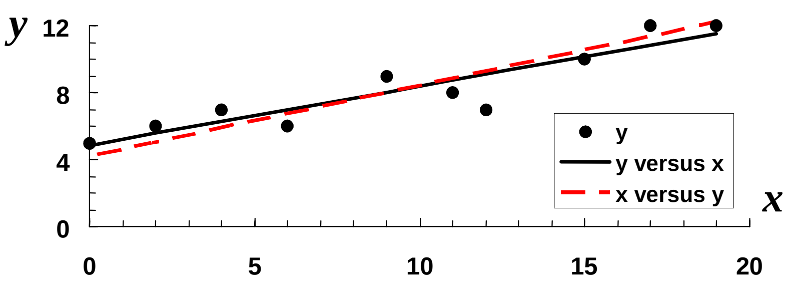
17.4 The results can be summarized as

	y versus x	x versus y
Best fit equation	$y = 4.851535 + 0.35247x$	$x = -9.96763 + 2.374101y$
Standard error	1.06501	2.764026
Correlation coefficient	0.914767	0.914767

We can also plot both lines on the same graph



Thus, the "best" fit lines and the standard errors differ. This makes sense because different errors are being minimized depending on our choice of the dependent (ordinate) and independent (abscissa) variables. In contrast, the correlation coefficients are identical since the same amount of uncertainty is explained regardless of how the points are plotted.

17.6 The sum of the squares of the residuals for this case can be written as

$$S_r = \sum_{i=1}^{n} (y_i - a_1 x_i)^2$$

The partial derivative of this function with respect to the single parameter a_1 can be determined as

$$\frac{\partial S_r}{\partial a_1} = -2\sum \left[(y_i - a_1 x_i) x_i \right]$$

Setting the derivative equal to zero and evaluating the summations gives

$$0 = \sum y_i x_i - a_1 \sum x_i^2$$

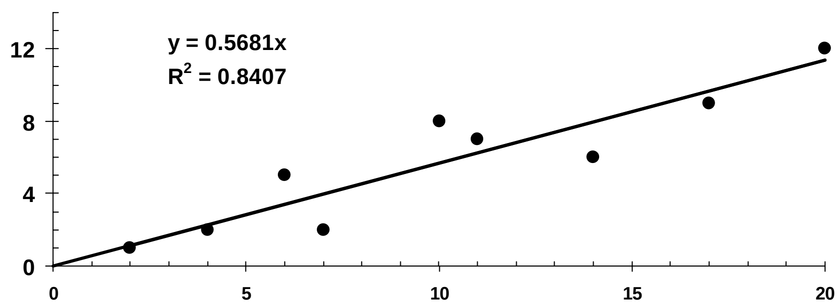
which can be solved for

$$a_1 = \frac{\sum y_i x_i}{\sum x_i^2}$$

So the slope that minimizes the sum of the squares of the residuals for a straight line with a zero intercept is merely the ratio of the sum of the dependent variables (y) times the sum of the independent variables (x) over the sum of the independent variables squared (x^2). Application to the data gives

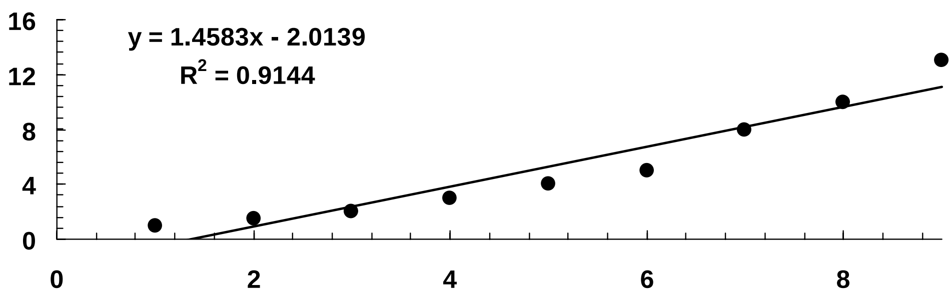
x	y	xy	x^2
2	1	2	4
4	2	8	16
6	5	30	36
7	2	14	49
10	8	80	100
11	7	77	121
14	6	84	196
17	9	153	289
20	12	240	400
		688	1211

Therefore, the slope can be computed as 688/1211 = 0.5681. The fit along with the data can be displayed as



17.7 (a) The results can be summarized as

$$y = -2.01389 + 1.458333x \qquad (s_{y/x} = 1.306653; r = 0.956222)$$

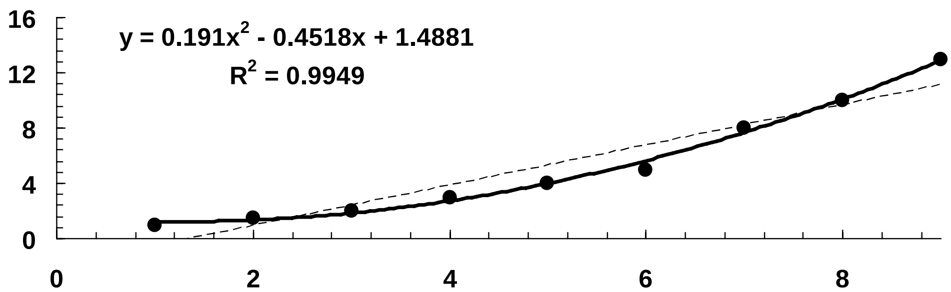


As can be seen, although the correlation coefficient appears to be close to 1, the straight line does not describe the data trend very well.

