrix} 1 & & & 0 \\ & \dots & & \\ 0 & & & \sigma^2/\sigma_{h_b}^2 \end{bmatrix}$$

That is,

$$S(\underline{b}) = \left[Y_1 - (b_1 X_{11} + b_2 X_{12} + b_3 X_{13}) \right]^2 + \dots + \left[Y_{n_s} - (b_1 X_{n_s,1} + b_2 X_{n_s,2} + b_3 X_{n_s,3}) \right]^2 + \sigma^2 \left[h_b - b_2 \right]^2 / \sigma_{h_b}^2$$

Problem 3.2-1

a. Note that if $\underline{\omega}$ is diagonal

$$\underline{X}^T \underline{\omega} \underline{X} = \left\{ \sum_{i=1}^{n_s} X_{ik} \omega_i X_{ij} + \delta_{k2} \delta_{2j} \sigma^2 / \sigma_{h_b}^2 \right\} = \left\{ \sum_{i=1}^{n_s+1} X_{ik} \omega_i X_{ij} \right\}$$

and

$$\underline{X}^T \underline{\omega} \underline{Y} = \left\{ \sum_{i=1}^{n_s} X_{ik} \omega_i Y_i + \delta_{k2} h_b \sigma^2 / \sigma_{h_b}^2 \right\} = \left\{ \sum_{i=1}^{n_s+1} X_{ik} \omega_i Y_i \right\}$$

where

$$\delta_{ij} = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases}$$

$$\underline{X}^T = \begin{bmatrix} X_{11} & X_{21} & & X_{n_s,1} & 0 \\ X_{12} & X_{22} & \dots & X_{n_s,2} & 1 \\ X_{13} & X_{23} & & X_{n_s,3} & 0 \end{bmatrix}$$

$$= \begin{bmatrix} X_{11} & X_{21} & X_{n_s,1} & X_{n_s+1,1} \\ X_{12} & X_{22} & \dots & X_{n_s,2} & X_{n_s+1,2} \\ X_{13} & X_{23} & X_{n_s,3} & X_{n_s+1,3} \end{bmatrix}$$

$$\underline{\omega} = \begin{bmatrix} 1 & & & 0 \\ & \dots & & \\ 0 & & & \sigma^2/\sigma_{h_b}^2 \end{bmatrix}$$

$$= \begin{bmatrix} \omega_1 & & & 0 \\ & \dots & & \\ 0 & & & \omega_{n_s} \omega_{n_s+1} \end{bmatrix}$$

and

$$\underline{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \dots \\ Y_{n_s} \\ h_b \end{bmatrix} = \begin{bmatrix} Y_1 \\ Y_2 \\ \dots \\ Y_{n_s} \\ Y_{n_s+1} \end{bmatrix}.$$

Thus, the normal equations

$$\underline{X}^T \omega \underline{X} \hat{\underline{b}} = \underline{X}^T \omega \underline{Y}$$

can be written

$$\sum_{j=1}^p \sum_{i=1}^{n_s+1} X_{ik} \omega_i X_{ij} \hat{b}_j = \sum_{i=1}^{n_s+1} X_{ik} \omega_i Y_i, \quad k=1,2,\dots,p$$

or

$$\sum_{i=1}^{n_s+1} \left(\sum_{j=1}^p X_{ik} \omega_i X_{ij} \hat{b}_j \right) = \sum_{i=1}^{n_s+1} X_{ik} \omega_i Y_i, \quad k=1,2,\dots,p.$$

As a comparison, the normal equations may be derived without using matrix techniques. Let $n=n_s+1$ so that

$$S(\underline{b}) = \sum_{i=1}^n e_i^2 \omega_i.$$

The model equations are given as

$$Y_i = \sum_{j=1}^p X_{ij} b_j + e_i, \quad i=1,2,\dots,n.$$

Therefore

$$S(\underline{b}) = \sum_{i=1}^n \left(Y_i - \sum_{j=1}^p X_{ij} b_j \right)^2 \omega_i.$$

Take the derivative with respect to any parameter b_k ($k=1,2,\dots,p$):

$$\frac{\partial S}{\partial b_k} = \frac{\partial}{\partial b_k} \left[\sum_{i=1}^n \left(Y_i - \sum_{j=1}^p X_{ij} b_j \right)^2 \omega_i \right].$$

Because the derivative of a sum is the sum of derivatives, look at one term:

$$\begin{aligned} & \frac{\partial}{\partial b_k} \left[\left(Y_i - \sum_{j=1}^p X_{ij} b_j \right)^2 \omega_i \right] \\ &= -2 \left(Y_i - \sum_{j=1}^p X_{ij} b_j \right) \omega_i X_{ik}. \end{aligned}$$

Thus,

$$\frac{\partial S}{\partial b_k} = -2 \sum_{i=1}^n \left(Y_i - \sum_{j=1}^p X_{ij} b_j \right) \omega_i X_{ik}$$

Set $\frac{\partial S}{\partial b_k} = 0$ to find the minimum so that

$$\sum_{i=1}^n \left(Y_i - \sum_{j=1}^p X_{ij} \hat{b}_j \right) \omega_i X_{ik} = 0, \quad k=1,2,\dots,p$$

or

$$\sum_{i=1}^n \left(\sum_{j=1}^p X_{ik} \omega_i X_{ij} \hat{b}_j \right) = \sum_{i=1}^n X_{ik} \omega_i Y_i, \quad k=1,2,\dots,p.$$

b. Consider matrix \underline{A} such that

$$\underline{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}.$$

Assume \underline{A} is symmetric; its cofactor matrix \underline{A}_c is

$$\underline{A}_c = \begin{bmatrix} (a_{22}a_{33}-a_{23})^2 & (a_{13}a_{23}-a_{12}a_{33}) & (a_{12}a_{23}-a_{13}a_{22}) \\ (a_{13}a_{23}-a_{12}a_{33}) & (a_{11}a_{33}-a_{13})^2 & (a_{12}a_{13}-a_{11}a_{23}) \\ (a_{12}a_{23}-a_{13}a_{22}) & (a_{12}a_{13}-a_{11}a_{23}) & (a_{11}a_{22}-a_{12})^2 \end{bmatrix}.$$

The determinant of \underline{A} is

$$|\underline{A}| = a_{11}(a_{22}a_{33} - a_{23}^2) + a_{12}(a_{13}a_{23} - a_{12}a_{33}) + a_{13}(a_{12}a_{23} - a_{13}a_{22}) .$$

The inverse of \underline{A} is

$$\underline{A}^{-1} = \underline{A}_c^T / |\underline{A}|$$

Let $\underline{A} = \underline{X}^T \underline{\omega} \underline{X}$ where

$$\underline{\omega} = \begin{bmatrix} 1 & & & 0 \\ & \ddots & & \\ & & 1 & \\ 0 & & & \sigma^2 / \sigma_{h_b}^2 \end{bmatrix} .$$

Thus by adding the prior information to the information in table 3, there results:

	Data Set 1	Data Set 2
$\sum_j X_{j2}^2 \omega_j$	3.53161157	3.12700831
$\sum_j X_{j2} \omega_j Y_j$	127.0992273	122.5185789

and, for data set 1,

$$\underline{X}^T \underline{\omega} \underline{X} = \begin{bmatrix} 3.3250 & 1.6750 & 418,750 \\ & 3.53161157 & 418,750 \\ \text{symmetric} & & 83,340,625,000 \end{bmatrix}$$

or, for data set 2,

$$\underline{X}^T \underline{\omega} \underline{X} = \begin{bmatrix} 2.8500 & 1.6500 & 412,500 \\ & 3.12700831 & 412,500 \\ \text{symmetric} & & 8.3325 \times 10^{10} \end{bmatrix} .$$

Then, for data set 1,

$$\underline{A}_c = \begin{bmatrix} 1.18975153 \times 10^{11} & 3.575601563 \times 10^{10} & -777,456.0949 \\ & 1.017560156 \times 10^{11} & -690,937.5 \\ \text{symmetric} & & 8.93698347 \end{bmatrix}$$

and

$$|\underline{X}^T \underline{\omega} \underline{X}| = 1.299239702 \times 10^{11} .$$

Therefore

$$[\underline{X}^T \underline{\omega} \underline{X}]^{-1} = \begin{bmatrix} 0.9157290438 & 0.2752072275 & -5.983931169 \times 10^{-6} \\ & 0.7831966299 & -5.318014058 \times 10^{-6} \\ \text{symmetric} & & 6.878625596 \times 10^{-11} \end{bmatrix} .$$

Similarly, for data set 2

$$\underline{A}_c = \begin{bmatrix} 9.040171743 \times 10^{10} & 3.267 \times 10^{10} & -609,265.9279 \\ & 6.732 \times 10^{10} & -495,000 \\ \text{symmetric} & & 6.189473684 \end{bmatrix}$$

and

$$|\underline{X}^T \underline{\omega} \underline{X}| = 6.022819942 \times 10^{10} .$$

Therefore

$$[\underline{X}^T \underline{\omega} \underline{X}]^{-1} = \begin{bmatrix} 1.500986553 & 0.5424369368 & -1.011595787 \times 10^{-5} \\ & 1.117748839 & -8.218741466 \times 10^{-6} \\ \text{symmetric} & & 1.027670384 \times 10^{-10} \end{bmatrix} .$$

c. By adding the prior information to the information in table 3, we obtain for $\underline{X}^T \underline{\omega} \underline{Y}$:

	Data Set 1	Data Set 2
$\sum_j \underline{X}_{j1} \omega_j Y_j$	192.18350	168.2030
$\sum_j \underline{X}_{j2} \omega_j Y_j$	127.0992273	122.5185789
$\sum_j \underline{X}_{j3} \omega_j Y_j$	26,879,687.5	26,583,550

By evaluating $(\underline{X}^T \underline{\omega} \underline{X})^{-1} \underline{X}^T \underline{\omega} \underline{Y}$, estimates $\hat{\underline{b}}$ are obtained as:

	Data Set 1	Data Set 2
\hat{b}_1	50.12043881	50.01097198
\hat{b}_2	9.487418691	9.701194703
\hat{b}_3	0.00002302475114	0.00002342971729

