

Outline

- Definition & main principles
- Several extensions of linear regression
- Trees and forests
- Deep learning

Linear regression

$$Y = X\theta + \varepsilon$$

Y is a N -vector of output values,

X is a matrix N by P of inputs (design),

θ is a P -vector of parameters,

ε is a N -vector of residuals

- Simple linear regression (including one input only),
- Polynomial regression
- Linear model with interactions

$$Y = X\theta + \varepsilon$$

$$\begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_N \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1P} \\ x_{21} & x_{22} & \dots & x_{2P} \\ \dots & \dots & \dots & \dots \\ x_{N1} & x_{N2} & \dots & x_{NP} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \\ \dots \\ \theta_P \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_N \end{pmatrix}$$

$$Y = X\theta + \varepsilon$$

$$\begin{pmatrix} y_1 \\ \dots \\ y_N \end{pmatrix} = \begin{pmatrix} 1 & x_1 \\ \dots & \dots \\ 1 & x_N \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \dots \\ \varepsilon_N \end{pmatrix}$$

Several issues

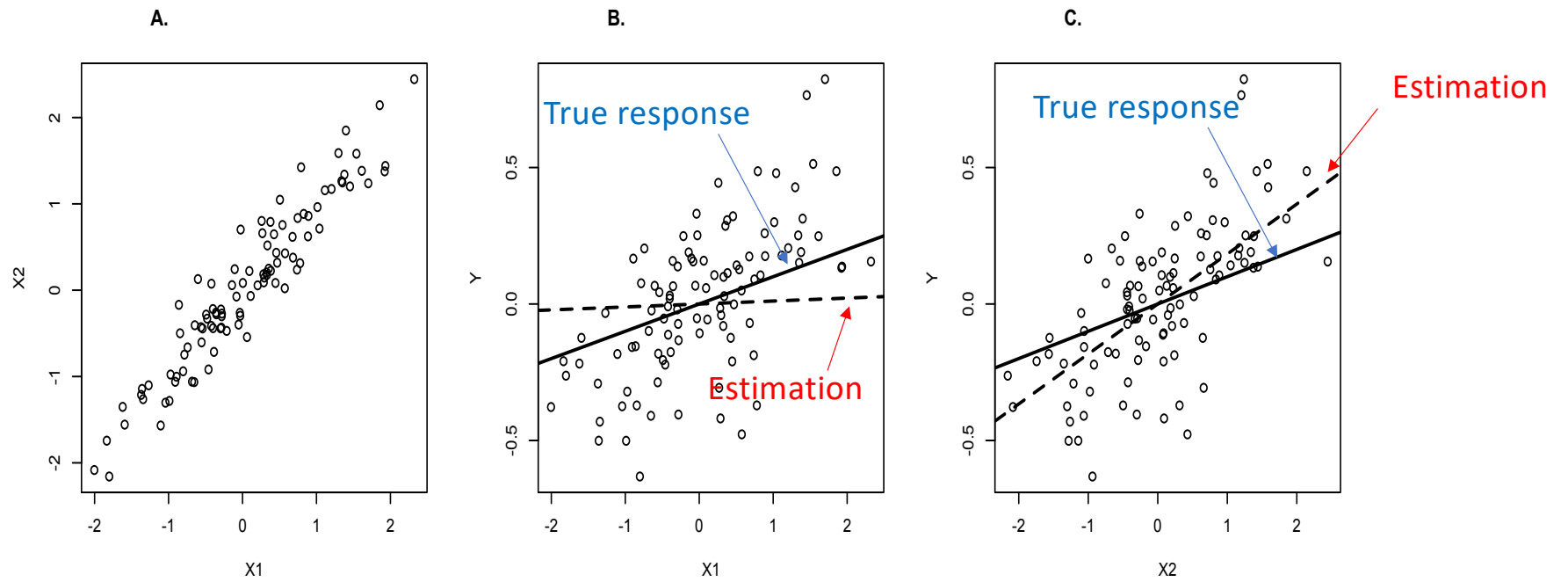
- Inputs X_1, \dots, X_p are sometimes (strongly) correlated
- Inputs X_1, \dots, X_p may have non-linear effects (unknown response shape),
- Too many inputs
- Need to estimate extreme responses, not mean response

Several issues

- **Inputs X_1, \dots, X_p are sometimes (strongly) correlated**
- Inputs X_1, \dots, X_p may have non-linear effects (unknown response shape),
- Too many inputs
- Need to estimate extreme responses, not mean response

Why can correlated inputs be an issue?

100 data generated with $Y = 0.1X_1 + 0.1X_2 + \varepsilon$



Correlation between X_1 and $X_2 = 0.95$

glm(Y~X1+X2-1)

Case 1

Correlated X1 and X2

Case 2

Independent X1 and X2

	Estimate	Std. Error	t value	Pr(> t)
X1	0.01082	0.07183	0.151	0.8805
X2	0.18313	0.07121	2.572	0.0116 *

	Estimate	Std. Error	t value	Pr(> t)
X1	0.08352	0.01728	4.835	4.94e-06 ***
X2	0.08829	0.01857	4.755	6.81e-06 ***

Both results are obtained with 100 data

glm(Y~X1+X2-1)

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Question 1. Effect of X1 significant in cases 1 and 2?

A. Yes

B. No

glm(Y~X1+X2-1)

Case 1

Correlated X1 and X2

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Question 1. Effect of X1 significant in cases 1 and 2?

A. Yes

B. No

Question 2. Which case shows the most accurate estimated values?

A. Case 1

B. Case 2

Idea: use independent combinations of X_1, X_2, \dots, X_p

- Principal component regression (PCR)
- Partial least square regression (PLSR)

Principal component analysis

- Replace the initial input variables (X_1, \dots, X_p) with new independent variables
- The new variables correspond to linear combinations of the old ones
- These linear combinations are chosen so as to have a maximum variance

$$Y = \alpha_0 + \alpha_1 X_1 + \cdots + \alpha_P X_P + \varepsilon$$

$$Z_1 = \sum_{j=1}^P \beta_{1j} X_j \quad Z_2 = \sum_{j=1}^P \beta_{2j} X_j \quad \text{etc.}$$

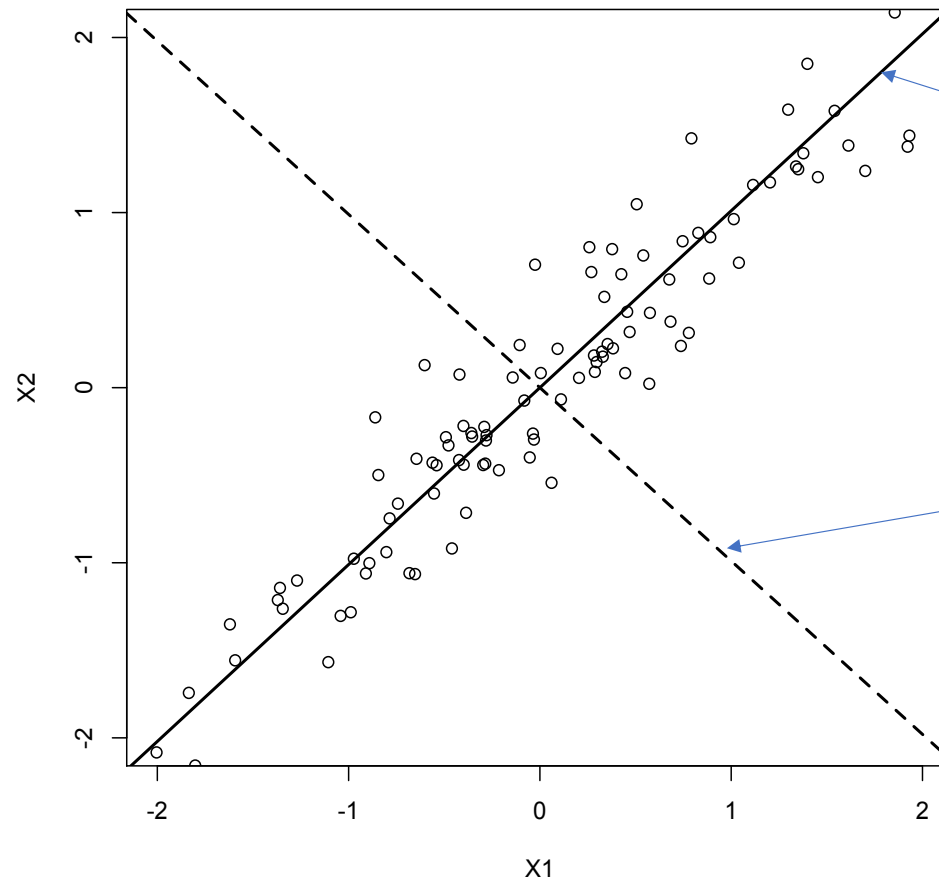
$$Y = \gamma_0 + \gamma_1 Z_1 + \cdots + \gamma_K Z_K + \varepsilon$$

Principal components



The components are calculated from the eigenvectors of
the variance-covariance matrix of
 X_1, \dots, X_p