(b) The results can be summarized as

$$y = 1.488095 - 0.45184x + 0.191017x^2 \qquad (s_{y/x} = 0.344771; r = 0.997441)$$

A plot indicates that the quadratic fit does a much better job of fitting the data.



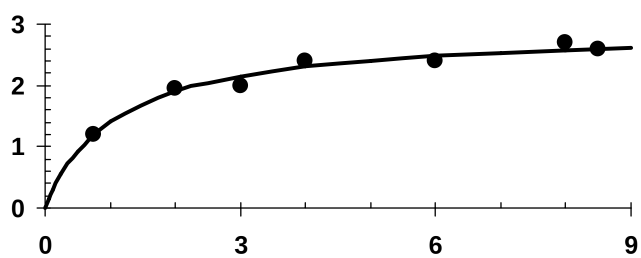
17.8 (a) We regress 1/*y* versus 1/*x* to give

$$\frac{1}{y} = 0.34154 + 0.36932\frac{1}{x}$$

Therefore, α_3 = 1/0.34154 = 2.927913 and β_3 = 0.36932(2.927913) = 1.081337, and the saturation-growth-rate model is

$$y = 2.927913\frac{x}{1.081337 + x}$$

The model and the data can be plotted as



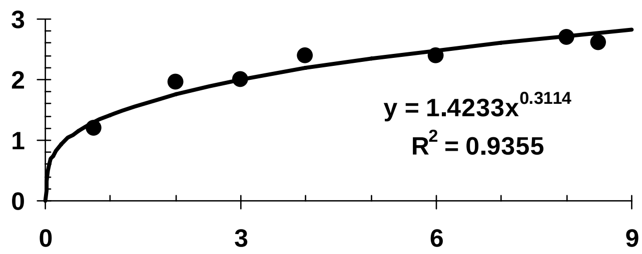
(b) We regress $\log_{10}(y)$ versus $\log_{10}(x)$ to give

$$\log_{10} y = 0.153296 + 0.311422\log_{10} x$$

Therefore, $\alpha_2 = 10^{0.153296}$ = 1.423297 and β_2 = 0.311422, and the power model is

$$y = 1.423297x^{0.311422}$$

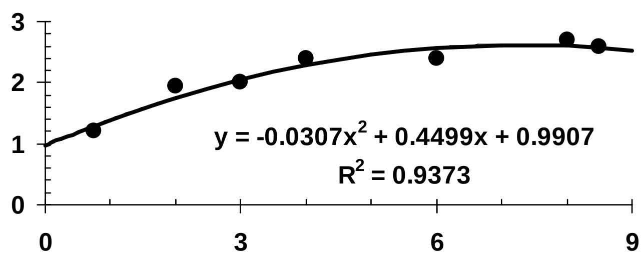
The model and the data can be plotted as



(c) Polynomial regression can be applied to develop a best-fit parabola

$$y = -0.03069x^2 + 0.449901x + 0.990728$$

The model and the data can be plotted as



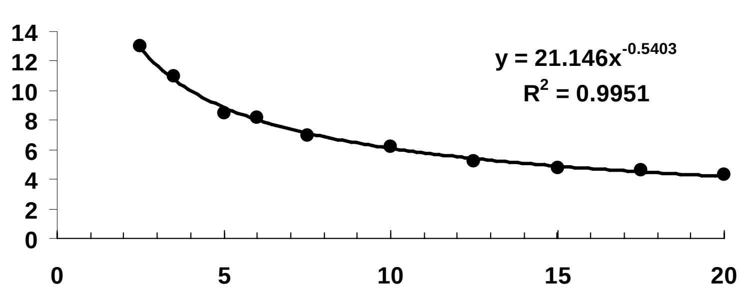
17.9 We regress $\log_{10}(y)$ versus $\log_{10}(x)$ to give

$$\log_{10} y = 1.325225 - 0.54029 \log_{10} x$$

Therefore, $\alpha_2 = 10^{1.325225} = 21.14583$ and $\beta_2 = -0.54029$, and the power model is

$$y = 21.14583x^{-0.54029}$$

The model and the data can be plotted as



The model can be used to predict a value of $21.14583(9)^{-0.54029} = 6.451453$.