Problem 3.3-1

The answers to parts a, b, and c are found in the section at the end of the problem where aids in debugging the computer code are given. The authors' computer code and output are:

```

    DIMENSION T(10),S(10),F(10),Z(2,10),C(2,2),G(2),D(2)
10  FORMAT (I5,6F10.0,I5)
20  FORMAT (1H1,35HNO. OF OBSERVATIONS (N) ----- = ,I7
    $/1H ,35HPUMPING RATE (Q) ----- = ,G11.5
    $/1H ,35HDISTANCE FROM WELL CENTER (R) -- = ,G11.5
    $/1H ,35HINITIAL TRANSMISSIVITY (T0) ---- = ,G11.5
    $/1H ,35HINITIAL STORAGE COEFFICIENT (S0) = ,G11.5
    $/1H ,35HDAMPING PARAMETER (AP) ----- = ,G11.5
    $/1H ,35HCLOSURE CRITERION (ER) ----- = ,G11.5
    $/1H ,35HMAXIMUM NO. OF ITERATIONS (ITMX) = ,I7)
30  FORMAT (8F10.0)
32  FORMAT (10HOTIMES (T))
34  FORMAT (23HOBSERVED DRAWDOWNS (S))
36  FORMAT (15HOITERATION NO. ,I4
    $/36H CURRENT ESTIMATES OF PARAMETERS (B))
38  FORMAT (28HOSOLUTION FAILED TO CONVERGE)
40  FORMAT ((1H ,10(G11.5,2X)))
42  FORMAT (19HOSOLUTION CONVERGED)
44  FORMAT (29HOFINAL COMPUTED DRAWDOWNS (F))
46  FORMAT (16HORESIDUALS (F-S))
48  FORMAT (18HOERROR VARIANCE = ,G11.5)
50  FORMAT (12HOVAR(T) = ,G11.5/12H COV(T,S) = ,G11.5
    $/12H VAR(S) = ,G11.5)
52  FORMAT (26HOSCALED SENSITIVITIES (Z):/5H TO T)
54  FORMAT (5H TO S)
C    READ AND PRINT INPUT DATA
    READ(5,10) N,Q,R,T0,SO,AP,ER,ITMX
    WRITE(6,20) N,Q,R,T0,SO,AP,ER,ITMX
    READ(5,30) (T(I),I=1,N)
    WRITE(6,32)
    WRITE(6,40) (T(I),I=1,N)
    READ(5,30) (S(I),I=1,N)
    WRITE(6,34)
    WRITE(6,40) (S(I),I=1,N)
    FU=R*R/4.
    FW=Q/12.5664
    DMAX=ER+1.
    DO 140 KNT=1,ITMX
    UTMP=FU*SO/T0
    WTMP=FW/T0
    DO 80 I=1,N
C      COMPUTE NEW DRAWDOWN (F(I))
C      COMPUTE U AND W(U) FIRST
    U=UTMP/T(I)
    WU=W(U)
C      THEN F(I)
    F(I)=WTMP*WU
C      COMPUTE SCALED SENSITIVITIES (Z(I,J))
    TMP=EXP(-U)
    Z(1,I)=WTMP*(TMP-WU)
80  Z(2,I)=-WTMP*TMP
C      CHECK FOR CONVERGENCE
    IF(DMAX.LT.ER) GO TO 150
C      ASSEMBLE COEFFICIENT MATRIX (C(I,J)) AND
C      GRADIENT VECTOR (G(J))
    DO 86 J=1,2
    DO 84 I=J,2
    C(I,J)=0.
84  C(J,I)=0.
86  G(J)=0.
    DO 110 K=1,N
    TMP=S(K)-F(K)
    DO 100 J=1,2
    DO 90 I=J,2
    C(I,J)=Z(I,K)*Z(J,K)+C(I,J)

```

```

90 C(J,I)=C(I,J)
100 G(J)=Z(J,K)*TMP+G(J)
110 CONTINUE
C      INVERT COEFFICIENT MATRIX
      DET=C(1,1)*C(2,2)-C(1,2)*C(2,1)
      TMP=C(1,1)
      C(1,1)=C(2,2)/DET
      C(2,2)=TMP/DET
      C(1,2)=-C(1,2)/DET
      C(2,1)=C(1,2)
C      COMPUTE PARAMETER DISPLACEMENTS (D(I)), MAX. DISPLACEMENT
C      (DMAX), AND PARAMETERS (TO AND SO)
      DMAX=0.
      DO 130 J=1,2
      D(J)=C(1,J)*G(1)+C(2,J)*G(2)
      TMP=ABS(D(J))
      IF(TMP.GT.DMAX) DMAX=TMP
130 CONTINUE
      TO=TO*(1.+AP*D(1))
      SO=SO*(1.+AP*D(2))
C      PRINT PARAMETERS
      WRITE(6,36) KNT
      WRITE(6,40) TO,SO
140 CONTINUE
      WRITE(6,38)
      GO TO 160
150 WRITE(6,42)
C      PRINT DRAWDOWNS, RESIDUALS (F(I)-S(I)), AND SCALED
C      SENSITIVITIES
160 WRITE(6,44)
      WRITE(6,40) (F(I),I=1,N)
      DO 170 I=1,N
170 F(I)=F(I)-S(I)
      WRITE(6,46)
      WRITE(6,40) (F(I),I=1,N)
      WRITE(6,52)
      WRITE(6,40) (Z(1,I),I=1,N)
      WRITE(6,54)
      WRITE(6,40) (Z(2,I),I=1,N)
C      COMPUTE AND PRINT ERROR VARIANCE (VAR) AND
C      COVARIANCE MATRIX FOR PARAMETERS
      VAR=0.
      DO 180 I=1,N
180 VAR=VAR+F(I)*F(I)
      VAR=VAR/(N-2.)
      WRITE(6,48) VAR
      C(1,1)=TO*C(1,1)*TO*VAR
      C(1,2)=TO*C(1,2)*SO*VAR
      C(2,2)=SO*C(2,2)*SO*VAR
      WRITE(6,50) C(1,1),C(1,2),C(2,2)
      STOP
      END
      FUNCTION W(X)
C      COMPUTE THE WELL FUNCTION OF X
      W=0.
      IF(X.GT.10.) GO TO 20
      W=-0.577216-ALOG(X)+X
      TERM=X
      DO 10 J=2,36
      RJ=J
      TERM=-TERM*X/RJ
      TMP=TERM/RJ
      W=W+TMP
      IF(ABS(TMP).LT.1.E-7) GO TO 20
10 CONTINUE
20 RETURN
      END

```


c.

$$\underline{J}_1 = \begin{bmatrix} h_2 + h_4 - 2h_1 \\ h_1 + h_5 - 2h_2 \\ 0 \\ h_1 + 2h_5 - 4h_4 + h_{B1} \\ h_2 + 2h_4 + h_8 - 4h_5 \\ 0 \\ 0 \\ h_5 - 2h_8 + h_{B1} \\ 0 \end{bmatrix}$$

$$\underline{J}_2 = \begin{bmatrix} 0 \\ h_3 + h_5 - 2h_2 \\ h_2 + h_6 - 2h_3 \\ 0 \\ h_2 + 2h_6 + h_8 - 4h_5 \\ h_3 + 2h_5 + h_9 - 4h_6 \\ 0 \\ h_5 + h_9 - 2h_8 \\ h_6 + h_8 - 2h_9 \end{bmatrix}$$

$$\underline{J}_3 = \begin{bmatrix} \frac{1}{2}a^2 \\ \frac{1}{2}a^2 \\ 0 \\ a^2 \\ a^2 \\ 0 \\ 0 \\ \frac{1}{2}a^2 \\ 0 \end{bmatrix} \quad \underline{J}_4 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ a \\ 0 \\ 0 \\ a \end{bmatrix}$$

d.

1. Let $r=0$.
2. Compute \underline{D}_r and q_r .
3. $\underline{h}_r = \underline{D}_r^{-1} q_r$
4. Obtain $f(\underline{\xi}, \underline{b}_r)$ from \underline{h}_r by deleting node 7.
- 5.

$$\left(\frac{\partial \underline{h}}{\partial b_j} \right)_r = \underline{D}_r^{-1} \left[\left(\frac{\partial q}{\partial b_j} \right)_r - \left(\frac{\partial \underline{D}}{\partial b_j} \right)_r \underline{h}_r \right] \quad j=1,2,\dots,p$$

Obtain \underline{X}_j^r from $\left(\frac{\partial \underline{h}}{\partial b_j} \right)_r$ by deleting node 7.

6. Compute $\underline{X}_r^T \omega \underline{X}_r$ and $\underline{X}_r^T \omega (Y - f(\underline{\xi}, \underline{b}_r))$.
7. Define $\underline{C}_r = \{C_{ii}^r\} = \{(\underline{X}_r^T \omega \underline{X}_r)_{ii}^{-1/2}\}$.
8. Compute $\underline{S}_r^T \omega \underline{S}_r$ and $\underline{S}_r^T \omega (Y - f(\underline{\xi}, \underline{b}_r))$ where $\underline{S}_r = \underline{X}_r \underline{C}_r$.
9. $\underline{\delta}_{r+1} = (\underline{S}_r^T \omega \underline{S}_r + \mu \underline{I})^{-1} \underline{S}_r^T \omega (Y - f(\underline{\xi}, \underline{b}_r))$
10. $\underline{d}_{r+1} = \underline{C}_r \underline{\delta}_{r+1}$.
11. $\underline{b}_{r+1} = \rho \underline{d}_{r+1} + \underline{b}_r$.
12. If $|d_i^{r+1}/c_i| > \epsilon$ (where $c_i = b_i^r$ for $b_i^r \neq 0$, and $c_i = 1$ for $b_i^r = 0$) for any $i=1,2,\dots,p$, then increment r by one and return to 2. If not then:
13. $\underline{h}_{\text{final}} = \underline{D}_{r+1}^{-1} q_{r+1}$.

Values of μ and ρ can be computed at each iteration by using algorithms defined by equations 3.3-28 through 3.3-30 if desired.

Problem 4.2-1

Data Set 1

Nodes in columns 2 through 11 have observations. Nodes in columns 1 and 12 form specified head boundaries. Spacing: Cell row 1, 1 ft; cell columns 1 and 11, 50 ft; cell columns 2 through 10, 100 ft (figure 1).

Data Set 2.

Nodes in columns 2 through 10 have observations. Nodes in columns 1 and 11 form specified head boundaries. Spacing: Cell row 1, 1 ft; cell columns 1 through 10, 100 ft (figure 2). The input data to the regression program for the two data sets are shown in figures 3 and 4.

If both T and W were estimated, the problem would be singular because the only unique parameter is W/T .

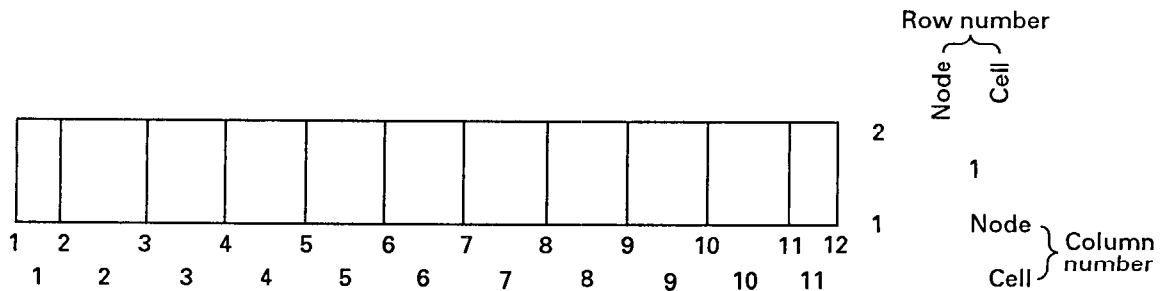


Figure 1

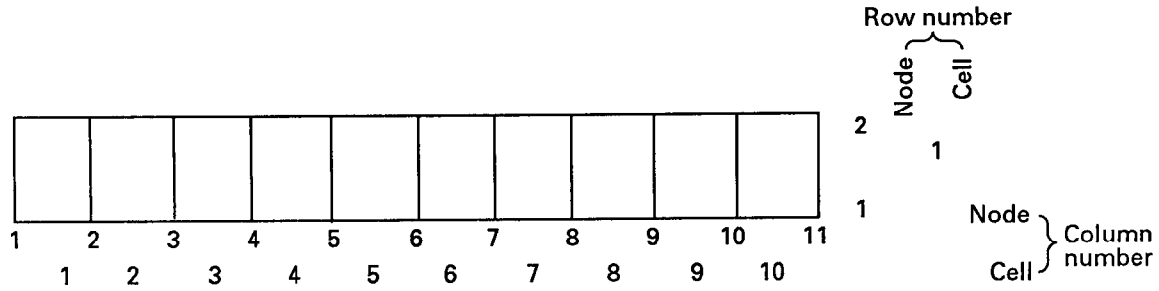


Figure 2

LAKE OHPUPU, DATA SET 1.