→ Diagonalization of the variance-covariance matrix



Component 1

$$Z_1 = 0.704X_1 + 0.711X_2$$

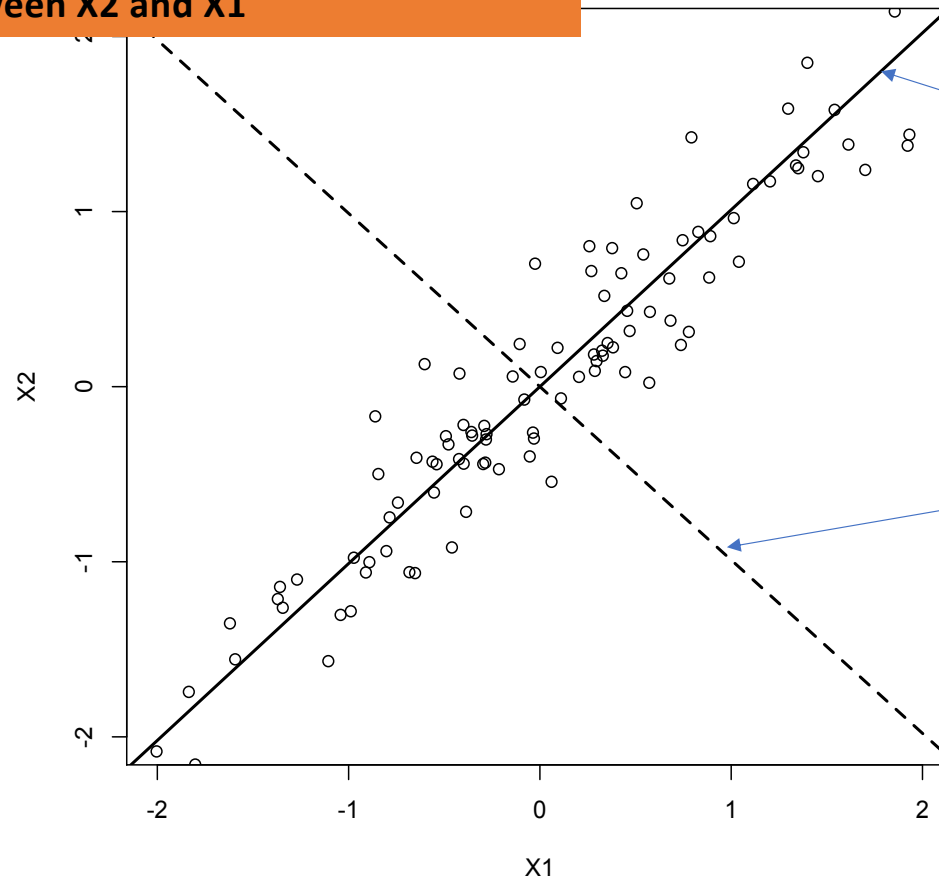
Component 2

$$Z_2 = 0.711X_1 - 0.704X_2$$

Question 1: Component 1 is closer to

A. The mean of X1 and X2

B. The difference between X2 and X1



Component 1

$$Z_1 = 0.704X_1 + 0.711X_2$$

Component 2

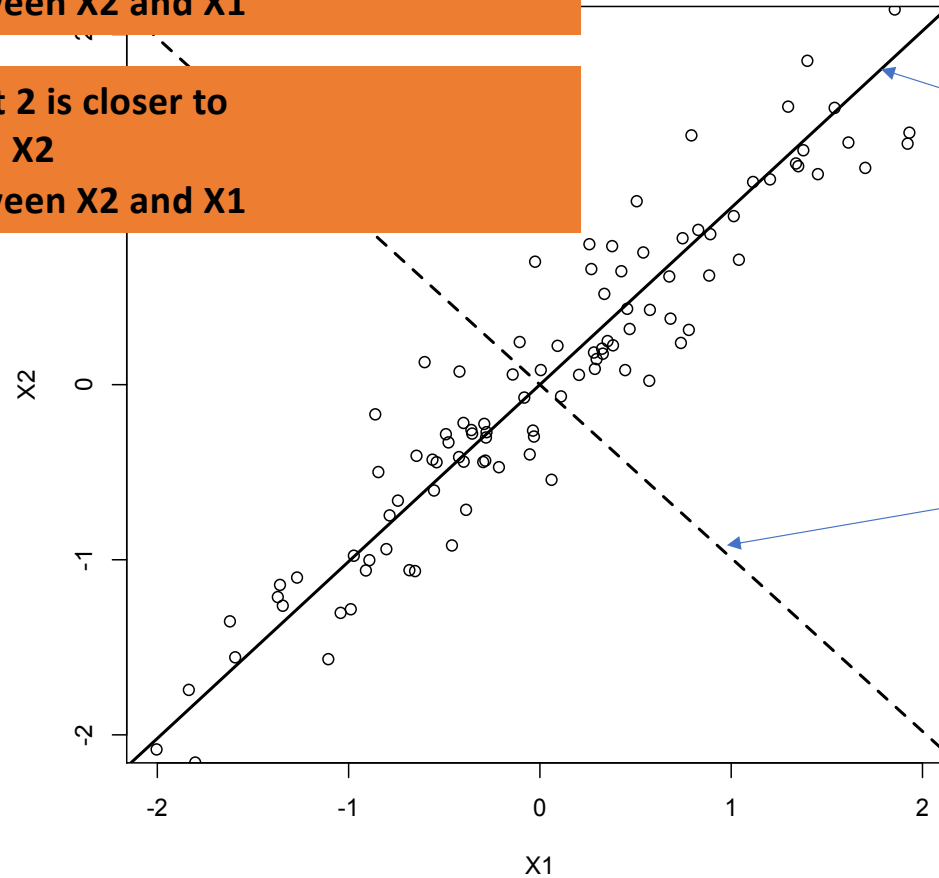
$$Z_2 = 0.711X_1 - 0.704X_2$$

Question 1: Component 1 is closer to

- A. The mean of X_1 and X_2**
- B. The difference between X_2 and X_1**

Question 2: Component 2 is closer to

- A. The mean of X_1 and X_2**
- B. The difference between X_2 and X_1**



Component 1

$$Z_1 = 0.704X_1 + 0.711X_2$$

Component 2

$$Z_2 = 0.711X_1 - 0.704X_2$$

Replace

$$Y = \alpha_1 X_1 + \alpha_2 X_2 + \varepsilon$$

by

$$\begin{aligned} Y &= b_1 CP_1 + \varepsilon \\ &= b_1 (0.704X_1 + 0.711X_2) + \varepsilon \\ &= 0.097X_1 + 0.098X_2 + \varepsilon \end{aligned}$$

Example: maize biomass prediction

Objective :

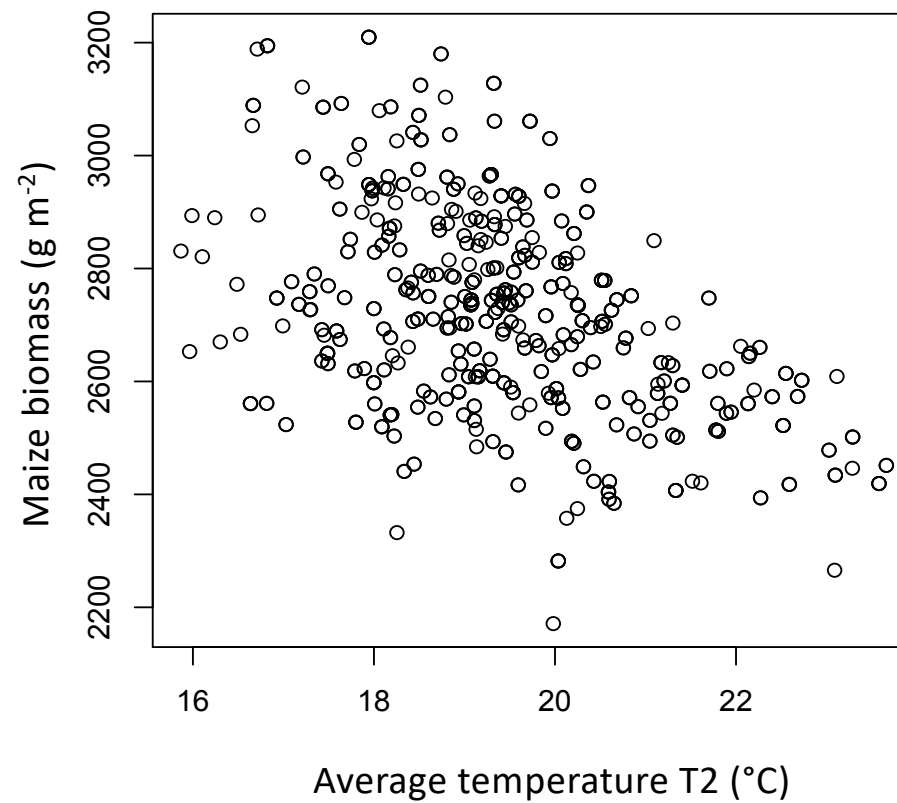
Develop a simple model predicting the final biomass of maize, noted B (g m^{-2}), from 6 input variables describing the climatic conditions during the growing season, under optimal water conditions.

Data :

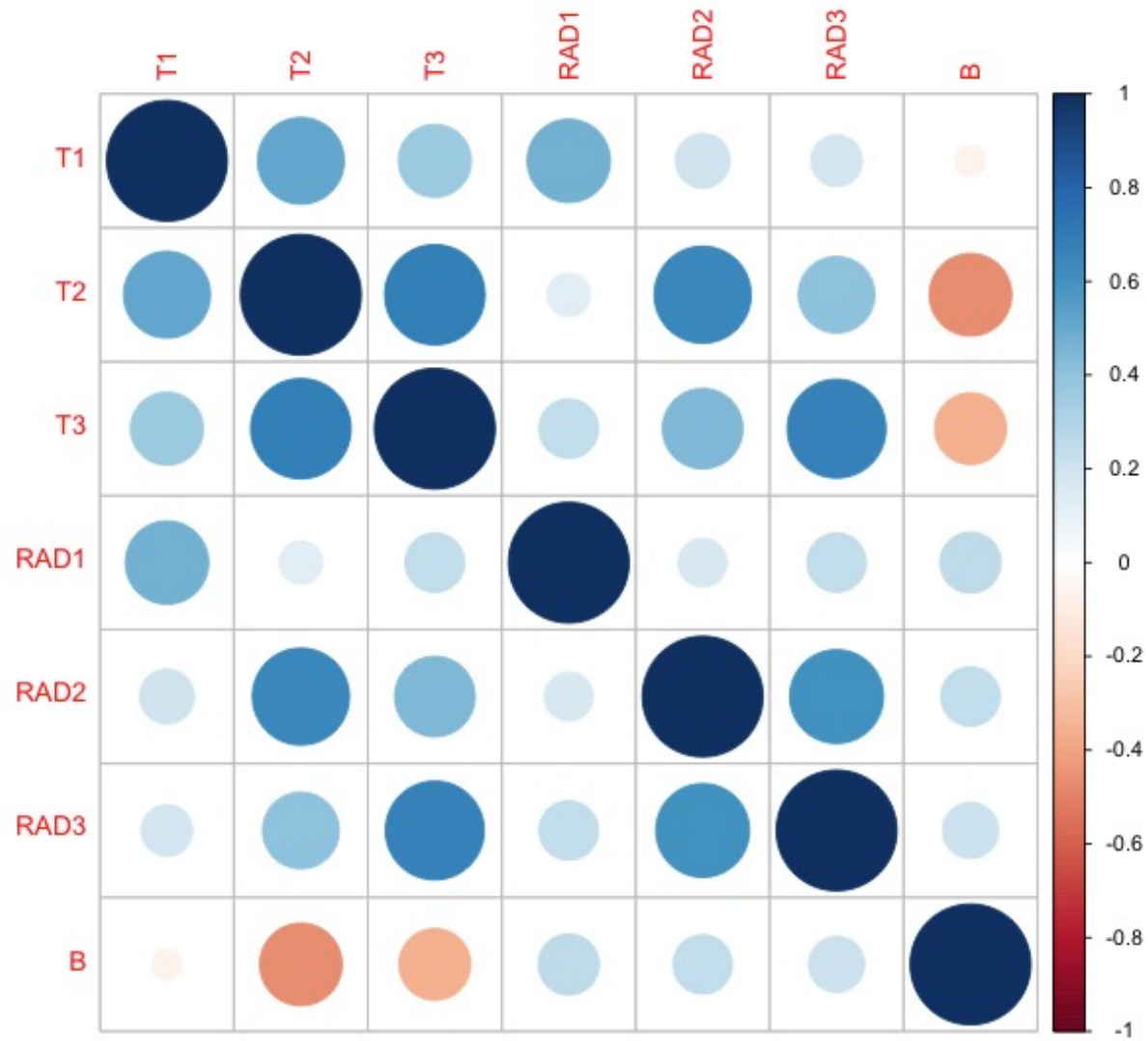
- 680 biomass data obtained for 40 different sites in France and for 17 years (1995 to 2011).
- Mean temperatures during the first part of the growing season (day 1 to day 50), during the second part of the growing season (day 51 to day 100) and during the last part of the growing season (day 101 to day 150). They are noted (T1, T2, T3).
- Average radiations during the same periods (RAD1, RAD2, RAD3).

https://github.com/davemakowski/TP_machinelearning

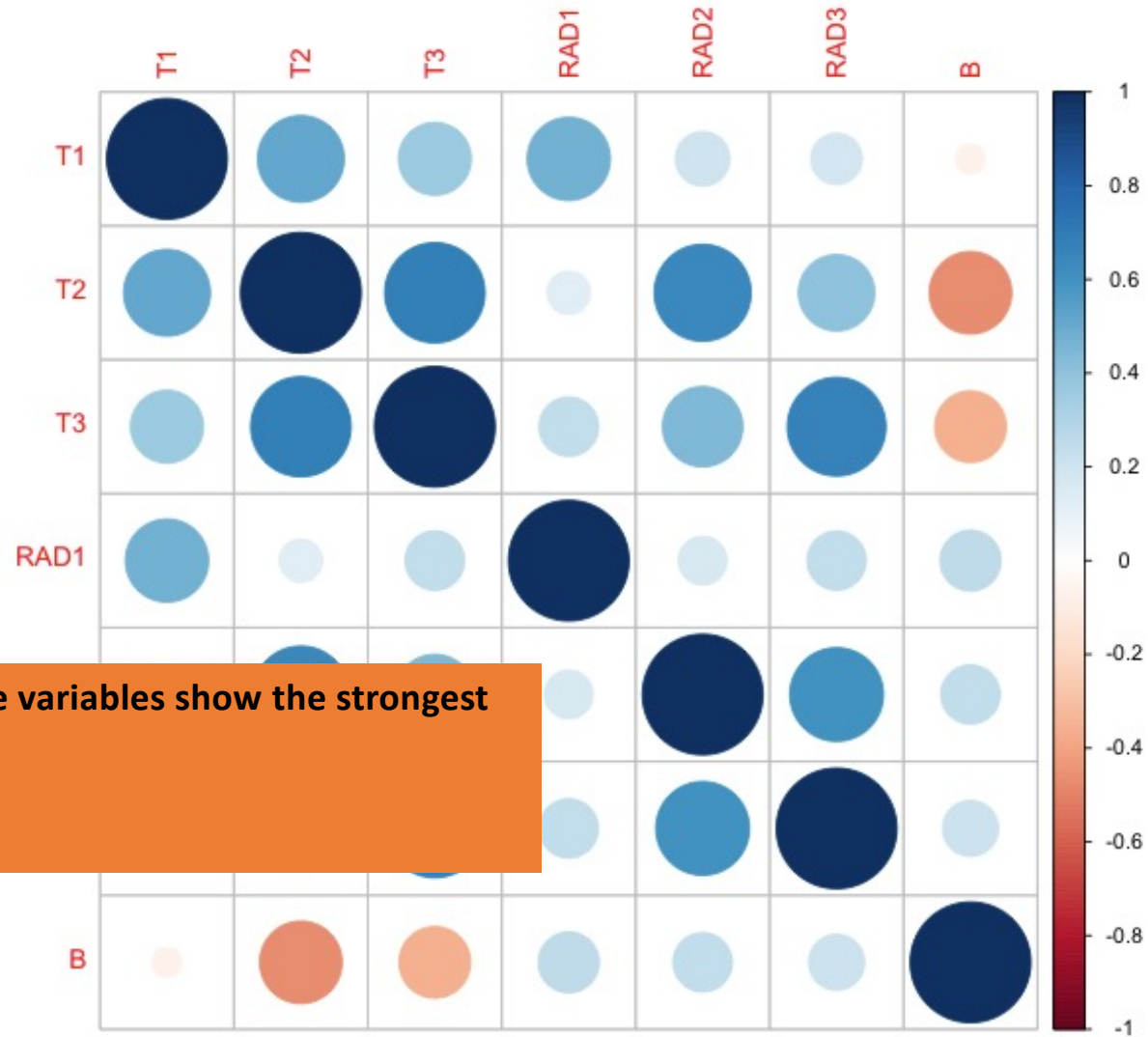
Example: maize biomass



Example: maize biomass



Example: maize biomass



Question : Which climate variables show the strongest effects on the biomass?

