

# Standard course – Modelling

## Lesson SM1.4 – How to build a data-driven model - exercises

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## • Exercise 1

```
R = corrccoef(data, 'Rows', 'complete');
```

7.

	NEE	ER	Pressure	Soil moisture	Soil temp.	Air moisture	Air temp.	Irradiance	GPP
NEE	1.00	-0.65	-0.27	-0.32	-0.35	-0.18	-0.34	-0.39	0.93
ER	-0.65	1.00	0.06	0.60	0.36	0.19	0.21	0.50	-0.89
Pressure	-0.27	0.06	1.00	0.02	-0.07	0.04	0.32	-0.21	-0.20
Soil moisture	-0.32	0.60	0.02	1.00	-0.02	0.21	0.04	0.20	-0.49
Soil temp.	-0.35	0.36	-0.07	-0.02	1.00	-0.32	0.73	0.55	-0.39
Air moisture	-0.18	0.19	0.04	0.21	-0.32	1.00	-0.54	-0.22	-0.20
Air temp	-0.34	0.21	0.32	0.04	0.73	-0.54	1.00	0.30	-0.31
Irradiance	-0.39	0.50	-0.21	0.20	0.55	-0.22	0.30	1.00	-0.48
GPP	0.93	-0.89	-0.20	-0.49	-0.39	-0.20	-0.31	-0.48	1.00

8.

7.



## • Exercise 2

### ER models

```
clear y x1 X
y=A(:,9);
x1=A(:,15);
X=[ones(size(x1)),x1];
```

```
b=regress(y,X);
```

Model:

$$1. ER = a_0 + a_1 \text{ soil moisture}$$

$$a_0 = 0.23 \text{ mol/m}^2/\text{day}$$

$$a_1 = 0.013 \text{ mol/m}^2/\text{day}$$

```
x2=A(:,31);
X=[X,x2];
b2=regress(y,X);
```

$$2. ER = a_0 + a_1 \text{ soil moisture} + a_2 \text{ irradiance}$$

$$a_0 = -0.07 \text{ mol/m}^2/\text{day}$$

$$a_1 = 0.011 \text{ mol/m}^2/\text{day}$$

$$a_2 = 4.6 * 10^{-4} \text{ mol/W/day}$$



## • Exercise 2

### GPP models

```
clear y x1 X
y=A(:,7)-A(:,9);
x1=A(:,15);
X=[ones(size(x1)),x1];
```

```
b=regress(y,X);
```

```
x2=A(:,31);
```

```
X=[X,x2];
```

```
b2=regress(y,X);
```

Model:

1.  $GPP = a_0 + a_1 \text{ soil moisture}$

$$a_0 = -0.57 \text{ mol/m}^2/\text{day}$$

$$a_1 = -0.018 \text{ mol/m}^2/\text{day}$$

2.  $GPP = a_0 + a_1 \text{ soil moisture} + a_2 \text{ irradiance}$

$$a_0 = 0.14 \text{ mol/m}^2/\text{day}$$

$$a_1 = -0.015 \text{ mol/m}^2/\text{day}$$

$$a_2 = -0.0011 \text{ mol/W/day}$$



## • Exercise 3

### ER model

```
clear y x1 b model beta0
```

```
y=A(:,9);
```

```
x1=A(:,27);
```

```
model = @(b, x) (b(1) * exp (b(2) * x));
```

```
beta0=[1;1];
```

```
[b, R, J, covb, mse] = nlinfit (x1, y, model, beta0);
```

```
N=length(y);
```

```
k=length(b)+1;
```

```
AIC=N*log(sum(R.^2)/N)+2*k;
```

Estimate	
b1	0.38
b2	0.03

**AIC = -149.66**



## • Exercise 3

### GPP model

```
clear y x1 b model beta0
```

```
y=A(:,7)-A(:,9);
```

```
x1=A(:,31);
```

```
model=@(b, x) (b(1) * b(2) * x / ( b(1) + b(2) * x));
```

```
beta0=[-3;-0.003];
```

```
[b, R, J, covb, mse] = nlinfit (x1, y, model, beta0);
```

```
N=length(y);
```

```
k=length(b)+1;
```

```
AIC=N*log(sum(R.^2)/N)+2*k;
```

Estimate	
b1	-3.3
b2	-0.0022

**AIC = -61.74**



## • Exercise 4

### ER model

```
clear y x1 x2 b model beta0
```

```
y=A(:,9);
```

```
x1=A(:,27);
```

```
x2=A(:,15);
```

```
model = @(b, x) (exp (b(1) * x(:,1)) * (b(2)+b(3)*x(:,2)));
```

```
beta0=[1;1;1];
```

```
[b, R, J, covb, mse] = nlinfit ([x1,x2], y, model, beta0);
```

```
N=length(y);
```

```
k=length(b)+1;
```

```
AIC=N*log(sum(R.^2)/N)+2*k;
```

Estimate	
b1	0.019
b2	0.18
b3	0.0098

**AIC = -174.70**

The AIC is lower than the one obtained for the univariate regression. Hence, the multi regression model is better.



## • Exercise 4

### GPP model

```
clear y x1 x2 b model beta0
```

```
y=A(:,7)-A(:,9);
```

```
x1=A(:,31);
```

```
x2=A(:,15);
```

```
model=@(b, x) ((b(1) * b(2) * x(:,1)/( b(1) + b(2) * x(:,1))) * (b(3)+b(4)*x(:,2)));  
beta0=[-1;-0.0002;2;0.05];
```

```
[b, R, J, covb, mse] = nlinfit ([x1,x2], y, model, beta0);
```

```
N=length(y);
```

```
k=length(b)+1;
```

```
AIC=N*log(sum(R.^2)/N)+2*k;
```

Estimate	
b1	-0.08
b2	-0.0003
b3	3.8
b4	0.07

**AIC = -81.34**

The AIC is lower than the one obtained for the univariate regression. Hence, the multi regression model is better.