	12	2	1	10	1	3	0	0	2	2	1	1	0
		50		0		0		0		.25			
DX		1	0										
	1	11	1	1		1	1						
		50		100		100		100		100		100	100
		100		100		50							
DY		1	0										
	1	1	1	1		1							
CX		1	0										
	1	11	1	1		1							
CY		1	0										
	1	11	1	1		1							
VL		1	0										
	1	11	1	1		0							
HR		1	0										
	1	12	1	2		0							
QR		1	0										
	1	11	1	1		1							
HC		1	0										
	2	11	1	2		11							
IZN		1	0										
	1	11	1	1	1								
	1	2	1		50		.5	48.33			1		
	2	3	1		150		.5	45.76			1		
	3	4	1		250		.5	42.08			1		
	4	5	1		350		.5	38.34			1		
	5	6	1		450		.5	35.30			1		
	6	7	1		550		.5	31.00			1		
	7	8	1		650		.5	25.85			1		
	8	9	1		750		.5	21.76			1		
	9	10	1		850		.5	16.11			1		
	10	11	1		950		.5	12.48			1		
	1	0	0	0	1								
	1		0										
	1		1		1		0	.001					
IN		2	0										
	1	1	1	2	-1								
	12	12	1	2	-1								
	1	2	2	2		0		0					
	1	1		49									
	1	2		49									
	2	2	3	3		1.1		1.1					
	12	1		11									
	12	2		11									

Figure 3

LAKE OHPUPU, DATA SET 2.

	11	2	1	9	1	3	0	0	2	2	1	1	0
		50		0		0		0		.25			
DX		1	0										
	1	10	1	1		100							
DY		1	0										
	1	1	1	1		1							
CX		1	0										
	1	10	1	1		1							
CY		1	0										
	1	10	1	1		1							
VL		1	0										
	1	10	1	1		0							
HR		1	0										
	1	11	1	2		0							
QR		1	0										
	1	10	1	1		1							
HC		1	0										
	2	10	1	2		10							
IZN		1	0										
	1	10	1	1	1								
	1	2	1			100	.5		47.13			1	
	2	3	1			200	.5		44.14			1	
	3	4	1			300	.5		39.89			1	
	4	5	1			400	.5		36.36			1	
	5	6	1			500	.5		32.48			1	
	6	7	1			600	.5		29.70			1	
	7	8	1			700	.5		24.33			1	
	8	9	1			800	.5		19.10			1	
	9	10	1			900	.5		14.96			1	
	1	0	0	0	1								
	1		0										
	1		1		1		1		.001				
IN		2	0										
	1	1	1	2	-1								
	11	11	1	2	-1								
	1	2	2	2			0		0				
	1	1		49									
	1	2		49									
	2	2	3	3		.95		.95					
	11	1		9.5									
	11	2		9.5									

Figure 4

Problem 4.2-2

Because prior information is available, all parameters can be estimated. Data points are located in areas of relatively high sensitivity for

all parameters. More data points in areas of highest sensitivity might improve results for parameters having low sensitivity. The input data to the regression program are shown in figure 1.

CLASS PROBLEM
TWO-DIMENSIONAL FLOW
SEVERAL ZONES

	15	16	4	32	7	14	0	4	2	10	1	1	0
		2		.08		0		0		1			
DX		1	0										
	1	14	1	1		1	1						
		1000		1000		1000		1000		1000		1000	400
		1000		1000		1000		1000		1000		1000	
DY		1	0										
	1	15	1	1		1	1						
		1000		1000		1000		1000		1000		400	1000
		1000		1000		1000		1000		1000		1000	1000
CX		2	0										
	6	14	1	8		1	0						
	1	14	9	15		1	0						
CY		2	0										
	6	14	1	8		1	0						
	1	14	9	15		1	0						
VL		2	0										
	8	14	6	6		1	0						
	8	8	7	15		1	0						
HR		2	0										
	8	15	6	7		4.5	0						
	8	9	7	16		4.5	0						
QR		2	0										
	6	14	1	8		1	0						
	1	14	9	15		1	0						
HC		1	0										
	1	15	1	16		0	0						
IZN		7	0										
	6	14	1	8	2	0							
	1	14	9	15	2	0							
	1	6	12	15	1	0							
	6	7	1	3	3	0							
	8	14	1	4	3	0							
	8	14	6	6	4	0							
	8	8	7	15	4	0							
	1	8	2		7000		1000		60.70			1	
	2	14	2		12400		1000		75.64			1	
	3	12	3		10400		2000		60.27			1	
	4	10	4		8400		3000		29.67			1	
	5	7	5		6000		4000		4.22			1	
	6	11	5		9400		4000		4.37			1	
	7	13	5		11400		4000		6.07			1	
	8	14	5		13400		4000		5.81			1	
	9	10	7		8400		5400		4.57			1	
	10	8	8		7000		6400		5.21			1	
	11	12	8		10400		6400		-44.89			1	
	12	14	8		13400		6400		7.01			1	
	13	7	9		6000		7400		6.95			1	
	14	4	10		3000		8400		12.21			1	
	15	9	10		7400		8400		4.04			1	

Figure 1

16	11	10	9400	8400	-89.36	1
17	7	11	6000	9400	6.68	1
18	13	11	11400	9400	-15.32	1
19	3	12	2000	10400	16.88	1
20	5	12	4000	10400	15.87	1
21	9	12	7400	10400	4.48	1
22	11	12	9400	10400	-18.34	1
23	13	13	11400	11400	-2.47	1
24	14	13	13400	11400	8.10	1
25	3	14	2000	12400	54.12	1
26	5	14	4000	12400	38.27	1
27	10	14	8400	12400	.053	1
28	12	14	10400	12400	-2.92	1
29	7	15	6000	13400	8.30	1
30	14	15	12400	13400	4.54	1
31	2	15	1000	14400	85.82	1
32	11	15	9400	14400	2.26	1
1	8	8	0	9		
2	10	10	0	11		
3	12	12	0	13		
4	10	10	14	0		
8		0				
9	.00012					
10	84					
11	0					
12	0					
13	.000051					
14	.008					
1	70	70	0	.0004		
2	420	420	0	-.0002		
3	15	15	0	.00017		
4	420	420	.08	0		
1	16	7	16	1	45	0
7	16	15	16	2	420	0
11	10	11	10	3	-97000	1940
12	8	12	8	4	-51000	1020
IN	1	0				
15	15	5	16	-1	0	
1	10	5	6	1.04	.48	
15	16	10.4				
15	15					
15	14					
15	13					
15	12					
15	11					
15	10					
15	9					
15	8					
15	7	4.8				
2	2	6	7	.48	.54	
15	6	4.8				
15	5	5.4				

Figure 1

Problem 5.4-1

a. Let $b_0=0$. Then

$$s^2 = \frac{\underline{Y}^T \underline{\omega} \underline{Y} - \hat{\underline{b}}^T \underline{X}^T \underline{\omega} \underline{Y}}{n-p}$$

$$\underline{Y} = \begin{bmatrix} 48.33 \\ 45.76 \\ 42.08 \\ 38.34 \\ 35.30 \\ 31.00 \\ 25.85 \\ 21.76 \\ 16.11 \\ 12.48 \\ 11 \end{bmatrix} \text{ for data set 1, or } \begin{bmatrix} 47.13 \\ 44.14 \\ 39.89 \\ 36.36 \\ 32.48 \\ 29.70 \\ 24.33 \\ 19.10 \\ 14.96 \\ 9.5 \end{bmatrix} \text{ for data set 2}$$

$$\underline{\omega} = \begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \\ 0.25 \\ (1.1)^2 \end{bmatrix} \text{ or } \begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \\ 0.25 \\ (0.95)^2 \end{bmatrix}$$

$$\hat{\underline{b}} = \begin{bmatrix} 50.12043881 \\ 9.487418691 \\ 0.00002302475114 \end{bmatrix} \text{ or}$$

$$\begin{bmatrix} 50.01097198 \\ 9.701194703 \\ 0.00002342971729 \end{bmatrix}$$

$$\underline{X}^T \underline{\omega} \underline{Y} = \begin{bmatrix} 192.18350 \\ 127.0992273 \\ 26,879,687.5 \end{bmatrix} \text{ or } \begin{bmatrix} 168.2030 \\ 122.5185789 \\ 26,583,550 \end{bmatrix}$$

$$\underline{Y}^T \underline{\omega} \underline{Y} = 11,459.5411 \text{ or } 10,225.4391$$

$$\hat{\underline{b}}^T \underline{X}^T \underline{\omega} \underline{Y} = 11,457.06305 \text{ or } 10,223.41717$$

$$s^2 = 0.30975625 \text{ or } 0.2888471429$$

$$s/\Delta Y_s = 0.5565574993/(48.33-12.48)=0.0155 \text{ or } 0.5374450138/(47.13-14.96)=0.0167$$

The fit is fairly good.

b.

$$(\underline{X}^T \underline{\omega} \underline{X})^{-1} s^2 = \begin{bmatrix} 0.9157290438 & 0.2752072275 & -5.983931169 \times 10^{-6} \\ 0.30975625 & 0.7831966299 & -5.318014058 \times 10^{-6} \\ \text{symmetric} & & 6.878625596 \times 10^{-11} \end{bmatrix}$$

$$= \begin{bmatrix} 0.2836527946 & 0.08524715876 & -1.853560079 \times 10^{-6} \\ & 0.2426000511 & -1.647288092 \times 10^{-6} \\ \text{symmetric} & & 2.130697270 \times 10^{-11} \end{bmatrix}$$

or

$$0.2888471429 \begin{bmatrix} 1.500986553 & 0.5424369368 & -1.011595787 \times 10^{-5} \\ & 1.117748839 & -8.218741466 \times 10^{-6} \\ \text{symmetric} & & 1.027670384 \times 10^{-10} \end{bmatrix}$$

$$= \begin{bmatrix} 0.4335556774 & 0.1566813594 & -2.921965528 \times 10^{-6} \\ & 0.3228585586 & -2.373959991 \times 10^{-6} \\ \text{symmetric} & & 2.968396543 \times 10^{-11} \end{bmatrix}$$

Because the standard errors (the square roots of the diagonal elements) are small, the parameters are well determined.

c.

$$\underline{r} = \begin{bmatrix} 1 & 0.3249682531 & -0.7539668635 \\ & 1 & -0.7245414573 \\ \text{symmetric} & & 1 \end{bmatrix}$$

or

$$\begin{bmatrix} 1 & 0.4187827075 & -0.8145011290 \\ & 1 & -0.7668426954 \\ \text{symmetric} & & 1 \end{bmatrix}$$

The problem is fairly well conditioned.