- A. RAD2, RAD3
- B. T2, T3

```
library(pls)
```

```
Mod_pcr<-pcr(B~T1+T2+T3+RAD1+RAD2+RAD3, data=DataSet,  
validation="L00", scale="TRUE")
```

```
summary(Mod_pcr)
```



```
> summary(Mod_pcr)
```

```
Data: X dimension: 680 6
```

```
      Y dimension: 680 1
```

```
Fit method: svdpc
```

```
Number of components considered: 6
```

```
VALIDATION: RMSEP
```

```
Cross-validated using 680 leave-one-out segments.
```

	(Intercept)	1 comps	2 comps	3 comps	4 comps	5 comps	6 comps
CV	182.1	182.3	180.2	138.3	120.4	71.92	64.51
adjCV	182.1	182.3	180.2	138.3	120.4	71.92	64.51

```
TRAINING: % variance explained
```

	1 comps	2 comps	3 comps	4 comps	5 comps	6 comps
X	49.60384	71.917	84.77	93.65	98.51	100.0
B	0.05284	2.998	43.12	56.92	84.66	87.7

Question : Is the average error of prediction lower than 100 g/m² ?

A. No

B. Yes

C. It depends on the number of components included

```
> summary(Mod_pcr)
```

```
Data: X dimension: 680 6
```

```
      Y dimension: 680 1
```

```
Fit method: svdpc
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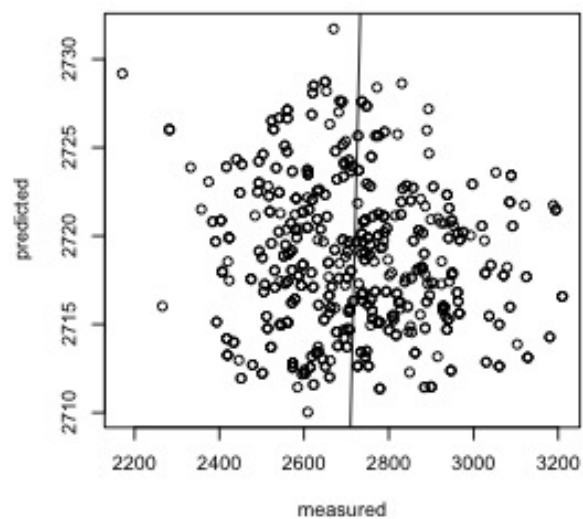
```
par(mfrow=c(2,3))
```

```
plot(Mod_pcr, line=TRUE, ncomp=1)  
plot(Mod_pcr, line=TRUE, ncomp=2)  
plot(Mod_pcr, line=TRUE, ncomp=3)  
plot(Mod_pcr, line=TRUE, ncomp=4)  
plot(Mod_pcr, line=TRUE, ncomp=5)  
plot(Mod_pcr, line=TRUE)
```

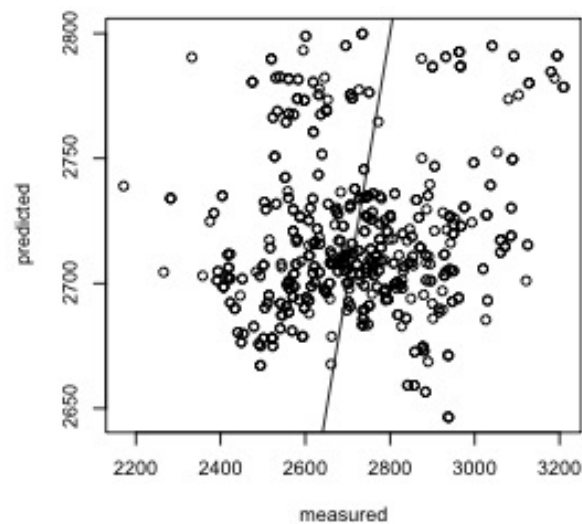
```
par(mfrow=c(1,1))
```

```
plot(RMSEP(Mod_pcr), legend ="topright")  
plot(Mod_pcr, "loadings", comps=1:2, legendpos="topleft", ylim=c(-1,1))
```

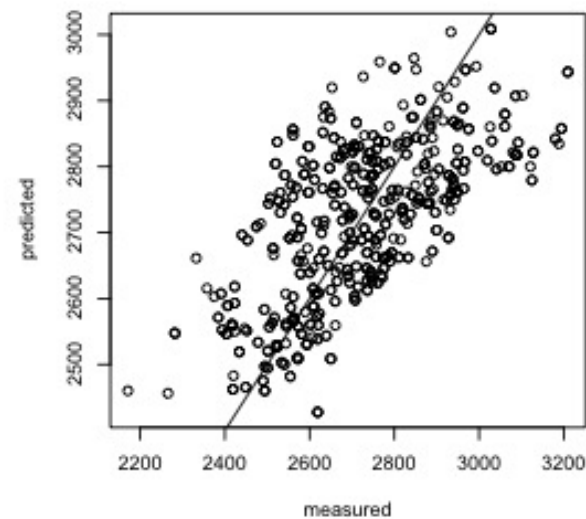
B, 1 comps, validation



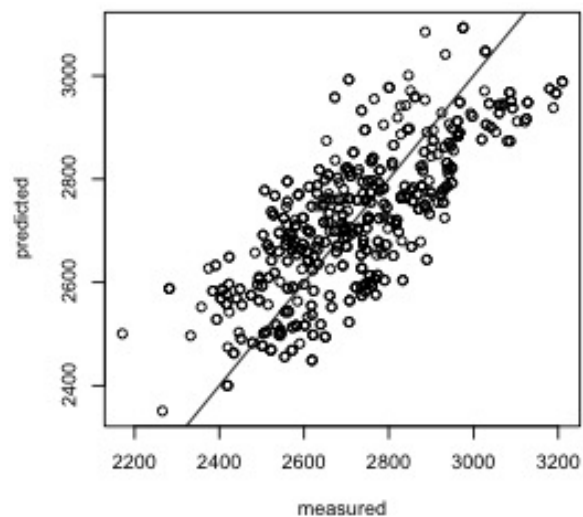
B, 2 comps, validation



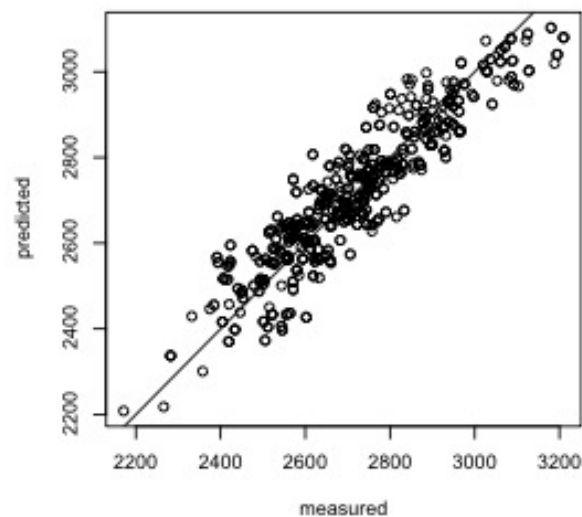
B, 3 comps, validation



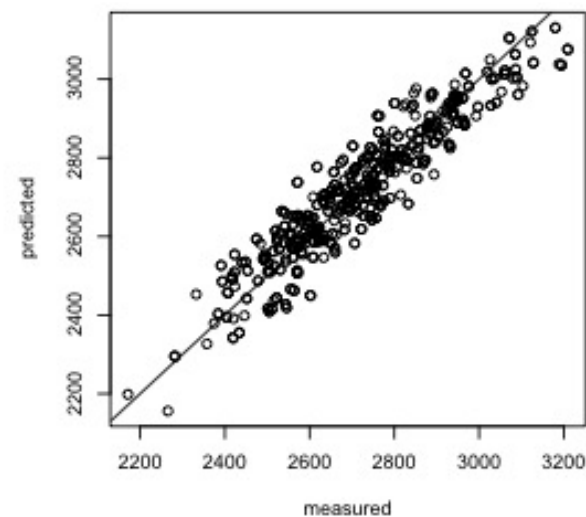
B, 4 comps, validation

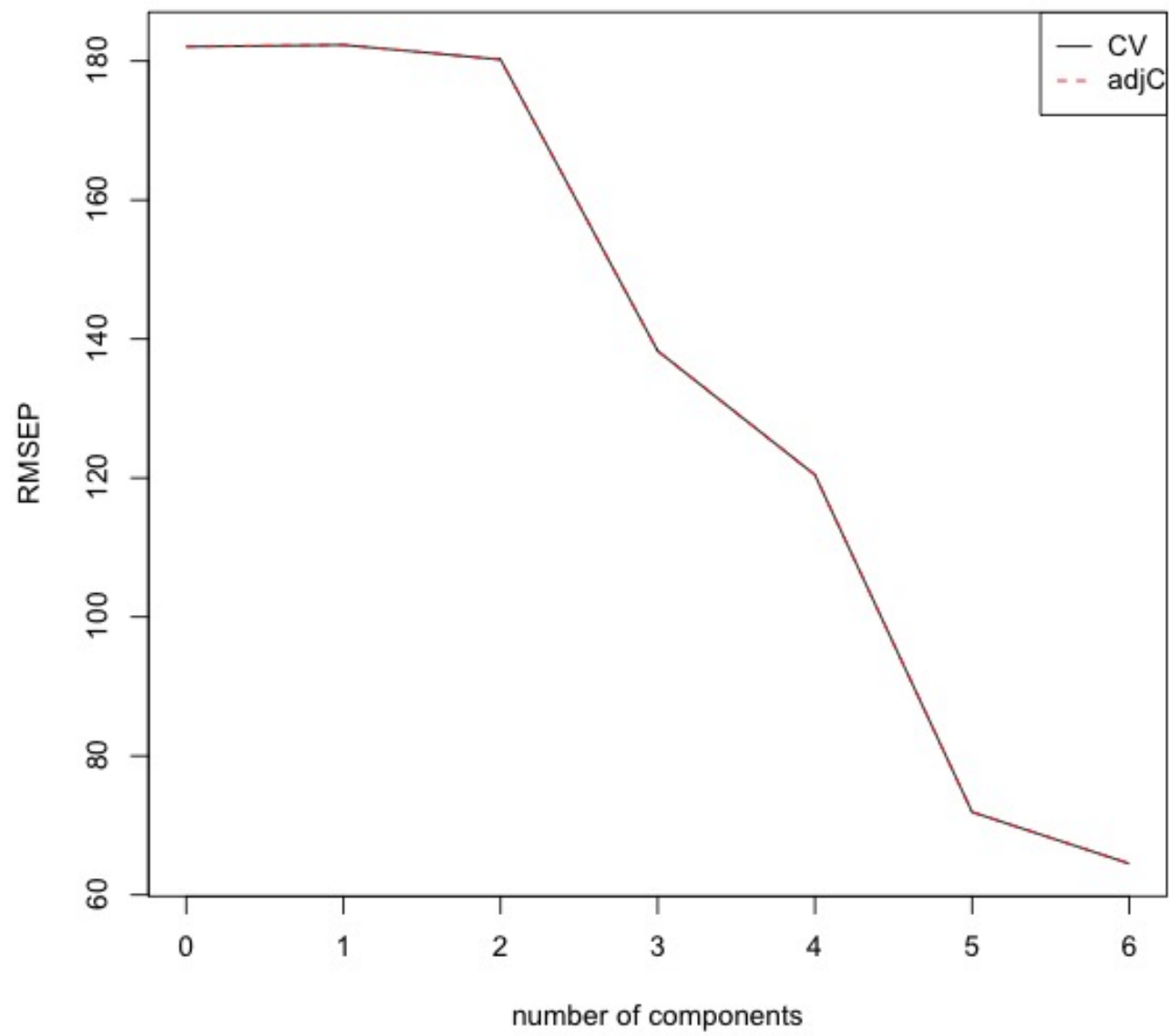


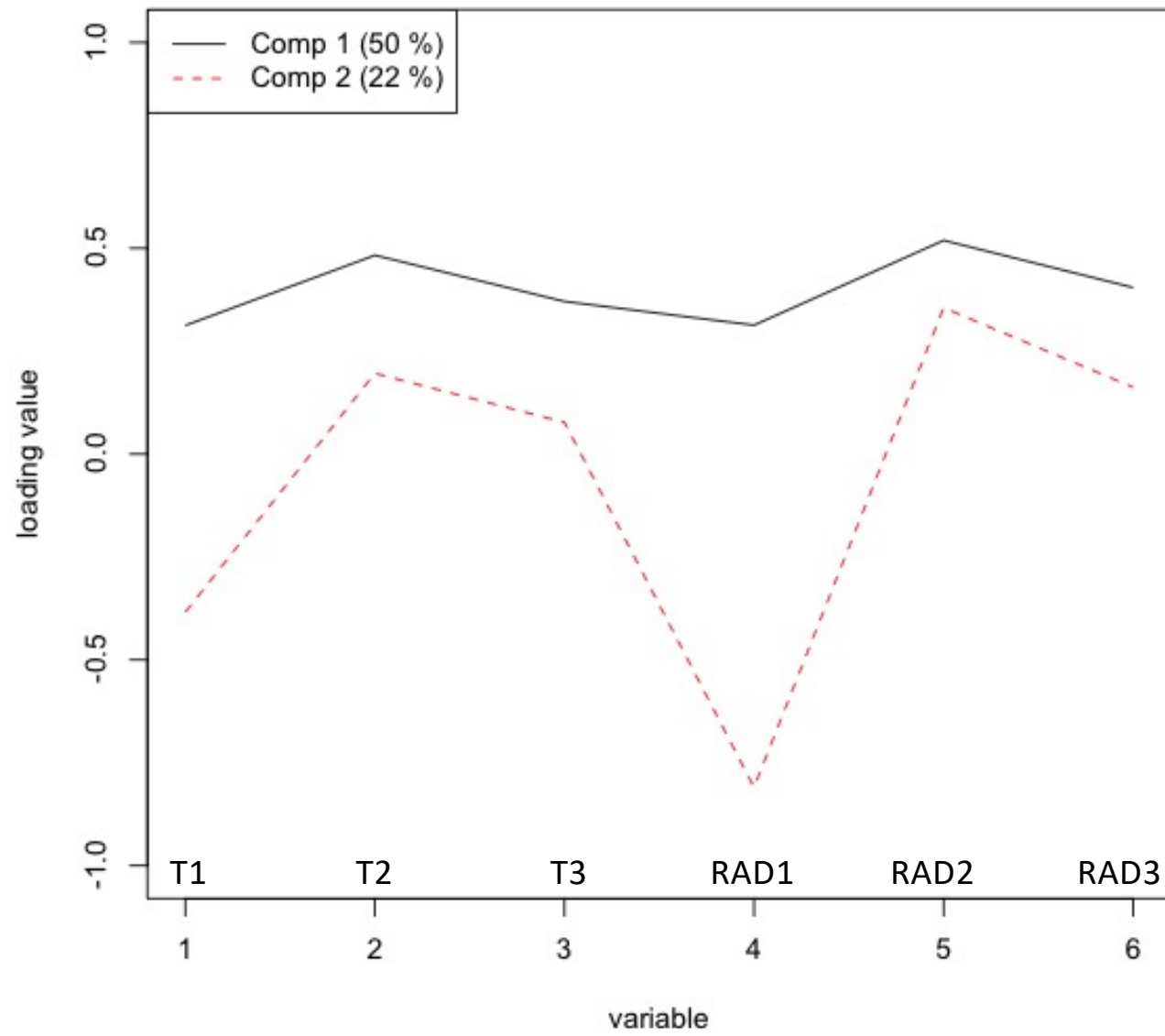
B, 5 comps, validation



B, 6 comps, validation







Difference between PCR and PLSR

- In PLSR, the components are determined to be **strongly correlated** to the values of Y
- Iterative determination of the components in PLSR
- Rarely large differences between PCR and PLSR, but PLSR often require fewer components