Problem 5.5-1

The plots of \underline{d} and \underline{g} (figures 1,2) suggest that correlation manifests itself in two ways: The variability of \underline{g} from set to set is smaller than the variability of \underline{d} from set to set, and the plots of \underline{g} do not appear to be linear on normal probability paper. The plot of \hat{e} (figure 3) does not appear to differ very much from either the plots of \underline{d} or \underline{g} , although the plot of \hat{e} does show the same nonlinear trend as displayed by the plots of \underline{g} . Therefore, one may say that the plot of \hat{e} does not appear to differ significantly from the plot of a $N(0, (\underline{I}-\underline{R})s^2)$ random variable. Furthermore, this distribution of residuals suggests that the Theis model is adequate to describe the observed-drawdown data set. Input data for the residuals analysis program are shown in figure 4.

Problem 5.5-2

- a. $s^2 = 0.98677$
 $R_y = 0.99964$
 $s/\Delta Y_s = 0.99336297/175.18 = 0.00567$
- b. The problem is not well conditioned. Entries (1,8), (1,9), (8,9), and (12,13) (and their symmetric counterparts) of the scaled least squares matrix have absolute values greater than 0.9, although these large values yielded large (absolute value >0.9) parameter correlations only for entries (1,8) and (12,13). The correlation between

parameters 12 and 13 is exceptionally large so that these parameters are behaving as one. Because parameters 12 and 13 are the transmissivity T_3 and recharge W_3 in zone 3, respectively, the physical interpretation is that the ratio W_3/T_3 is much more unique than either W_3 or T_3 . The only poorly determined parameter is the flow across boundary zone 2, q_{B2} . Because of the large value of transmissivity in the aquifer zone adjacent to this boundary flow zone, the gradient near the boundary is low. Hence, the flow across the boundary is estimated poorly. Well discharges Q_1 and Q_2 and transmissivity T_2 are estimated quite well. The draw-down cones provide large gradients that serve to determine Q_1 , Q_2 , and T_2 precisely.

- c. Effects of correlation within \underline{g} are not large. They may be exhibited as a slight steepening of the curves for \underline{g} (figure 2) compared to those for \underline{d} (figure 1) on the normal probability plots. The plot of \hat{u} (figure 3) is very similar to those of \underline{g} , which suggests that the distribution of \hat{u} does not differ significantly from a $N(0, (\underline{I}-\underline{R})s^2)$ distribution. Note that \hat{e} could not have been used instead of \hat{u} to make the comparison because the weight matrix $\underline{\omega}$ is not equal to \underline{I} . The plot of \hat{u}_j versus \hat{j}_j (figure 4) shows no pattern. However, the plot of \hat{e}_j versus Cartesian coordinate (figure 5) shows a group of negative residuals in the upper center of the area. This sign pattern was inherited from the sign pattern of the original errors $\underline{\epsilon}$ that were generated (recall that this exercise is based on a hypothetical problem), and the original errors are random $N(0,1)$ deviates. Hence, the sign pattern occurred entirely by chance. The lesson is that apparently nonrandom patterns can, and often do, develop by chance, and the analyst must learn to distinguish true problem areas from apparent ones.

The input data for the residuals analysis program are shown in figure 6.

Ordered residual distribution: (The calculated values are prior information residuals $\hat{u}_j = \hat{e}_j \omega_j^{1/2}$, where $\omega_j^{1/2} = s/(\text{Var}(\epsilon_{pj}))^{1/2}$.)

No.	\hat{u}_j	No.	\hat{u}_j
1	-2.3900	21	-0.013826
2	-1.4247	22	$(-97000+97000)5.1204 \times 10^{-4} \approx 0$
3	-1.3248	23	0.034151
4	-1.2986	24	0.036783
5	-1.1685	25	$(-50961+51000)9.7389 \times 10^{-4} = 0.037982$
6	-0.95063	26	$(0.080716-0.08)124.17 = 0.088906$
7	$(0.00031149-0.0004)8278.0 = -0.73269$	27	$(5.4730-5.4)1.8396 = 0.13429$
8	-0.72189	28	0.22868
9	-0.70275	29	0.24557
10	$(0.00013516-0.00017)19478 = -0.67861$	30	0.33619
11	-0.50751	31	0.40574
12	-0.43737	32	0.41665
13	-0.43737	33	0.64095
14	-0.35588	34	0.65517
15	-0.33702	35	$(5.1211-4.8)2.0695 = 0.66452$
16	-0.26802	36	$(487.89-420)0.011826 = 0.80287$
17	$(10.198-10.4)0.95516 = -0.19294$	37	0.90021
18	-0.18186	38	0.98513
19	-0.087697	39	1.1503
20	-0.080833	40	1.3703
		41	1.6158

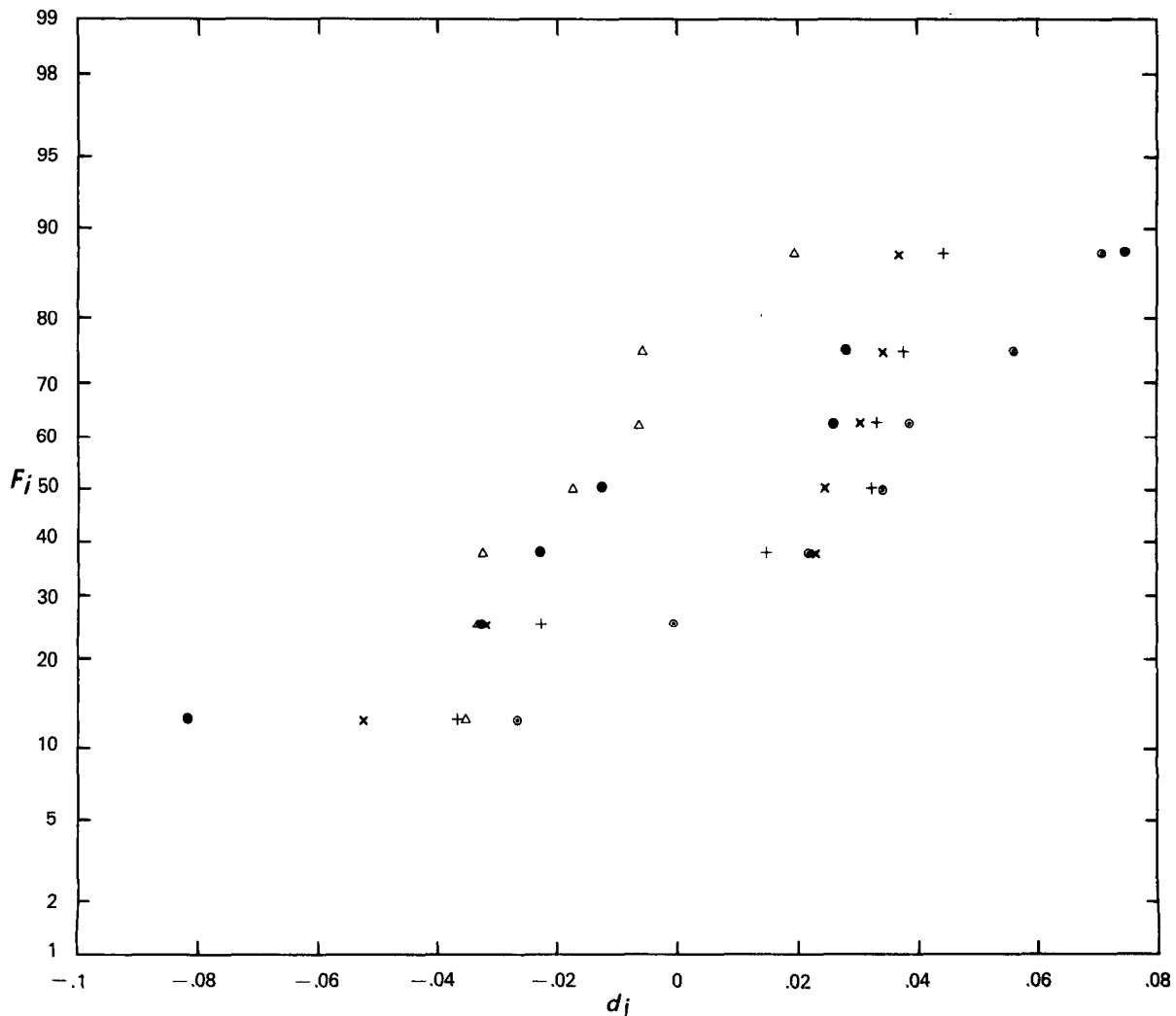


Figure 1

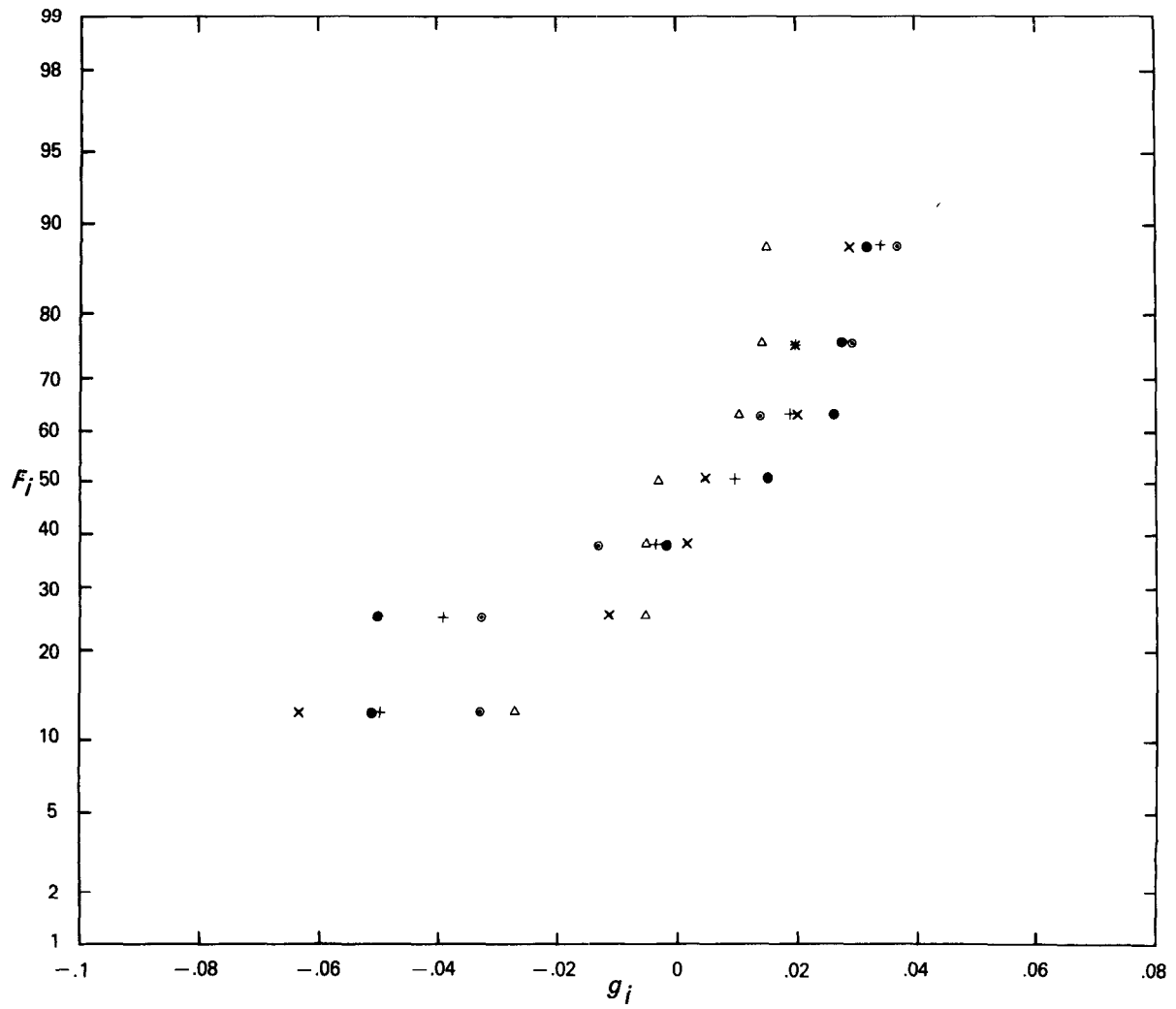


Figure 2

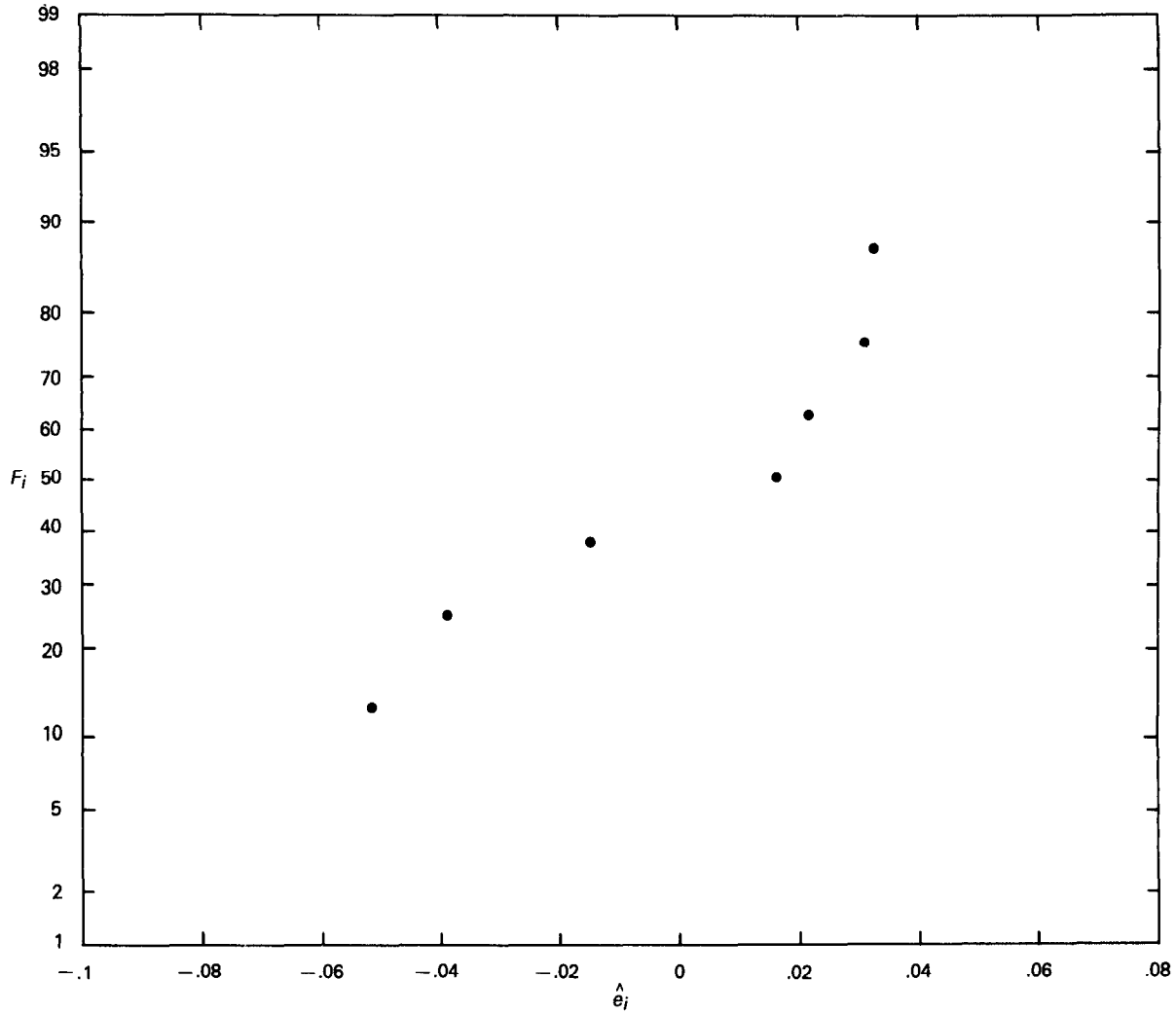


Figure 3

```

      2   7   0   5   1   .0014328
      .95030E-5-.11369E-6
      .14595E-8
      1           1           1           1           1
      -8.09604  -1362.96
      -12.9342  -1420.13
      -15.5344  -1436.83
      -17.6456  -1446.30
      -19.5912  -1452.76
      -21.8336  -1458.27
      -23.8030  -1461.84
    
```

Figure 4

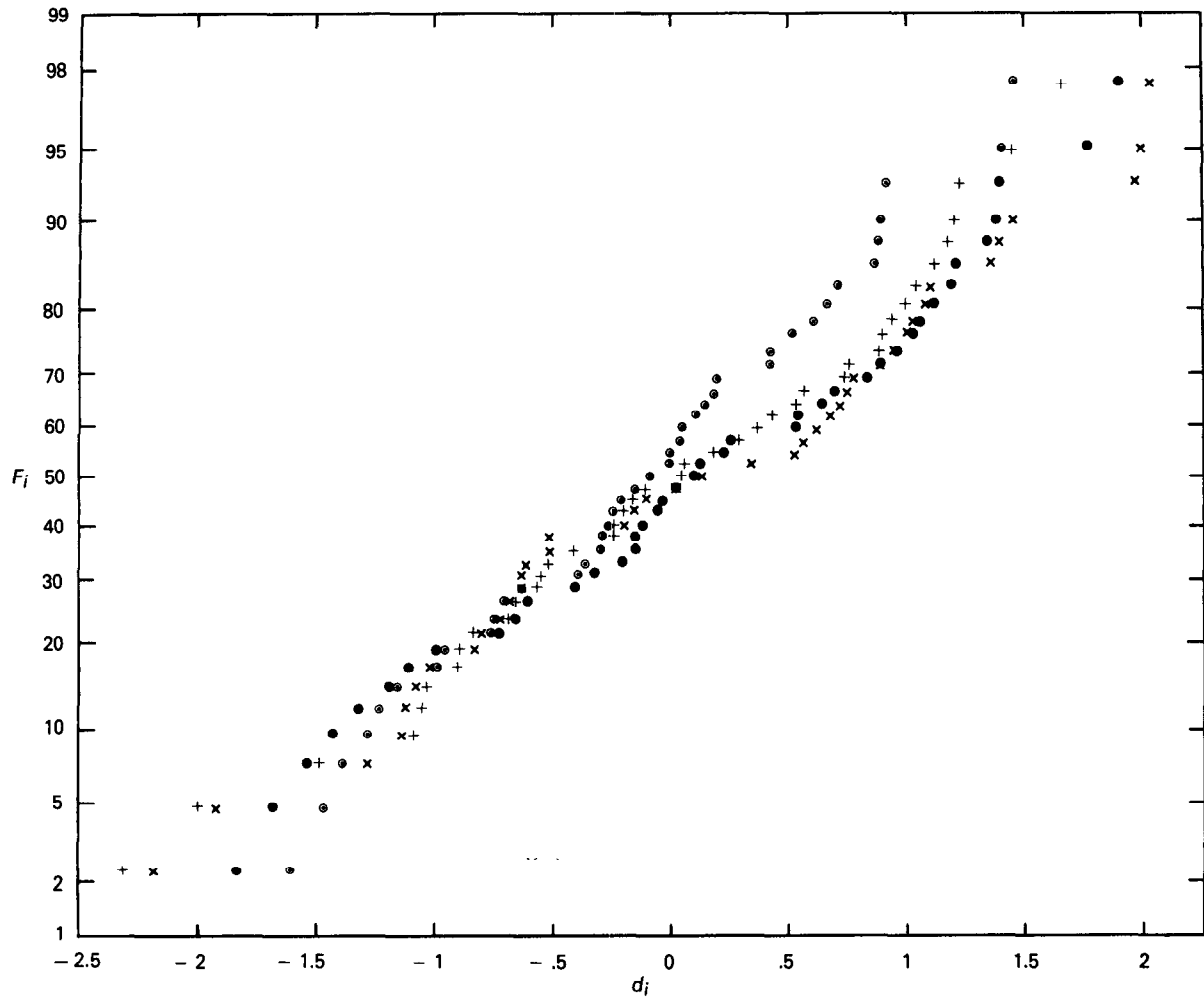
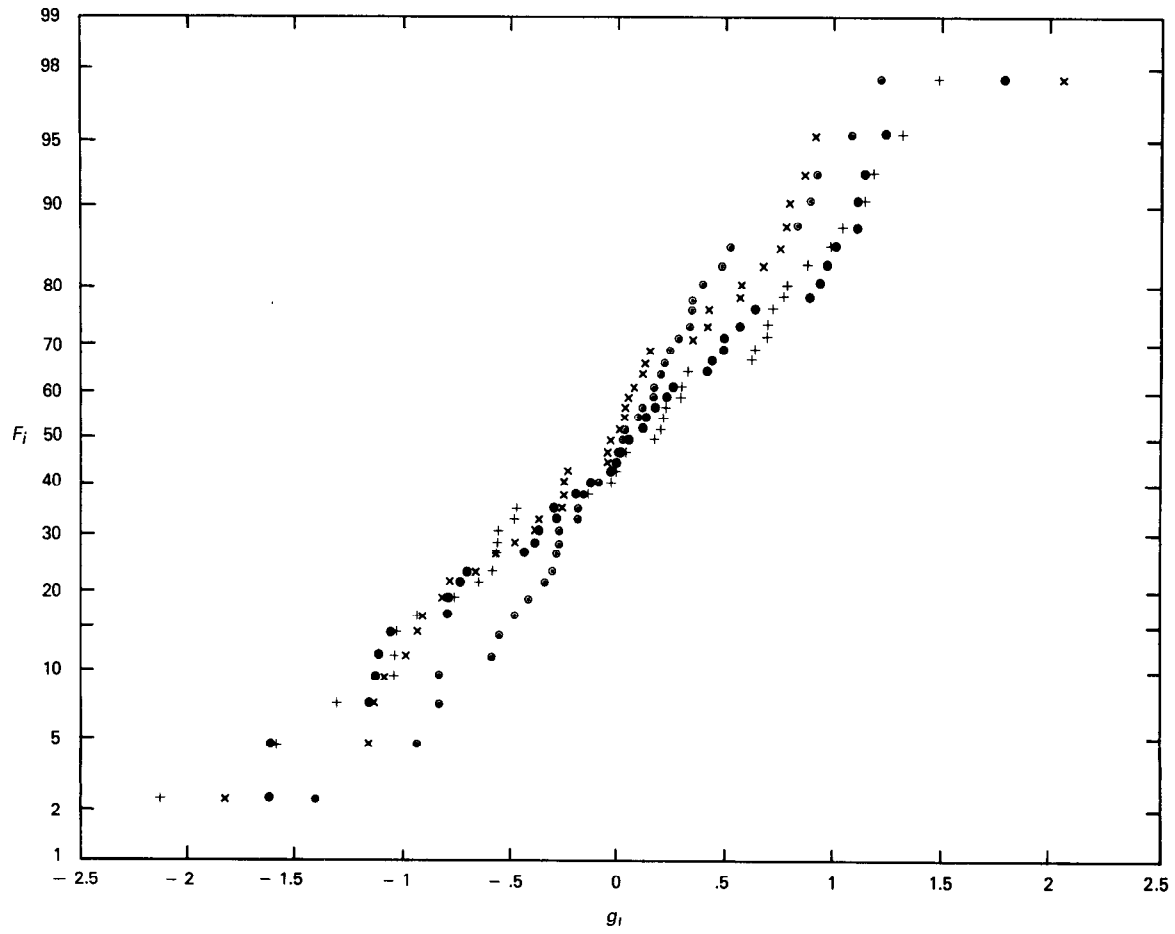