```
Mod_pls<-plsr(B~T1+T2+T3+RAD1+RAD2+RAD3, data=DataSet, validation="L00",  
scale="TRUE")  
  
summary(Mod_pls)
```


Question : Is the average error of prediction lower than 100 g/m² ?

A. No

B. Yes

C. It depends on the number of components included

```
> summary(Mod_pls)
```

```
Data: X dimension: 680 6
```

```
      Y dimension: 680 1
```

```
Fit method: kernelppls
```

```
Number of components considered: 6
```

VALIDATION: RMSEP

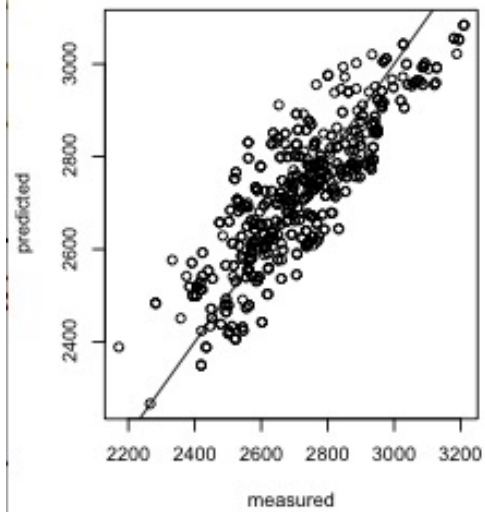
Cross-validated using 680 leave-one-out segments.

	(Intercept)	1 comps	2 comps	3 comps	4 comps	5 comps	6 comps
CV	182.1	98.03	83.19	73.48	67.29	65.85	64.51
adjCV	182.1	98.02	83.20	73.48	67.29	65.85	64.51

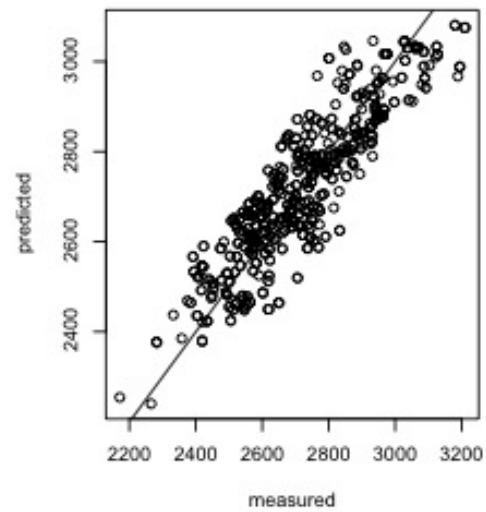
TRAINING: % variance explained

	1 comps	2 comps	3 comps	4 comps	5 comps	6 comps
X	13.75	45.09	74.99	89.61	97.43	100.0
B	71.76	79.45	83.97	86.57	87.17	87.7

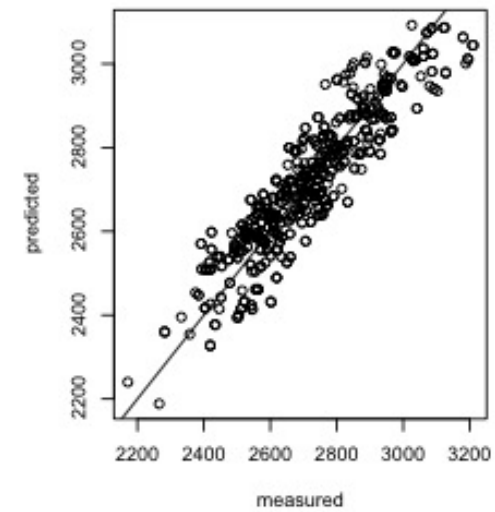
B, 1 comps, validation



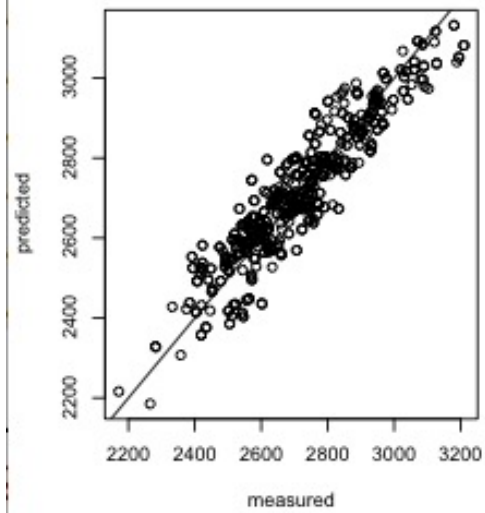
B, 2 comps, validation



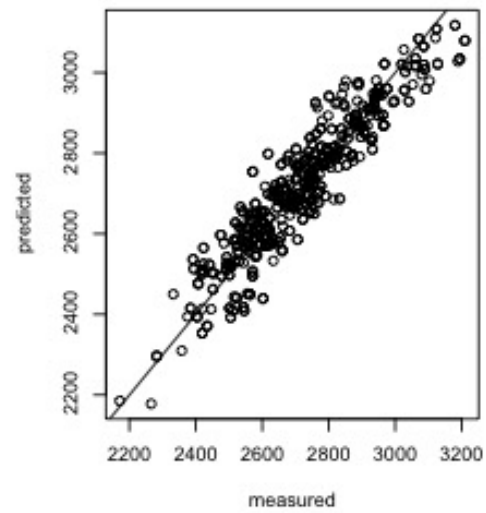
B, 3 comps, validation



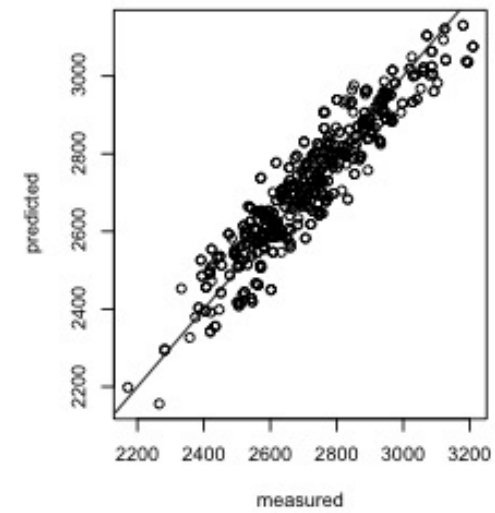
B, 4 comps, validation

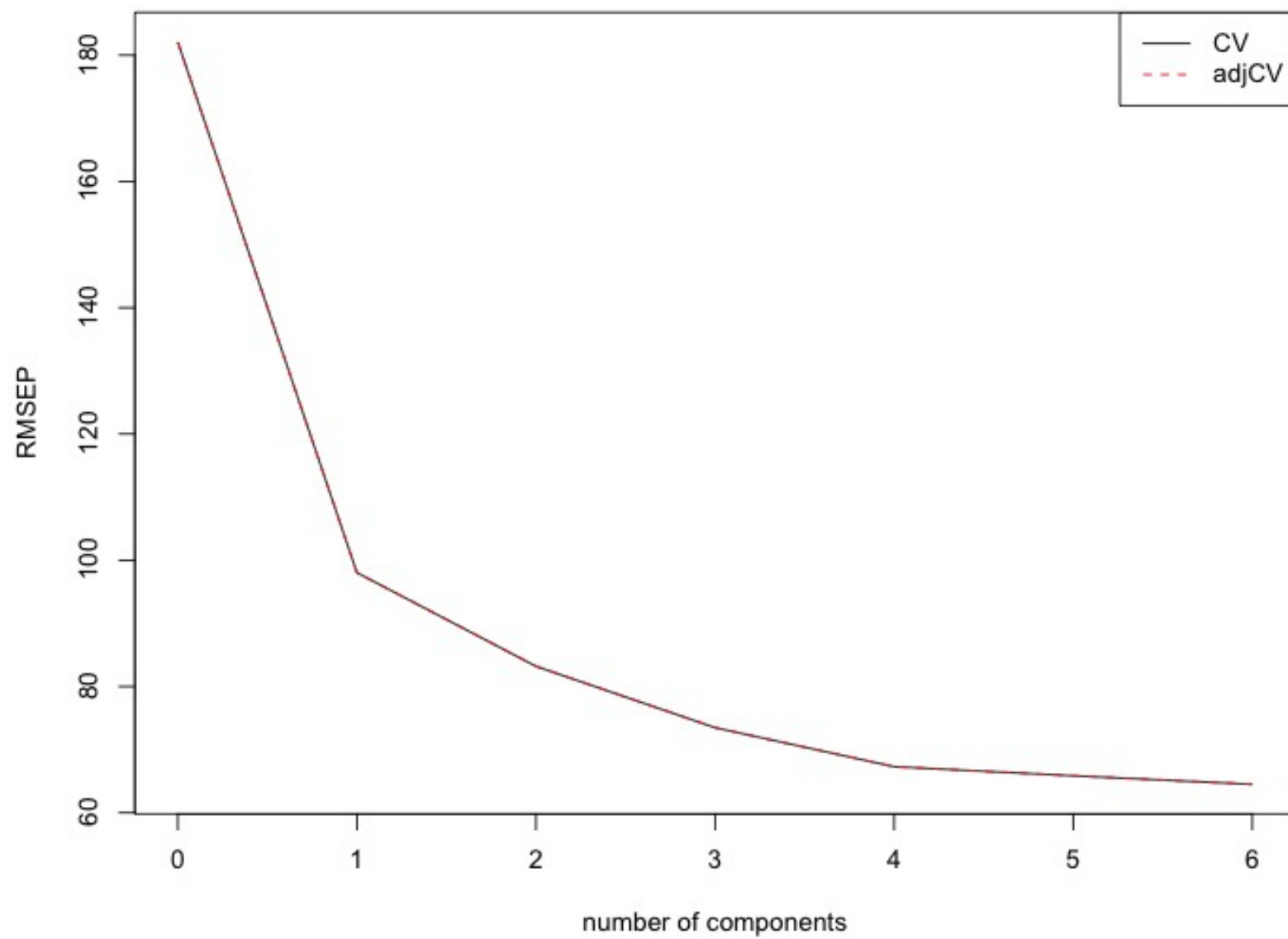


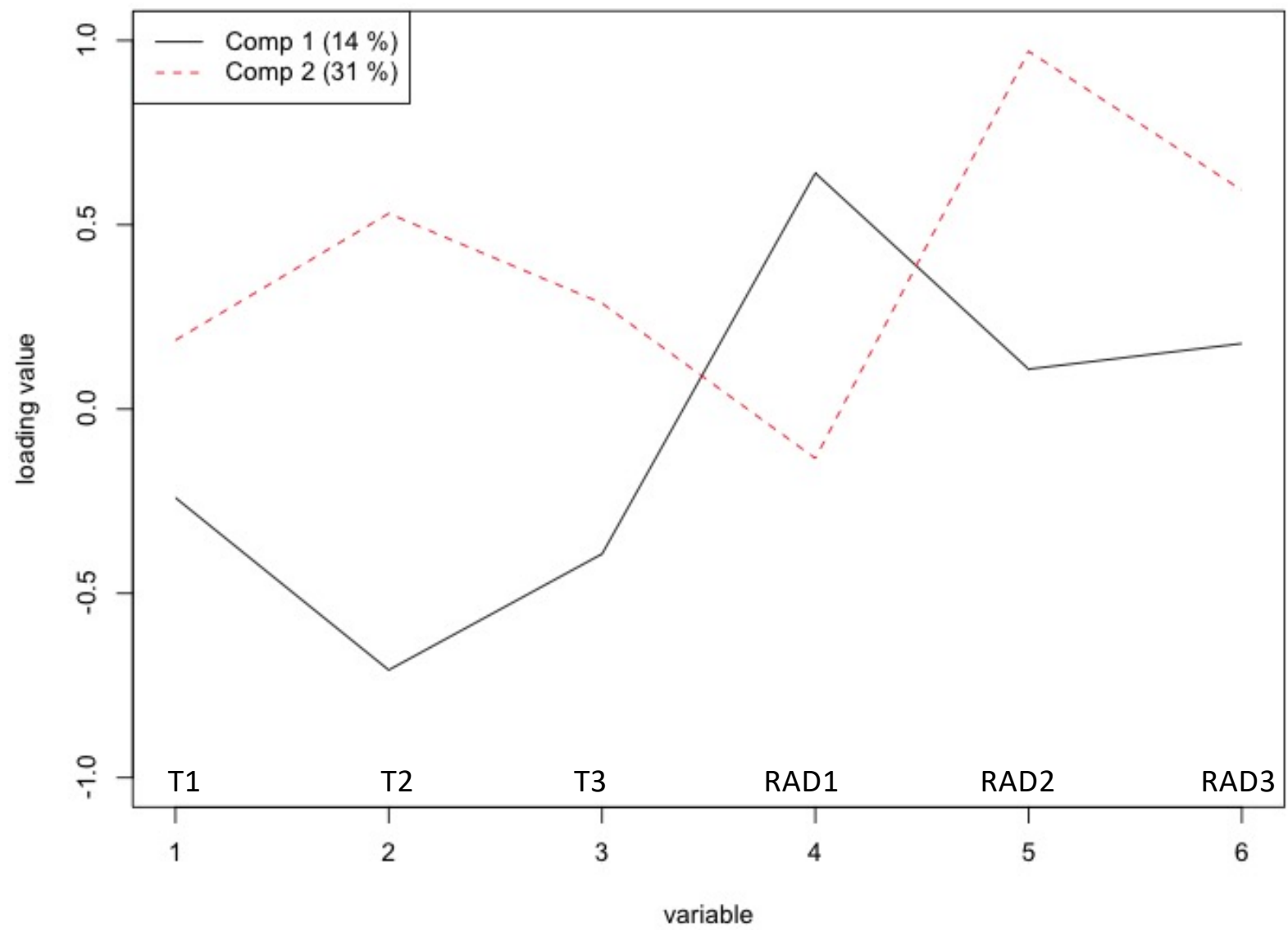
B, 5 comps, validation

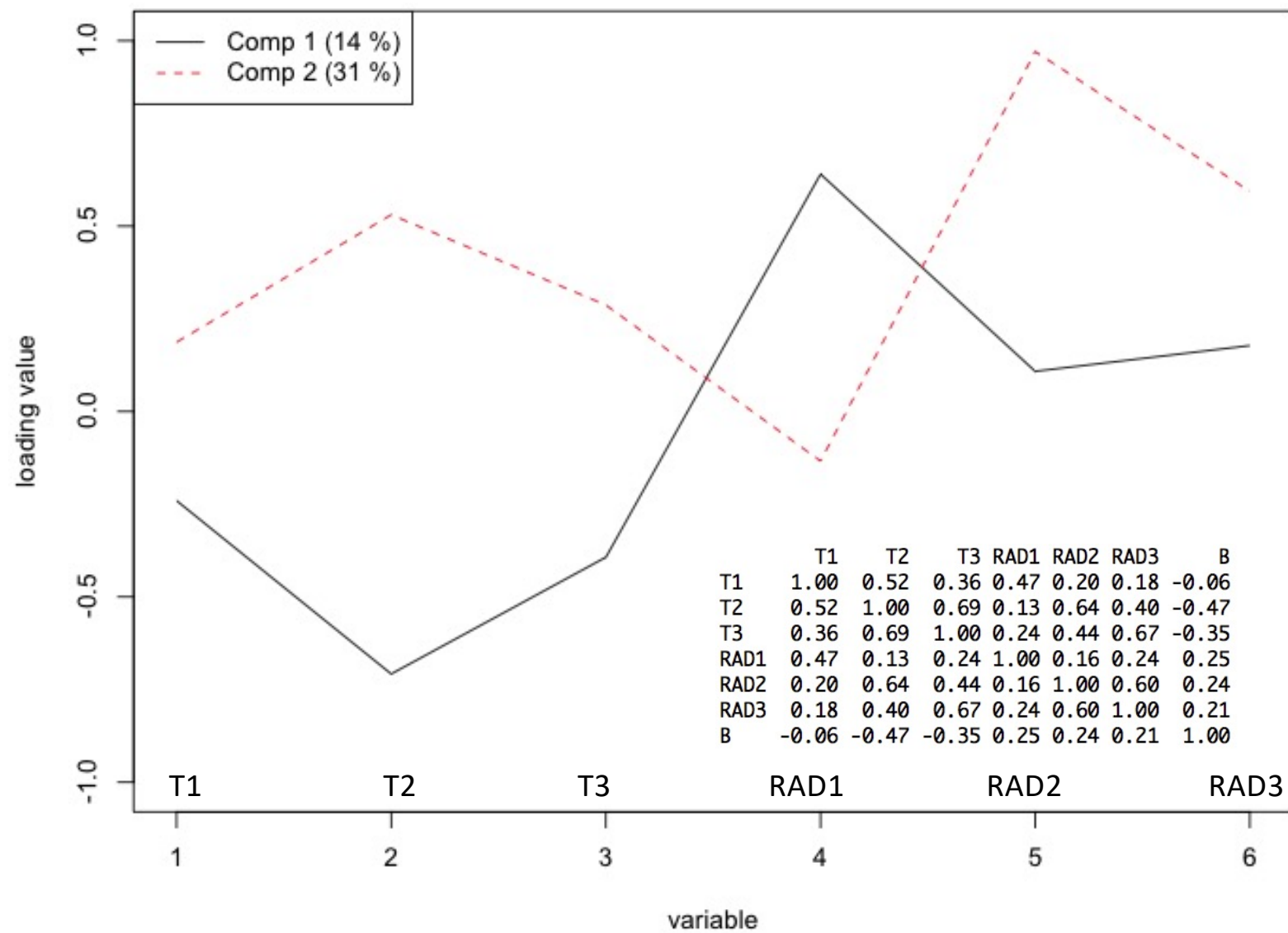


B, 6 comps, validation