Figure 1

**Figure 2**

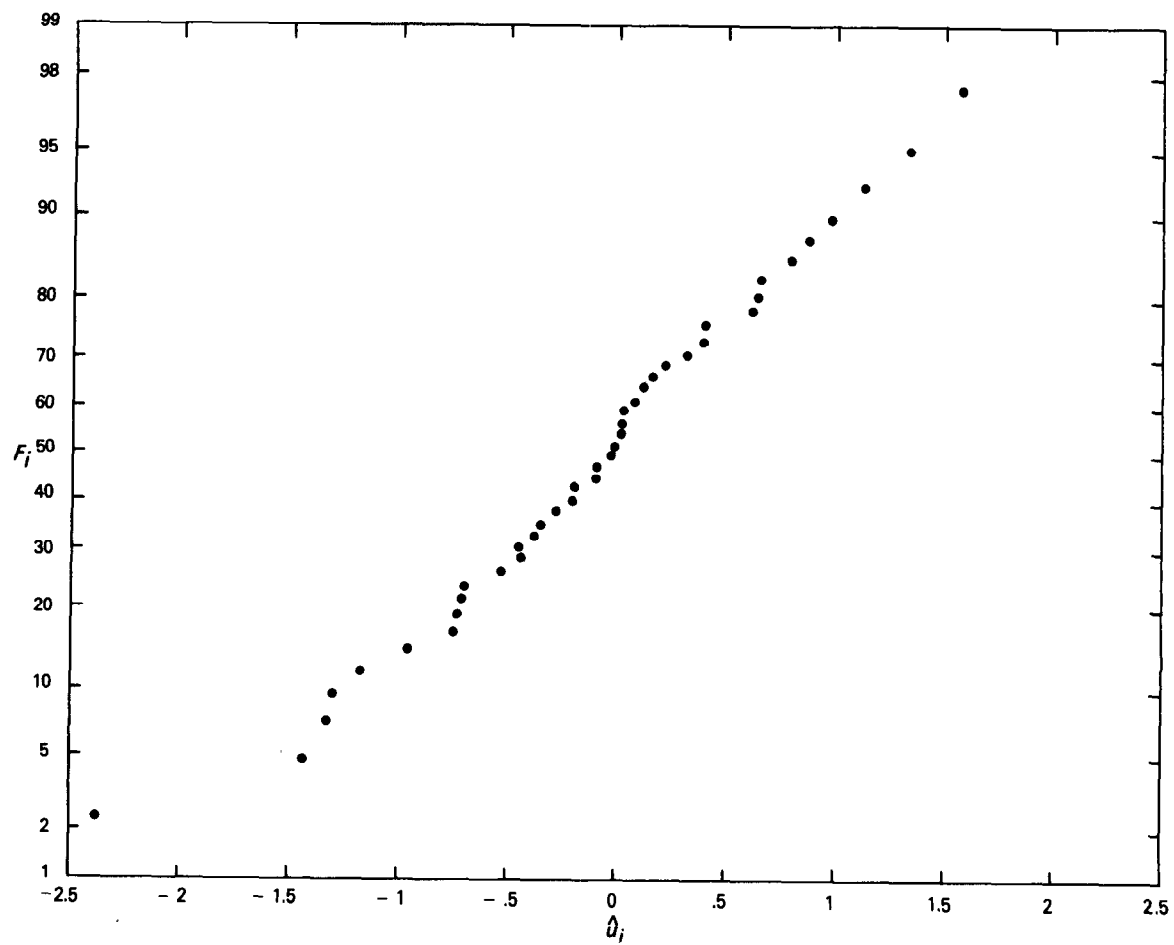


Figure 3

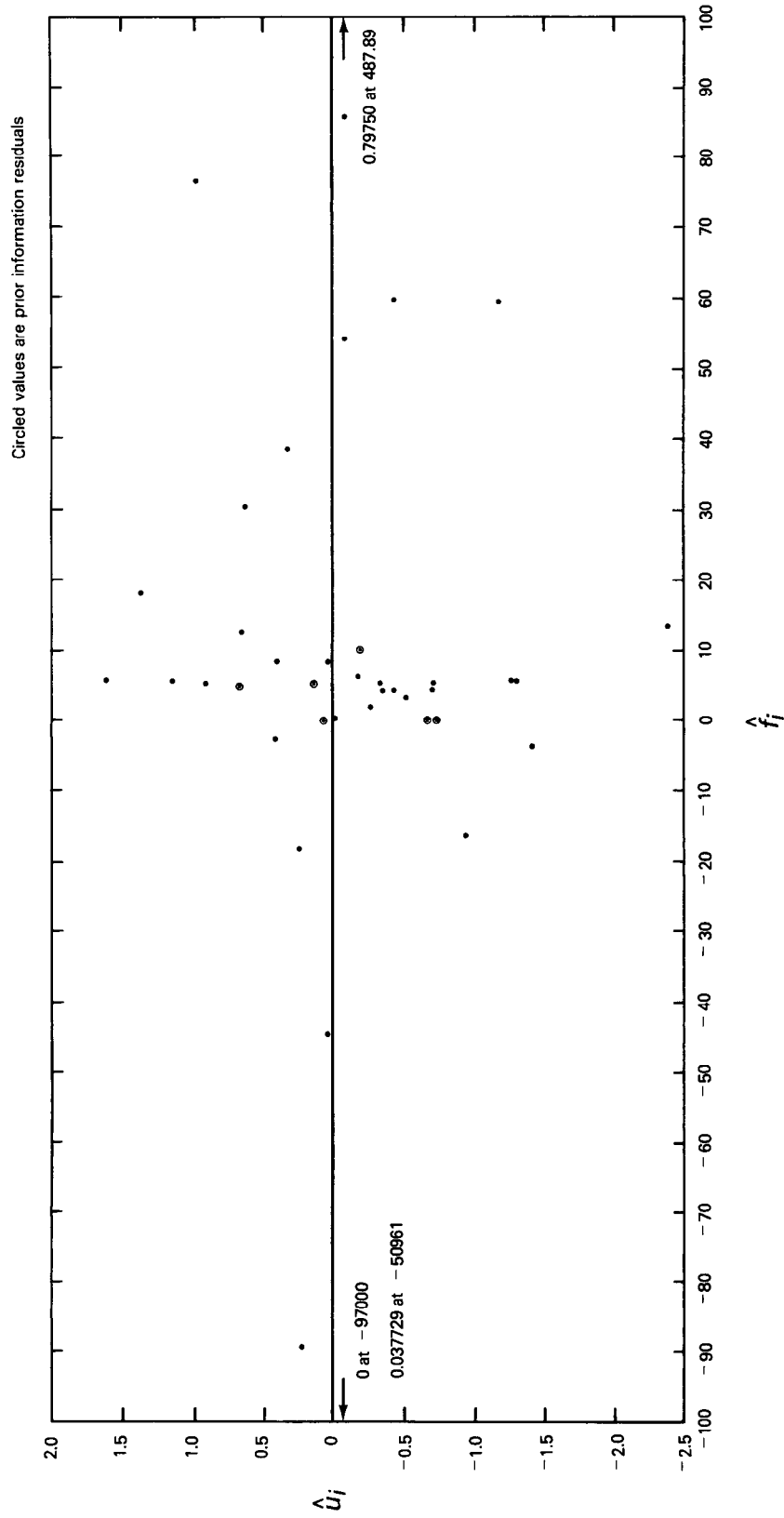


Figure 4

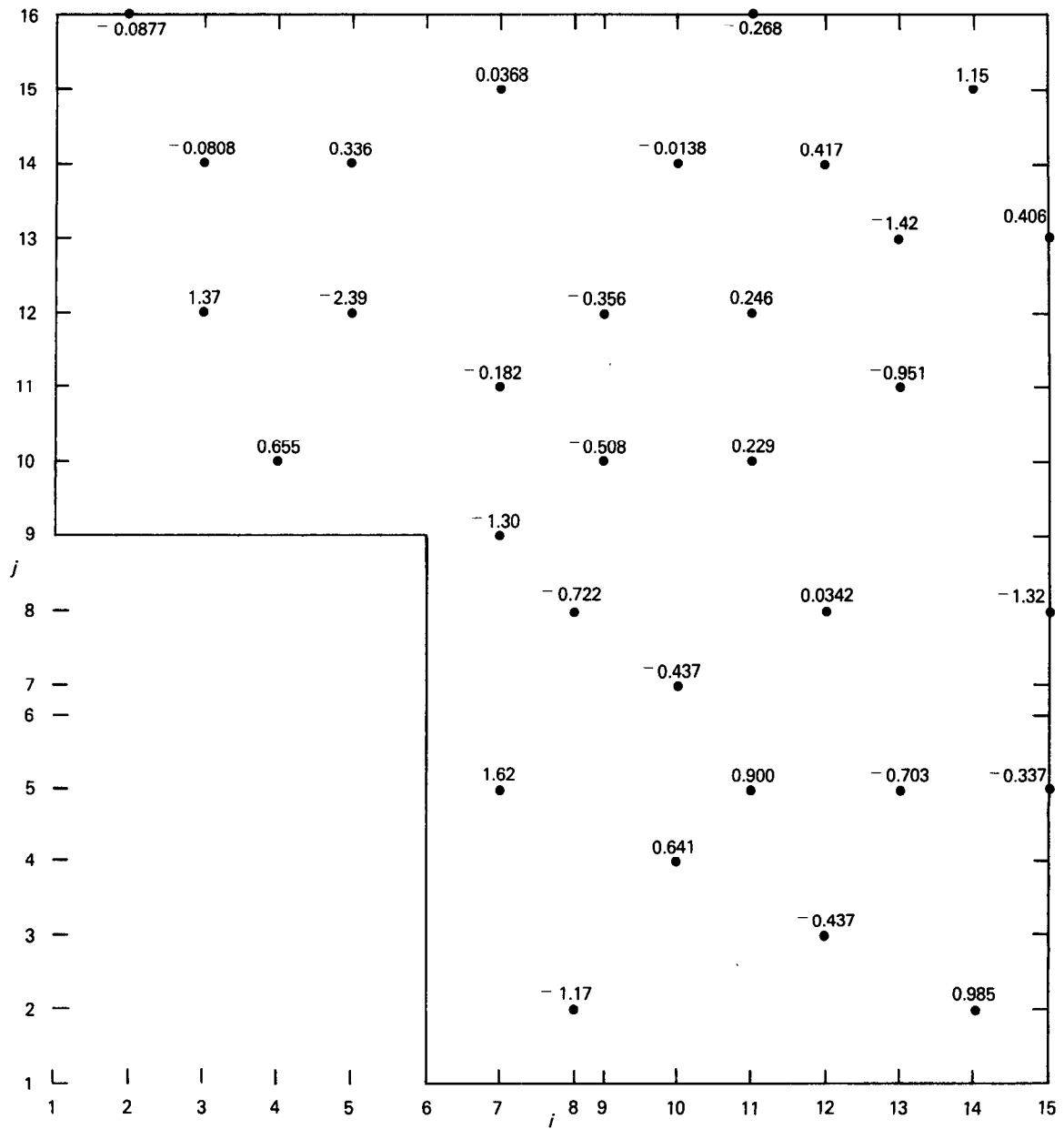


Figure 5

14	32	9	4	437	.98677									
	1													
3	4	5	6	7	9	10	13	14						
1940		1020		1.04			.48		.54	.00012		84	.000051	
.008														

Figure 6

Problem 5.6-1

a. Compute

$$\underline{H}(\underline{X}^T \underline{\omega} \underline{X})^{-1} \underline{H}^T$$

where $\underline{H} = [0 \ 0 \ 1]$. Then,

$$\underline{H}(\underline{X}^T \underline{\omega} \underline{X})^{-1} \underline{H}^T = \widehat{\text{Var}}(\hat{b}_3)/s^2.$$

By using equation 5.6-11,

$$W = \frac{(\tilde{\beta}_3 - \hat{b}_3)(\text{Var}(\hat{b}_3)/s^2)^{-1}(\tilde{\beta}_3 - \hat{b}_3)}{s^2}$$

$$= \frac{(\tilde{\beta}_3 - \hat{b}_3)^2}{\widehat{\text{Var}}(\hat{b}_3)}$$

$$H_0: \beta_3 = \frac{0.0003}{10} = 3 \times 10^{-5}$$

$$H_1: \beta_3 \neq 3 \times 10^{-5}$$

$$w = \frac{(3 \times 10^{-5} - 2.3025 \times 10^{-5})^2}{2.1307 \times 10^{-11}}$$

$$= 2.273 \text{ for data set 1.}$$

$$F_{0.05}(1,8) = 5.318 \text{ . } H_0 \text{ accepted}$$

Values of the ratio of recharge to transmissivity, $\beta_3 = W/T$, computed by the two methods are not significantly different.

$$w = \frac{(3 \times 10^{-5} - 2.3430 \times 10^{-5})^2}{2.9684 \times 10^{-11}}$$

$$= 1.454 \text{ for data set 2}$$

$$F_{0.05}(1,7) = 5.591 \text{ . } H_0 \text{ accepted.}$$

The Maxey-Eakin estimate of W/T could be used as prior information in the regression model, but an estimate of $\text{Var}(W/T)$ would also be needed.

b. This test is the same as the one in a except that

$$H_0: \beta_3 = 0 \quad H_1: \beta_3 \neq 0$$

$$w = \frac{(0 - 2.3025 \times 10^{-5})^2}{2.1307 \times 10^{-11}}$$

$$= 24.88 \text{ for data set 1}$$

. H_0 rejected.

$$w = \frac{(0 - 2.3430 \times 10^{-5})^2}{2.9684 \times 10^{-11}}$$

$$= 18.49 \text{ for data set 2}$$

. H_0 rejected.

W/T is significantly different from zero. Thus, recharge is a significant variable in the regression equation.

$$c. \quad \tilde{\beta}_3 = \hat{b}_3 \pm \sqrt{q F_{\alpha}(q, n-p)} s_{b_3}$$

$$= 2.3025 \times 10^{-5} \pm \sqrt{5.318} \times 4.6159 \times 10^{-6}$$

$$= 2.3025 \times 10^{-5}$$

$$\pm 1.0645 \times 10^{-5} \text{ for data set 1.}$$

$$\tilde{\beta}_3 = 2.3430 \times 10^{-5} \pm \sqrt{5.591} \times 5.4483 \times 10^{-6}$$

$$= 2.3430 \times 10^{-5}$$

$$\pm 1.2883 \times 10^{-5} \text{ for data set 2.}$$

Problem 5.6-2

For T extreme:

$$T = \hat{T} \pm \frac{\sqrt{2F_{0.05}(2,5)}}{s_{bT}} \widehat{\text{Var}}(T)$$

$$= 0.11349 \pm \frac{\sqrt{2 \times 5.7861}}{0.0030827} (0.95030 \times 10^{-5})$$

$$= 0.11349 \pm 0.010487$$

$$S = \hat{S} \pm \frac{\sqrt{2F_{0.05}(2,5)}}{s_{bT}} \widehat{\text{Cov}}(T, S)$$

$$= 0.00055221 \pm \frac{\sqrt{2 \times 5.7861}}{0.0030827} (-0.11369 \times 10^{-6})$$

$$= 0.00055221 \mp 0.00012546.$$

For S extreme:

$$T = \hat{T} \pm \frac{\sqrt{2F_{0.05}(2,5)}}{s_{bS}} \widehat{\text{Cov}}(T, S)$$

$$= 0.11349 \pm \frac{\sqrt{2 \times 5.7861}}{3.8203 \times 10^{-5}} (-0.11369 \times 10^{-6})$$

$$= 0.11349 \mp 0.010124$$

$$S = \hat{S} \pm \frac{\sqrt{2F_{0.05}(2,5)}}{s_{bS}} \widehat{\text{Var}}(S)$$

$$= 0.00055221 \pm \frac{\sqrt{2 \times 5.7861}}{3.8203 \times 10^{-5}} (0.14595 \times 10^{-8})$$

$$= 0.00055221 \pm 0.00012996$$

Problem 5.6-3

$$\bar{b} = \hat{b} \pm \frac{\sqrt{qF_{\alpha}(q, n-p)}}{s_{bi}} V_{bi}$$

where $V_b = (X^T \omega X)^{-1} s^2$. Let $(X^T \omega X)^{-1} s^2 = A = \{A_{ij}\}$. Then the above equation can be written in algebraic form for calculations as

$$\bar{b}_j = \hat{b}_j \pm \sqrt{qF_{\alpha}(q, n-p)} \frac{A_{ij}}{\sqrt{A_{ii}}}$$

Calculations:

$$\sqrt{qF_{\alpha}(q, n-p)} = \sqrt{2F_{0.05}(2, 27)} = \sqrt{2 \times 3.359} = 2.592$$

For $T_3 = \beta_{12}$ extreme:

$$\begin{aligned} \bar{b}_1 &= 80.978 \pm 9.2811 \\ \bar{b}_2 &= 935.15 \pm 208.42 \\ \bar{b}_3 &= -97000 \mp 85.314 \\ \bar{b}_4 &= -50961 \mp 29.377 \\ \bar{b}_5 &= 10.198 \pm 0.11520 \\ \bar{b}_6 &= 5.1211 \pm 1.3758 \times 10^{-2} \\ \bar{b}_7 &= 5.4730 \pm 1.2758 \times 10^{-2} \\ \bar{b}_8 &= 65.754 \pm 7.2341 \\ \bar{b}_9 &= 3.1149 \times 10^{-4} \pm 3.0988 \times 10^{-5} \end{aligned}$$

$$\begin{aligned} \bar{b}_{10} &= 487.89 \pm 2.5660 \\ \bar{b}_{11} &= -1.3995 \times 10^{-4} \mp 4.9215 \times 10^{-5} \\ \bar{b}_{12} &= 13.288 \pm 9.3998 \\ \bar{b}_{13} &= 1.3516 \times 10^{-4} \pm 9.3069 \times 10^{-5} \\ \bar{b}_{14} &= 8.0716 \times 10^{-2} \pm 3.5370 \times 10^{-5} \end{aligned}$$

For $q_{B1} = \beta_1$ extreme:

$$\begin{aligned} \bar{b}_1 &= 80.978 \pm 43.911 \\ \bar{b}_2 &= 935.15 \pm 489.14 \\ \bar{b}_3 &= -97000 \mp 222.36 \\ \bar{b}_4 &= -50961 \mp 73.632 \\ \bar{b}_5 &= 10.198 \pm 0.27770 \\ \bar{b}_6 &= 5.1211 \pm 3.2747 \times 10^{-2} \\ \bar{b}_7 &= 5.4730 \mp 3.2200 \times 10^{-3} \\ \bar{b}_8 &= 65.754 \pm 25.550 \\ \bar{b}_9 &= 3.1149 \times 10^{-4} \pm 5.4093 \times 10^{-5} \\ \bar{b}_{10} &= 487.89 \pm 6.2288 \\ \bar{b}_{11} &= -1.3995 \times 10^{-4} \mp 1.1701 \times 10^{-4} \\ \bar{b}_{12} &= 13.288 \pm 1.9832 \\ \bar{b}_{13} &= 1.3516 \times 10^{-4} \pm 2.0377 \times 10^{-5} \\ \bar{b}_{14} &= 8.0716 \times 10^{-2} \pm 1.5001 \times 10^{-4} \end{aligned}$$

Problem 5.7-1

a. Let $\underline{X} = \{X_{ij}\}$, $(\underline{X}^T \underline{\omega} \underline{X})^{-1} = \{A_{ij}\}$. Then

$$\underline{X}(\underline{X}^T \underline{\omega} \underline{X})^{-1} = \left\{ \sum_{k=1}^p X_{ik} A_{kl} \right\} = \{C_{il}\}$$

$$\underline{X}(\underline{X}^T \underline{\omega} \underline{X})^{-1} \underline{X}^T = \left\{ \sum_{l=1}^p C_{il} X_{jl} \right\} =$$

$$\left\{ \sum_{l=1}^p \sum_{k=1}^p X_{ik} A_{kl} X_{jl} \right\} = \left\{ \sum_{l=1}^p X_{jl} \sum_{k=1}^p X_{ik} A_{kl} \right\}$$

If $i=j$, then the entry is

$$\sum_{l=1}^p \sum_{k=1}^p X_{ik} A_{kl} X_{il} = \sum_{l=1}^p X_{il} \sum_{k=1}^p X_{ik} A_{kl}$$

Compute for $i=j=1$ for data set 1.

$$\underline{X}_1 = [0.95 \ 0.05 \ 23.750]$$

$$(\underline{X}^T \underline{\omega X})^{-1} = \begin{bmatrix} 0.9157290438 & 0.2752072275 & -5.983931169 \times 10^{-6} \\ & 0.7831966299 & -5.318014058 \times 10^{-6} \\ & & 6.878625596 \times 10^{-11} \end{bmatrix}$$

symmetric

$$\begin{aligned} \underline{X}_1(\underline{X}^T \underline{\omega X})^{-1} \underline{X}_1^T &= 0.95(0.95 \times 0.9157290438 \\ &+ 0.05 \times 0.2752072275 \\ &+ 23,750 \times (-5.983931169 \times 10^{-6}) \\ &+ 0.05(0.95 \times 0.2752072275 \\ &+ 0.05 \times 0.7831966299 \\ &+ 23,750 \times (-5.318014058 \times 10^{-6}) \\ &+ 23,750 \times (0.95 \times (-5.983931169 \times 10^{-6}) \\ &+ 0.05 \times (-5.318014058 \times 10^{-6}) \\ &+ 23,750 \times 6.878625596 \times 10^{-11})) \\ &= 0.6106927103 . \end{aligned}$$

$$\begin{aligned} \underline{X}(\underline{X}^T \underline{\omega X})^{-1} \underline{X}^T &= \underline{X} \underline{C} \underline{C}^{-1} (\underline{X}^T \underline{\omega X})^{-1} (\underline{C} \underline{C}^{-1})^T \underline{X}^T \\ &= \underline{X} \underline{C} (\underline{C}^T \underline{X}^T \underline{\omega X} \underline{C})^{-1} \underline{C}^T \underline{X}^T \\ &= (\underline{X} \underline{C}) (\underline{X} \underline{C})^T \underline{\omega} (\underline{X} \underline{C})^{-1} (\underline{X} \underline{C})^T \\ &= \underline{S} (\underline{S}^T \underline{\omega S})^{-1} \underline{S}^T . \end{aligned}$$

b. $\widehat{\text{Var}}(\hat{f}_j) = \underline{X}_j \widehat{\text{Var}}(\hat{b}) \underline{X}_j^T$