Several issues

- Inputs X_1, \dots, X_p are sometimes (strongly) correlated
- **Inputs X_1, \dots, X_p may have non-linear effects (unknown response shape),**
- Too many inputs
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Generalized Additive Model (GAM)

$$E(Y) = \mu + s(X_1) + \cdots + s(X_P)$$

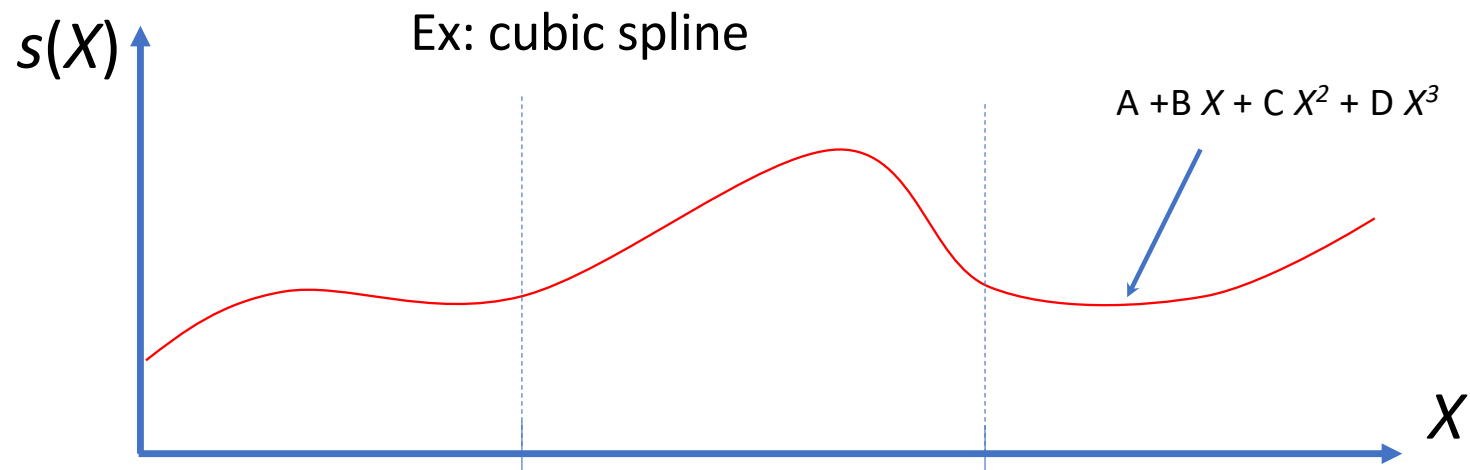
The expected value of Y expressed as a smooth function of the inputs $s(X)$.

- Different types of functions $s(X)$ can be used,
- Advantage of GAM : results easily interpreted.

Generalized Additive Model (GAM)

$$E(Y) = \mu + s(X_1) + \cdots + s(X_p)$$

$s(X)$ = spline = piece-wise polynomial function



Example: maize biomass

```
> head(DataSet)
```

	Site	Year	T1	T2	T3	RAD1	RAD2	RAD3	B
1	1	1995	13.44216	19.82255	22.27549	18.52941	21.44118	20.10784	2663.202
2	2	1995	13.37157	19.96961	23.05000	17.97059	21.80196	20.41373	2647.057
3	3	1995	13.30000	19.32157	21.35588	20.07647	22.48824	20.41176	2800.856
4	4	1995	12.47353	19.10882	22.37255	17.05882	20.19020	19.26471	2556.538
5	5	1995	11.34804	16.99216	20.64020	15.10980	18.83725	18.52157	2698.303
6	6	1995	12.71765	19.43529	22.35294	16.81765	20.81176	19.67255	2597.521

```
> dim(DataSet)
```

```
[1] 680  9
```

Example: maize biomass

```
library(mgcv)
```

```
Mod_gam<-  
gam(B~s(T1)+s(T2)+s(T3)+s(RAD1)+s(RAD2)+s(RAD3),  
data=DataSet)
```

```
summary(Mod_gam)  
plot(Mod_gam)
```

Family: gaussian
Link function: identity

Formula:

$B \sim s(T1) + s(T2) + s(T3) + s(RAD1) + s(RAD2) + s(RAD3)$

Parametric coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2718.716	1.944	1399	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

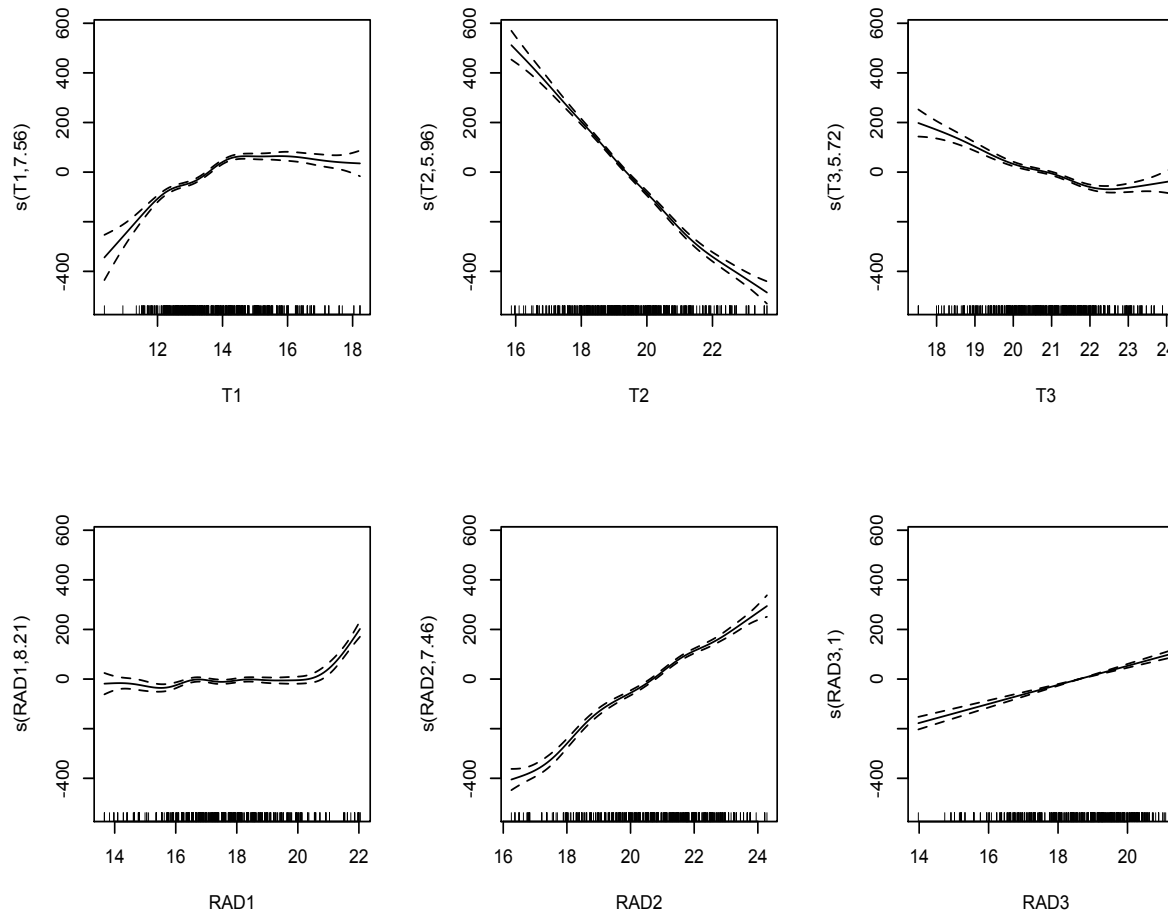
Approximate significance of smooth terms:

	edf	Ref.df	F	p-value
s(T1)	7.563	8.499	53.94	<2e-16 ***
s(T2)	5.962	7.148	282.88	<2e-16 ***
s(T3)	5.720	6.914	29.84	<2e-16 ***
s(RAD1)	8.206	8.826	21.84	<2e-16 ***
s(RAD2)	7.460	8.410	167.23	<2e-16 ***
s(RAD3)	1.000	1.000	197.49	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) = 0.922 Deviance explained = 92.7%

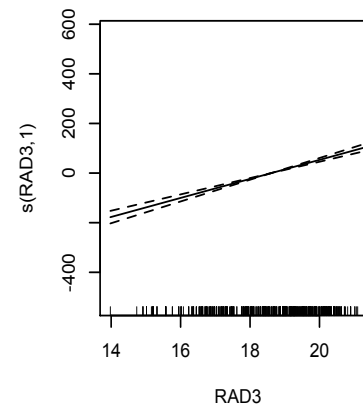
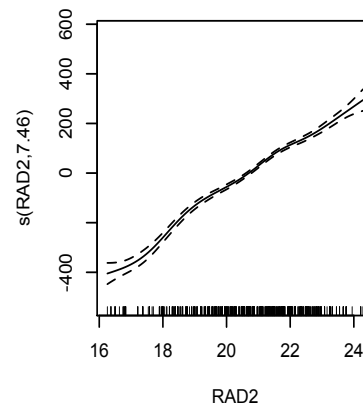
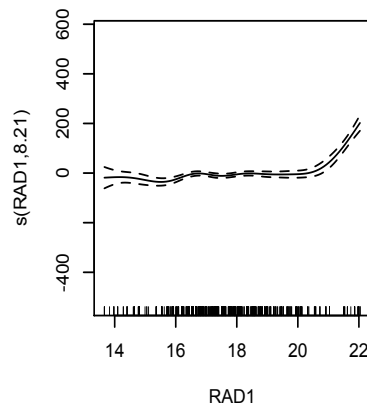
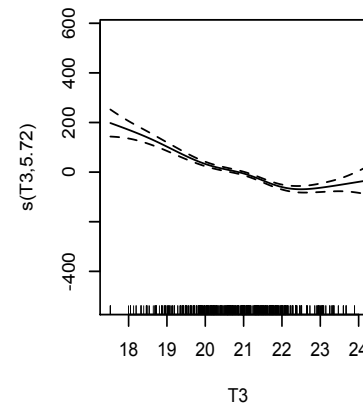
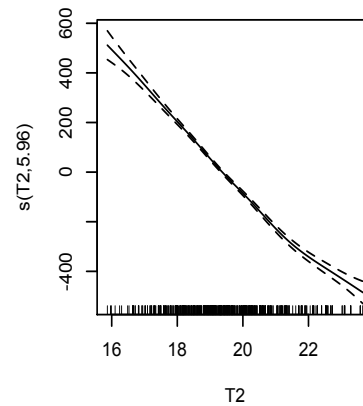
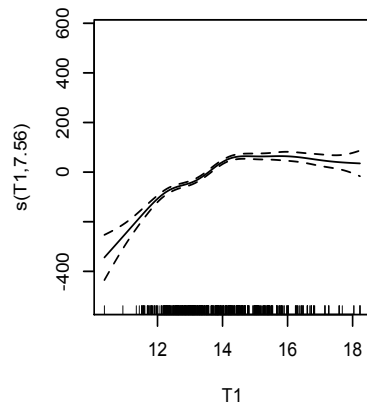
Example: maize biomass



Example: maize biomass

Question : Is the effect of T1 on the biomass linear ?

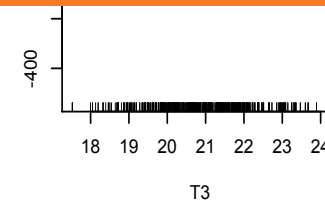
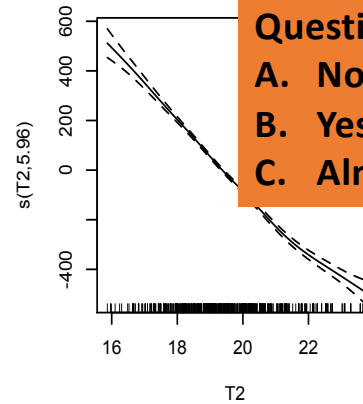
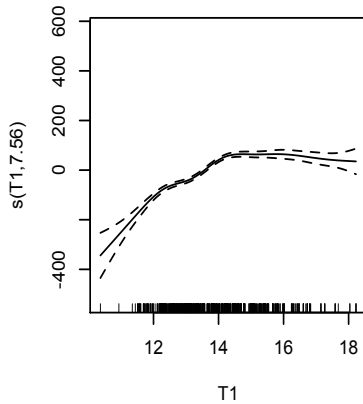
- A. No
- B. Yes
- C. Almost



Example: maize biomass

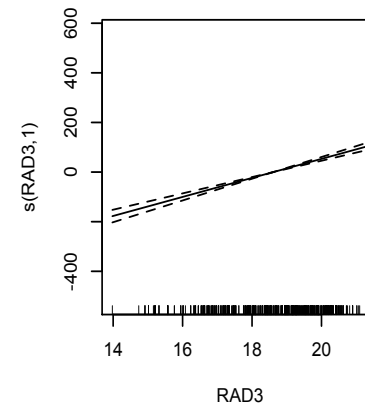
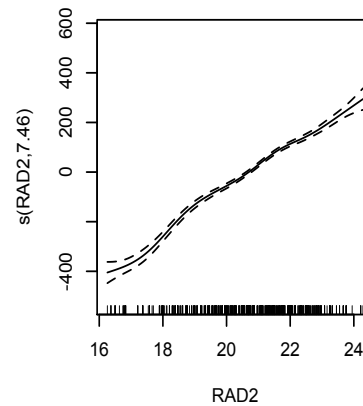
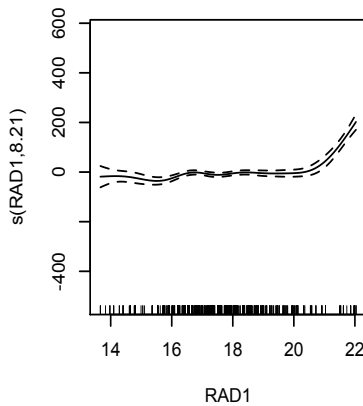
Question : Is the effect of T1 on the biomass linear?

- A. No
- B. Yes
- C. Almost



Question : Is the effect of RAD2 on the biomass linear?

- A. No
- B. Yes
- C. Almost



```
RMSE_gam<-sqrt(mean((DataSet$B-predict(Mod_gam))^2))  
RMSE_gam
```

```
#Cross-validation  
B_pred_gam<-rep(NA,length(DataSet$B))
```

```
List_year<-unique(DataSet$Year)
```

```
for (i in 1:length(List_year))  
{  
  Training_i<-DataSet[DataSet$Year!=List_year[i],]  
  Test_i<-DataSet[DataSet$Year==List_year[i],]  
  Mod_i<-gam(B~s(T1)+s(T2)+s(T3)+s(RAD1)+s(RAD2)+s(RAD3), data=Training_i)  
  B_gam_i<-predict(Mod_i, newdata=Test_i)  
  B_pred_gam[DataSet$Year==List_year[i]]<-B_gam_i  
}
```


```
RMSEP_gam<-sqrt(mean((DataSet$B-B_pred_gam)^2))  
RMSEP_gam
```

```
RMSE_gam<-sqrt(mean((DataSet$B-predict(Mod_gam))^2))
RMSE_gam
```

```
#Cross-validation
B_pred_gam<-rep(NA,length(DataSet$B))
```

```
List_year<-unique(DataSet$Year)
```

```
for (i in 1:length(List_year))
{
  Training_i<-DataSet[DataSet$Year!=List_year[i],]
  Test_i<-DataSet[DataSet$Year==List_year[i],]
  Mod_i<-gam(B~s(T1)+s(T2)+s(T3)+s(RAD1)+s(RAD2)+s(RAD3), data=Training_i)
  B_gam_i<-predict(Mod_i, newdata=Test_i)
  B_pred_gam[DataSet$Year==List_year[i]]<-B_gam_i
}
```



Question : The training dataset includes

- A. All data**
- B. All data but the i^{th}**
- C. Only the i^{th} data**

```
RMSEP_gam<-sqrt(mean((DataSet$B-B_pred_gam)^2))
RMSEP_gam
```



```
RMSE_gam<-sqrt(mean((DataSet$B-predict(Mod_gam))^2))
RMSE_gam
```

```
#Cross-validation
B_pred_gam<-rep(NA,length(DataSet$B))
```

```
List_year<-unique(DataSet$Year)
```

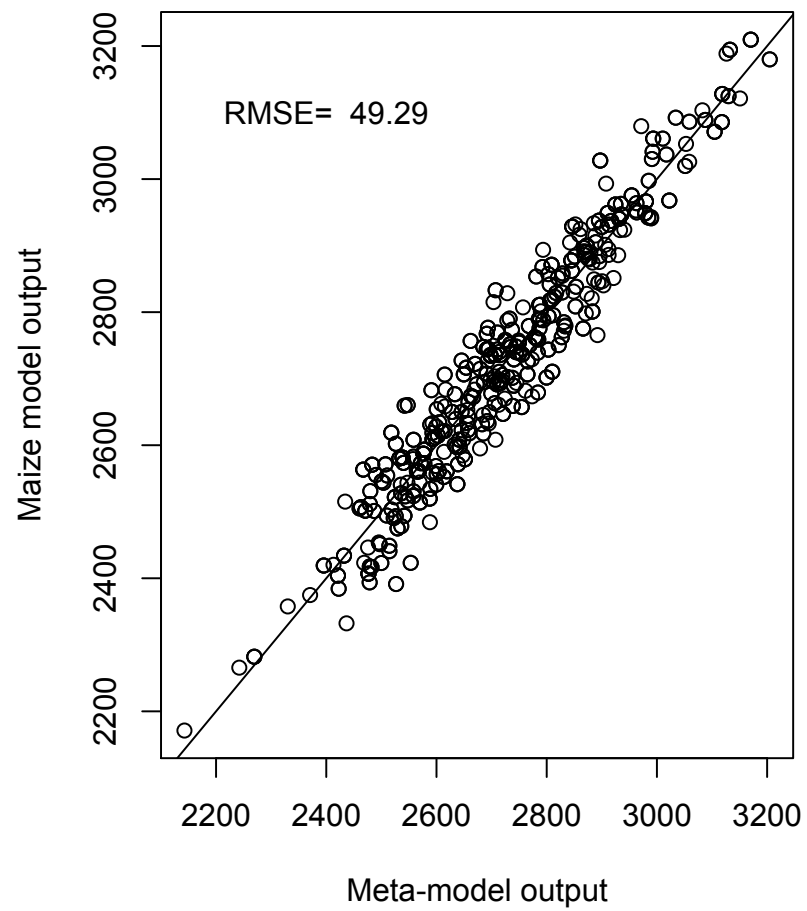
```
for (i in 1:length(List_year))
{
  Training_i<-DataSet[DataSet$Year!=List_year[i],]
  Test_i<-DataSet[DataSet$Year==List_year[i],]
  Mod_i<-gam(B~s(T1)+s(T2)+s(T3)+s(RAD1)+s(RAD2)+s(RAD3), data=Training_i)
  B_gam_i<-predict(Mod_i, newdata=Test_i)
  B_pred_gam[DataSet$Year==List_year[i]]<-B_gam_i
}
```