Let $j=1$, data set 1.

$$\begin{aligned} \widehat{\text{Var}}(\hat{f}_1) &= \underline{X}_1 (\underline{X}^T \underline{\omega X})^{-1} s^2 \underline{X}_1^T \\ &= 0.6106927103 \times 0.30975625 \\ &= 0.1891658838 . \end{aligned}$$

c. $f_{\beta j} = \hat{f}_j \pm \sqrt{p F_{\alpha}(p, n-p)} s_{y j}$
 $F_{0.05}(3, 8) = 4.066$
 $\hat{f}_1 = 0.95 \hat{b}_1 + 0.05 \hat{b}_2 + 23,750 \hat{b}_3$
 $= 0.95(50.1204) + 0.05(9.48742)$

2	2	7	0	2	.0014328			
.11349	.00055221							
1.6715	2.2521	2.5564	2.8012	3.0256	3.2832	3.5086		
1	1	1	1	1	1	1		
-8.09604	-1362.96							
-12.9342	-1420.13							
-15.5344	-1436.83							
-17.6456	-1446.30							
-19.5912	-1452.76							
-21.8336	-1458.27							
-23.8030	-1461.84							
.10300	.00067767							
1.5947	2.2223	2.5541	2.8218	3.0676	3.3503	3.5979		
.12361	.00042225							
1.7821	2.3239	2.6058	2.8320	3.0390	3.2763	3.4839		

Figure 1

$$\begin{aligned} &+ 23,750(2.30248 \times 10^{-5}) \\ &= 48.636 \end{aligned}$$

$$\begin{aligned} f_{\beta 1} &= 48.636 \pm \sqrt{3 \times 4.066} \times 0.434932 \\ &= 48.636 \pm 1.519 \end{aligned}$$

for $j=1$, data set 1.

Problem 6.2-1

Sets of parameters for the modified Beale's measure:

1. (0.12398, 0.00042675)
2. (0.10300, 0.00067767)
3. (0.10337, 0.00068217)
4. (0.12361, 0.00042225)

Only 2 and 4 need be used because the other two are nearly the same. By using 2, drawdown, s , is: 1.5947, 2.2223, 2.5541, 2.8218, 3.0676, 3.3503, 3.5979. By using 4, s is: 1.7821, 2.3239, 2.6058, 2.8320, 3.0390, 3.2763, 3.4839.

The resulting value of the modified Beale's measure is

$$\hat{N}_b = 0.027702$$

Because $F_{0.05}(2, 5) = 5.7861$, $0.09/F = 0.0156$ and $1/F = 0.173$, so that the model is almost roughly linear.

The input data for the modified Beale's measure program are shown in figure 1.

Problem 6.2-2

From the computer output, the modified Beale's measure is 0.29808. Based on $F_{0.05}(2,27) = 3.359$, the modified Beale's measure indicates that the model is at the point of being highly

nonlinear. Hence, linear theory can be applied to use the W statistic based on $q=2$ only as a very rough approximation.

The input data to the regression code, modified to compute the modified Beale's measure, are shown in figure 1.

CLASS PROBLEM													
TWO-DIMENSIONAL FLOW													
SEVERAL ZONES													
	15	16	4	32	7	14	0	4	2	10	0	0	0
		2		.08		0		0		1			
DX		1	0										
	1	14	1	1		1	1						
		1000		1000		1000		1000		1000		1000	400
DY		1000		1000		1000		1000		1000		1000	
	1	15	1	1		1	1						
		1000		1000		1000		1000		1000		400	1000
		1000		1000		1000		1000		1000		1000	1000
CX		2	0										
	6	14	1	8		1	0						
	1	14	9	15		1	0						
CY		2	0										
	6	14	1	8		1	0						
	1	14	9	15		1	0						
VL		2	0										
	8	14	6	6		1	0						
	8	8	7	15		1	0						
HR		2	0										
	8	15	6	7		4.5	0						
	8	9	7	16		4.5	0						
QR		2	0										
	6	14	1	8		1	0						
	1	14	9	15		1	0						
HC		1	0										
	1	15	1	16		0	0						
IZN		7	0										
	6	14	1	8	2	0							
	1	14	9	15	2	0							
	1	6	12	15	1	0							
	6	7	1	3	3	0							
	8	14	1	4	3	0							
	8	14	6	6	4	0							
	8	8	7	15	4	0							
	1	8	2		7000	1000		60.70				1	
	2	14	2		12400	1000		75.64				1	
	3	12	3		10400	2000		60.27				1	
	4	10	4		8400	3000		29.67				1	
	5	7	5		6000	4000		4.22				1	
	6	11	5		9400	4000		4.37				1	
	7	13	5		11400	4000		6.07				1	
	8	14	5		13400	4000		5.81				1	
	9	10	7		8400	5400		4.57				1	
	10	8	8		7000	6400		5.21				1	
	11	12	8		10400	6400		-44.89				1	
	12	14	8		13400	6400		7.01				1	
	13	7	9		6000	7400		6.95				1	
	14	4	10		3000	8400		12.21				1	
	15	9	10		7400	8400		4.04				1	

Figure 1

16	11	10	9400	8400	-89.36	1
17	7	11	6000	9400	6.68	1
18	13	11	11400	9400	-15.32	1
19	3	12	2000	10400	16.88	1
20	5	12	4000	10400	15.87	1
21	9	12	7400	10400	4.48	1
22	11	12	9400	10400	-18.34	1
23	13	13	11400	11400	-2.47	1
24	14	13	13400	11400	8.10	1
25	3	14	2000	12400	54.12	1
26	5	14	4000	12400	38.27	1
27	10	14	8400	12400	.053	1
28	12	14	10400	12400	-2.92	1
29	7	15	6000	13400	8.30	1
30	14	15	12400	13400	4.54	1
31	2	15	1000	14400	85.82	1
32	11	15	9400	14400	2.26	1
1	8	8	0	9		
2	10	10	0	11		
3	12	12	0	13		
4	10	10	14	0		
8		0				
9	.00012					
10	84					
11	0					
12	0					
13	.000051					
14	.008					
1	65.754	65.754		0	.00031149	
2	487.89	487.89		0	-.00013995	
3	13.288	13.288		0	.00013516	
4	487.89	487.89		.080716	0	
1	16	7	16	1	80.978	0
7	16	15	16	2	935.15	0
11	10	11	10	3	-97000	1940
12	8	12	8	4	-50961	1020
IN	1	0				
15	15	5	16	-1	0	
1	10	5	6	1.04	.48	
15	16	10.198				
15	15					
15	14					
15	13					
15	12					
15	11					
15	10					
15	9					
15	8					
15	7	5.1211				
2	2	6	7	.48	.54	
15	6	5.1211				
15	5	5.4730				
4						

Figure 1—Continued

1	90.259
2	1143.6
3	-97085
4	-50990
5	10.313
6	5.1349
7	5.4858
8	72.988
9	3.4248E-4
10	490.46
11	-1.8916E-4
12	22.688
13	2.2823E-4
14	8.0751E-2
1	71.697
2	726.73
3	-96915
4	-50932
5	10.083
6	5.1073
7	5.4602
8	58.520
9	2.8050E-4
10	485.32
11	-9.0735E-5
12	3.8882
13	4.2091E-5
14	8.0681E-2
1	124.97
2	1424.3
3	-97222
4	-51035
5	10.476
6	5.1538
7	5.4698
8	91.304
9	3.6558E-4
10	494.12
11	-2.5696E-4
12	15.271
13	1.5554E-4
14	8.0866E-2
1	36.987
2	446.01
3	-96778
4	-50887
5	9.9203
6	5.0884
7	5.4762
8	40.204
9	2.5740E-4
10	481.66
11	-2.2940E-5
12	11.305
13	1.1478E-4
14	8.0566E-2
2	.98677

Problem 6.3-1

Compute

$$\hat{\gamma} = (\underline{Y}_p - \underline{X}_p \hat{b}^*)^T [s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T + \underline{U}]^{-1} \cdot (\underline{Y}_p - \underline{X}_p \hat{b}^*)$$

For data set 1

$$\hat{b}^* = \begin{bmatrix} 50.018 \\ 9.1954 \\ 2.5008 \times 10^{-5} \end{bmatrix}$$

For data set 2

$$\hat{b}^* = \begin{bmatrix} 50.055 \\ 9.7914 \\ 2.2766 \times 10^{-5} \end{bmatrix}$$

For data set 1

$$(\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} s^2 =$$

$$\begin{bmatrix} 2.5550 \times 10^{-1} & 8.9780 \times 10^{-2} & -1.7349 \times 10^{-6} \\ & 2.5550 \times 10^{-1} & -1.7349 \times 10^{-6} \\ \text{symmetric} & & 2.0715 \times 10^{-11} \end{bmatrix}$$

$$s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T = 1 \times 2.5550 \times 10^{-1} \times 1 \\ = 0.25550$$

$$\underline{U} = (1.1)^2 = 1.21$$

$$s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T + \underline{U} = 0.25550 + 1.21 \\ = 1.46550$$

$$[s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T + \underline{U}]^{-1}$$

$$= 0.68236$$

$$\underline{Y}_p - \underline{X}_p \hat{b}^* = 11 - 9.1954 = 1.8046$$

$$\hat{\gamma} = 1.8046 \times 0.68236 \times 1.8046 = 2.222$$

$$\chi_{0.05}^2(1) = 3.841 \therefore H_0 \text{ accepted.}$$

Prior and pure regression estimates of $\beta_2 = h_b$ are in agreement.

For data set 2

$$(\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} s^2 =$$

$$\begin{bmatrix} 5.4121 \times 10^{-1} & 2.6265 \times 10^{-1} & -3.9795 \times 10^{-6} \\ & 5.4121 \times 10^{-1} & -3.9795 \times 10^{-6} \\ \text{symmetric} & & 4.3413 \times 10^{-11} \end{bmatrix}$$

$$s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T = 1 \times 5.4121 \times 10^{-1} \times 1 \\ = 0.54121$$

$$\underline{U} = (0.95)^2 = 0.9025$$

$$s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T + \underline{U} = 0.54121 + 0.9025 \\ = 1.44371$$

$$[s^2 \underline{X}_p (\underline{X}_s^T \underline{V}_s^{-1} \underline{X}_s)^{-1} \underline{X}_p^T + \underline{U}]^{-1}$$

$$= 0.69266$$

$$\underline{Y}_p - \underline{X}_p \hat{b}^* = 9.5 - 9.7914 = -0.2914$$

$$\hat{\gamma} = -0.2914 \times 0.69266 \times (-0.2914)$$

$$= 0.5882$$

$$\therefore H_0 \text{ accepted.}$$