```
RMSEP_gam<-sqrt(mean((DataSet$B-B_pred_gam)^2))
RMSEP_gam
```

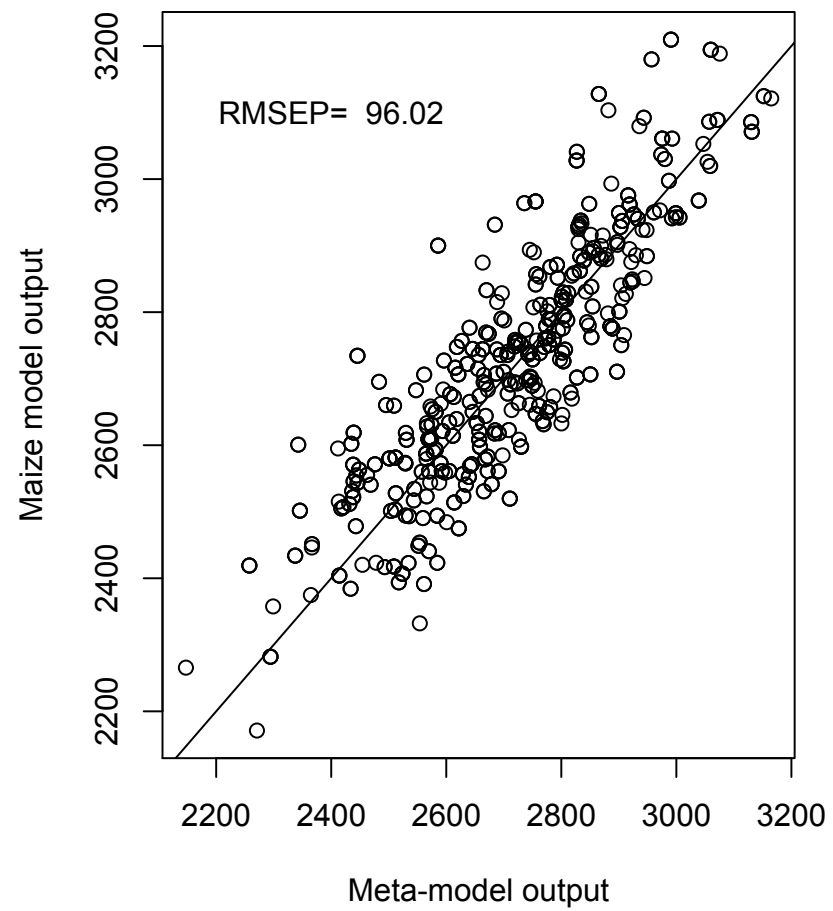
Question : The test dataset includes

- A. All data
- B. All data but the i^{th}
- C. Only the i^{th} data

A.



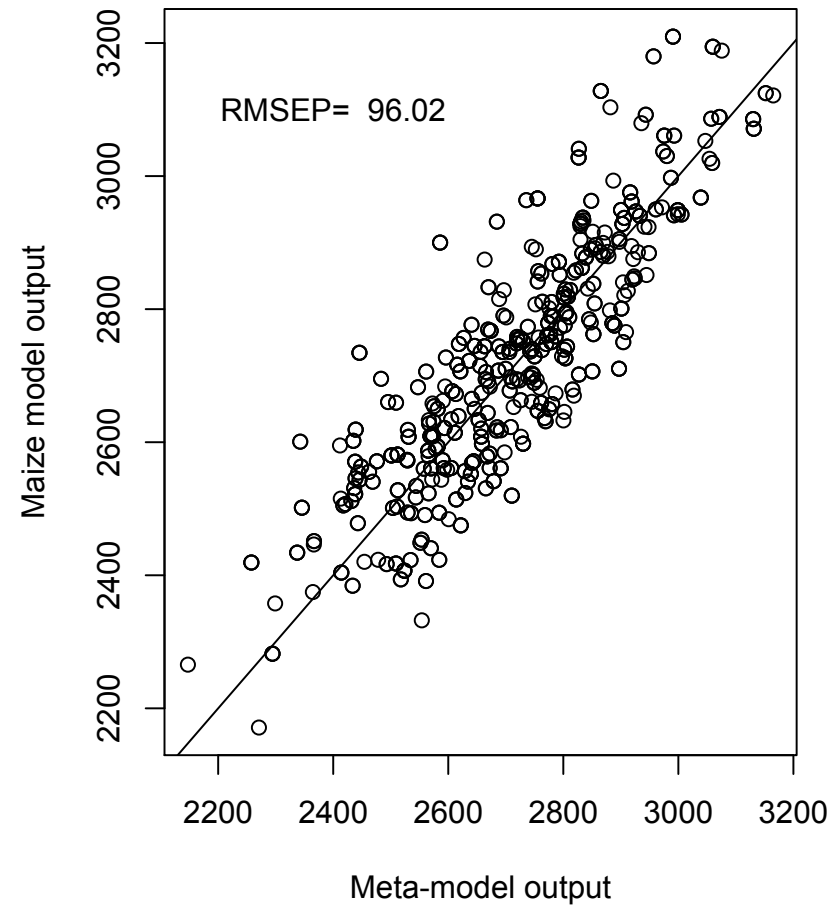
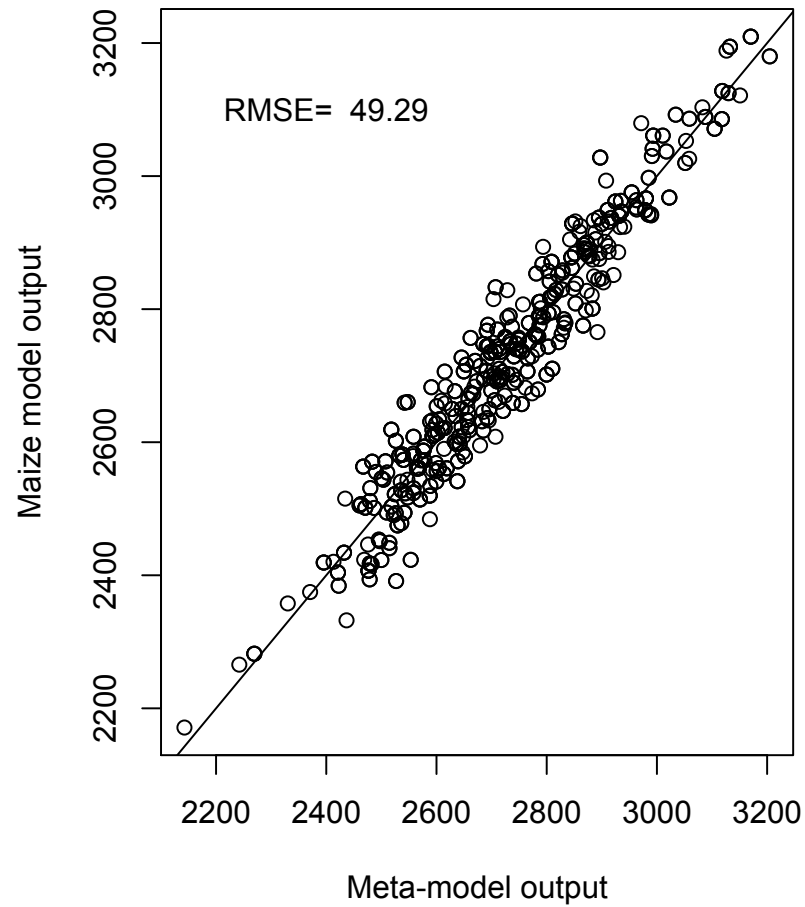
B.



Question : Are the prediction errors lower than 50 g/m² in average?

A. Yes

B. No



Several issues

- Inputs X_1, \dots, X_p are sometimes (strongly) correlated
- Inputs X_1, \dots, X_p may have non-linear effects (unknown response shape),
- **Too many inputs**
- Need to estimate extreme responses, not mean response

Other powerful regression techniques:
Penalized regression methods

LASSO, ridge and elastic net

$$Y = X\theta + \varepsilon$$

$$\hat{Y} = X\hat{\theta}$$

$\hat{\theta}$ est estimé en minimisant $\sum_i (Y_i - \hat{Y}_i)^2 + \lambda G$ } Penalty term

$$G = \sum_j |\theta_j| \quad \text{LASSO}$$

$$G = \sum_j \theta_j^2 \quad \text{Ridge}$$

$$G = \sum_j \alpha |\theta_j| + \sum_j (1 - \alpha) \theta_j^2 \quad \text{Elastic net}$$

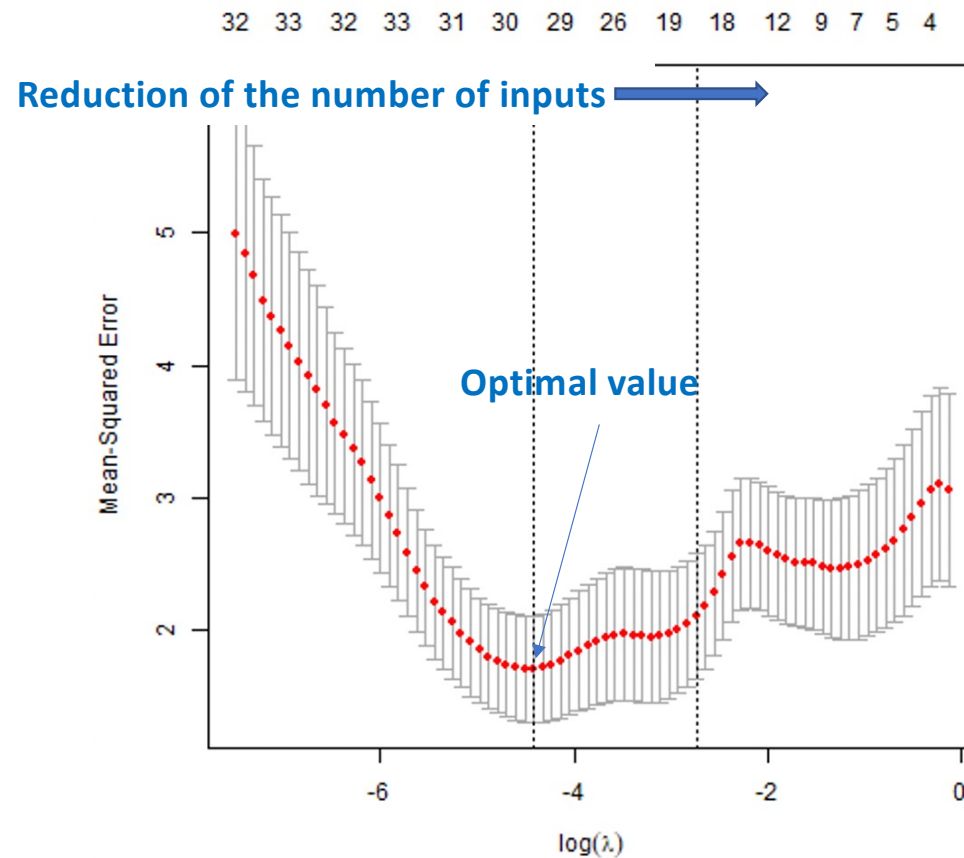
Additional parameter
(hyper-parameter)

Penalty level (hyper-parameter) optimized by cross validation

Example « spores »

Y=quantity of fungus spores

X=34 inputs representing climatic conditions



R package glmnet

```
cv <- cv.glmnet(x, y, alpha = 1)
model <- glmnet(x, y, alpha = 1, lambda = cv$lambda.min)
```


Example: maize biomass

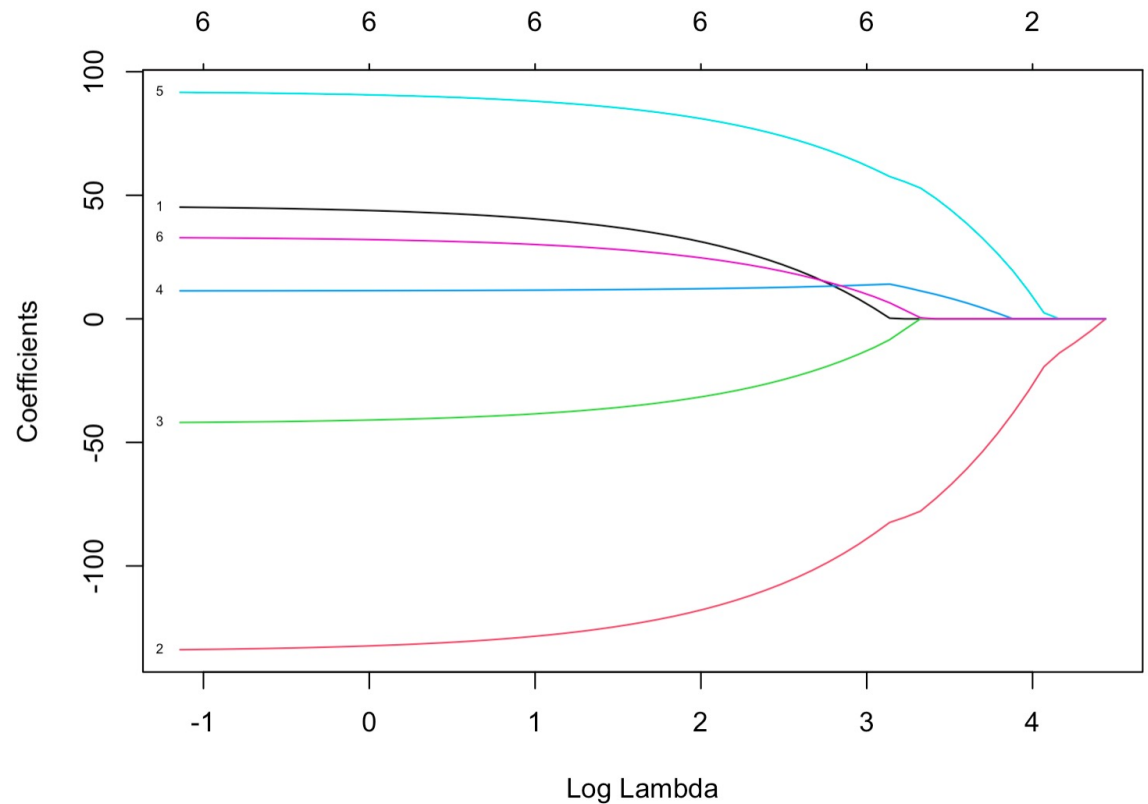
```
library(glmnet)
X=as.matrix(DataSet[,3:8])
Y=DataSet$B
```

#Fit LASSO

```
model <- glmnet(X, Y, alpha = 1)
```

#Plot coefficients for different penalty levels

```
plot(model, xvar="lambda", label=TRUE)
```



#Regression coefficients for two levels of penalty

```
coef(model, s=exp(4))
```

```
coef(model, s=exp(3.5))
```

```
> coef(model, s=exp(4))
```

```
7 x 1 sparse Matrix of class "dgCMatix"
```

```
1
```

```
(Intercept) 3050.708642
```

```
T1 .
```

```
T2 -26.696864
```

```
T3 .
```

```
RAD1 .
```

```
RAD2 9.025979
```

```
RAD3 .
```

```
> coef(model, s=exp(3.5))
```

```
7 x 1 sparse Matrix of class "dgCMatix"
```

```
1
```

```
(Intercept) 2962.356869
```

```
T1 .
```

```
T2 -67.604088
```

```
T3 .
```

```
RAD1 8.409119
```

```
RAD2 44.438812
```

```
RAD3 .
```

#Selection of a lambda value by year-by-year cross-validation

```
cv <- cv.glmnet(X, Y, alpha=1, foldid=as.numeric(as.factor(DataSet$Year)))
```

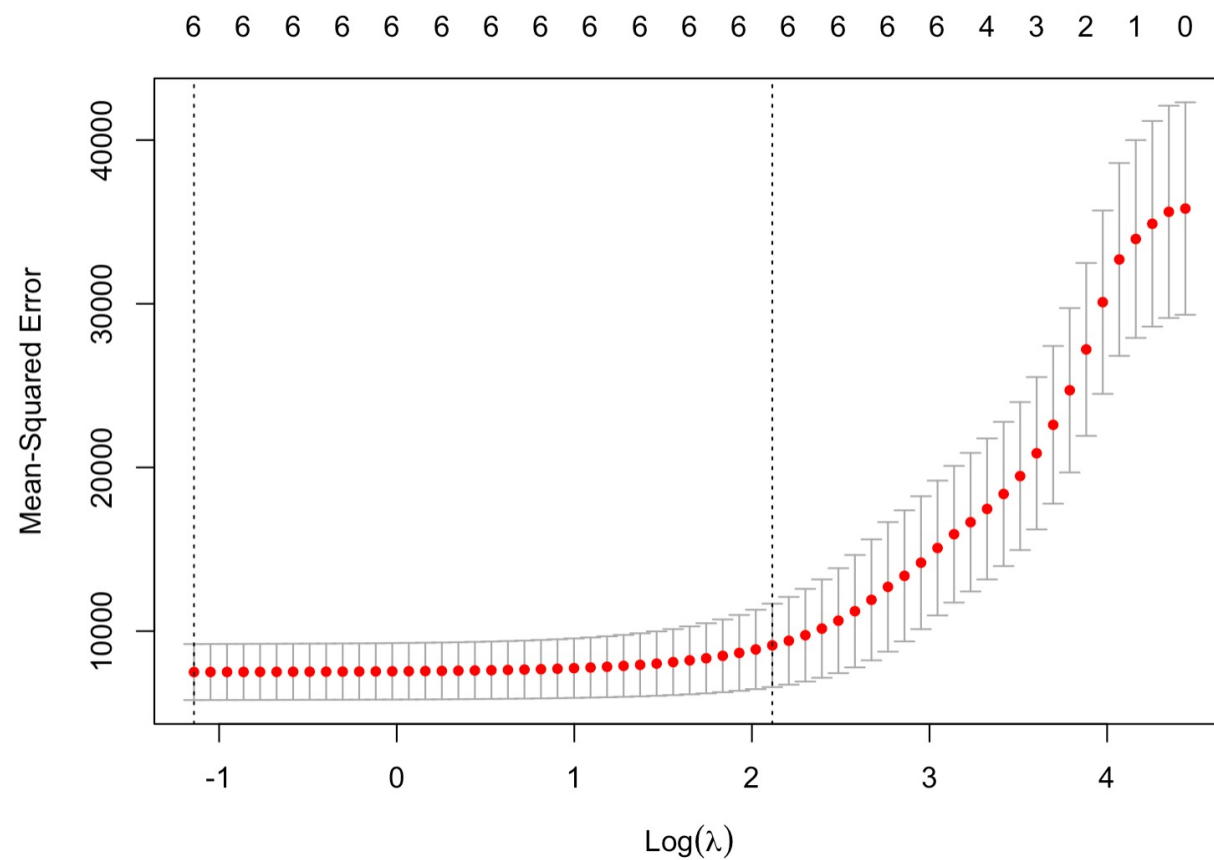
```
plot(cv)
```

```
coef(cv, s="lambda.min")
```

```
> coef(cv, s="lambda.min")
```

7 x 1 sparse Matrix of class "dgCMatrix"

	1
(Intercept)	2859.54398
T1	45.18485
T2	-133.90336
T3	-41.94147
RAD1	11.33300
RAD2	91.67204
RAD3	32.83682



Several issues

- Inputs X_1, \dots, X_p are sometimes (strongly) correlated
- Inputs X_1, \dots, X_p may have non-linear effects (unknown response shape),
- Too many inputs
- **Need to estimate extreme responses, not mean response**

Quantile regression

- Useful to estimate the response of Y to X for upper or lower quantiles of Y
- Relevant when using a limited number of inputs, i.e., one or two
- Useful for risk analysis
- Can be easily implemented with the R package quantreg

Example: maize biomass

```
library(quantreg)
```

```
mod<-rq(B~T2+I(T2^2), data=DataSet, tau=c(0.05,0.1, 0.5, 0.9, 0.95))  
print(coef(mod))
```

	tau= 0.05	tau= 0.10	tau= 0.50	tau= 0.90	tau= 0.95
(Intercept)	2660.507311	1658.472676	247.708516	2892.652836	1967.910435
T2	14.875536	115.001848	295.144193	95.822782	198.461026
I(T2^2)	-1.254486	-3.646621	-8.611448	-4.796667	-7.505065

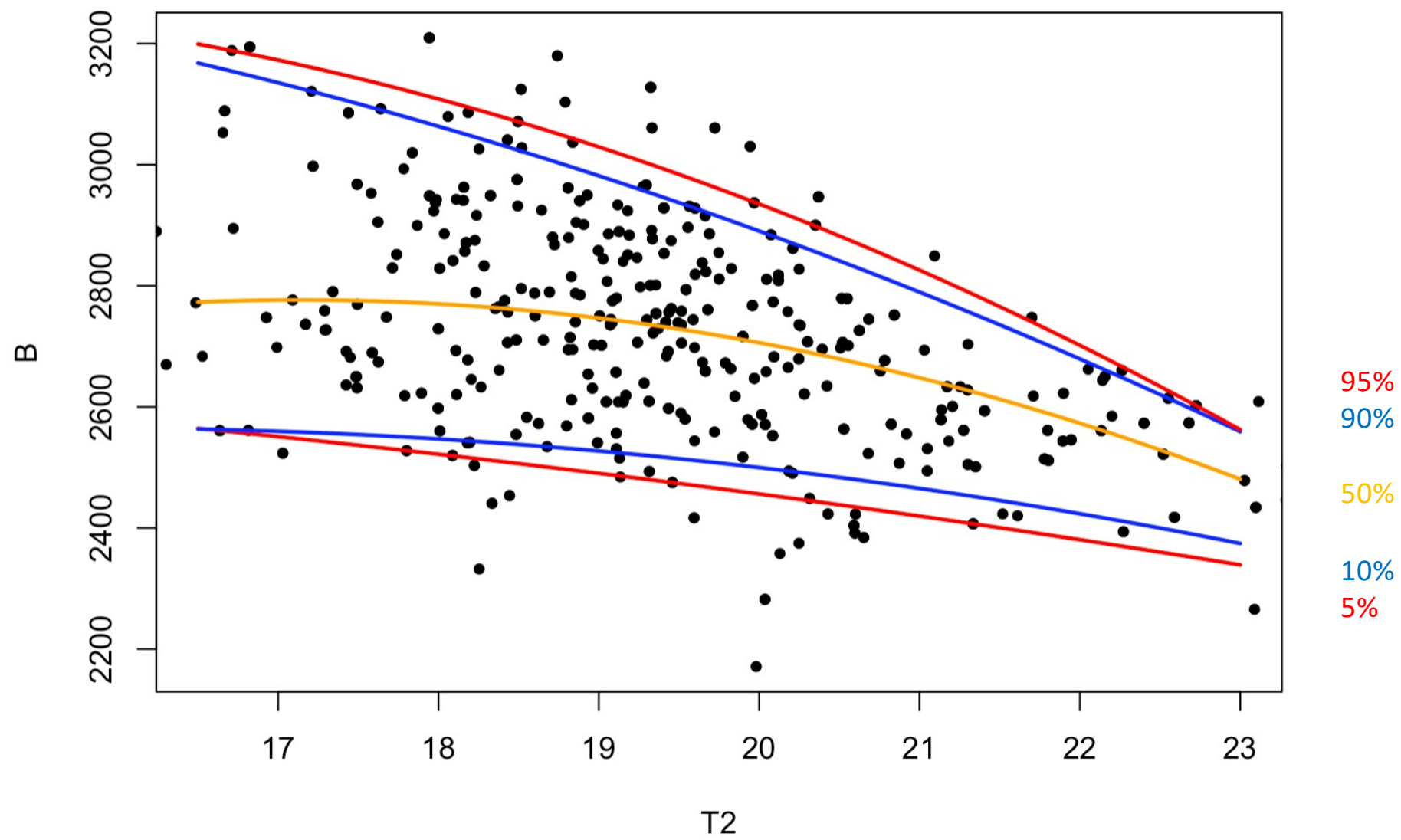
```
Xvec=seq(16.5,23,by=0.1)
Para=coef(mod)[,1]
lines(Xvec,Para[1]+Para[2]*Xvec+Para[3]*Xvec^2, col="red", lwd=2)

Para=coef(mod)[,2]
lines(Xvec,Para[1]+Para[2]*Xvec+Para[3]*Xvec^2, col="blue", lwd=2)

Para=coef(mod)[,3]
lines(Xvec,Para[1]+Para[2]*Xvec+Para[3]*Xvec^2, col="orange", lwd=2)

Para=coef(mod)[,4]
lines(Xvec,Para[1]+Para[2]*Xvec+Para[3]*Xvec^2, col="blue", lwd=2)

Para=coef(mod)[,5]
lines(Xvec,Para[1]+Para[2]*Xvec+Para[3]*Xvec^2, col="red", lwd=2)
```



Conclusion

- How to deal with strongly correlated inputs?
→ PCR, PLSR
- How to analyze the non linear relationships between Y and X_1, \dots, X_p ?
→ GAM
- How to obtain accurate predictions with a simplified model?
→ Penalized regressions
- How to analyse responses at upper or lower quantiles?
→ Quantile regression