

STA303/1002 - Week 8 R Markdown

March 4-8, 2019

Case Study IV: The Data

Get the data (from R library):

```
#load Sleuth3 R data library; see case2101  
→ library(Sleuth3); krunnit = case2101  
→ str(krunnit)
```

```
## 'data.frame':   18 obs. of  4 variables:  
## $ Island : Factor w/ 18 levels "Hietakraasukka",...: 16 6 11 2 1 3 4 7 15 12  
xi → ## $ Area  : num  185.8 105.8 30.7 8.5 4.8 ...  
mi → ## $ AtRisk : int   75 67 66 51 28 20 43 31 28 32 ...  
yi → ## $ Extinct: int    5 3 10 6 3 4 8 3 5 6 ...
```

Case Study IV: New variables

Get the data (from R library):

```
attach(krunnit); head(krunnit)
```

##	Island	Area	AtRisk	Extinct
## 1	Ulkokrunni	185.8	75	5
## 2	Maakrunni	105.8	67	3
## 3	Ristikari	30.7	66	10
## 4	Isonkivenletto	8.5	51	6
## 5	Hietakraasukka	4.8	28	3
## 6	Kraasukka	4.5	20	4

```
logitpi<-log(Extinct/AtRisk/(1-(Extinct/AtRisk))) #observed logits
```

```
logarea<-log(Area) # log transformed Area
```

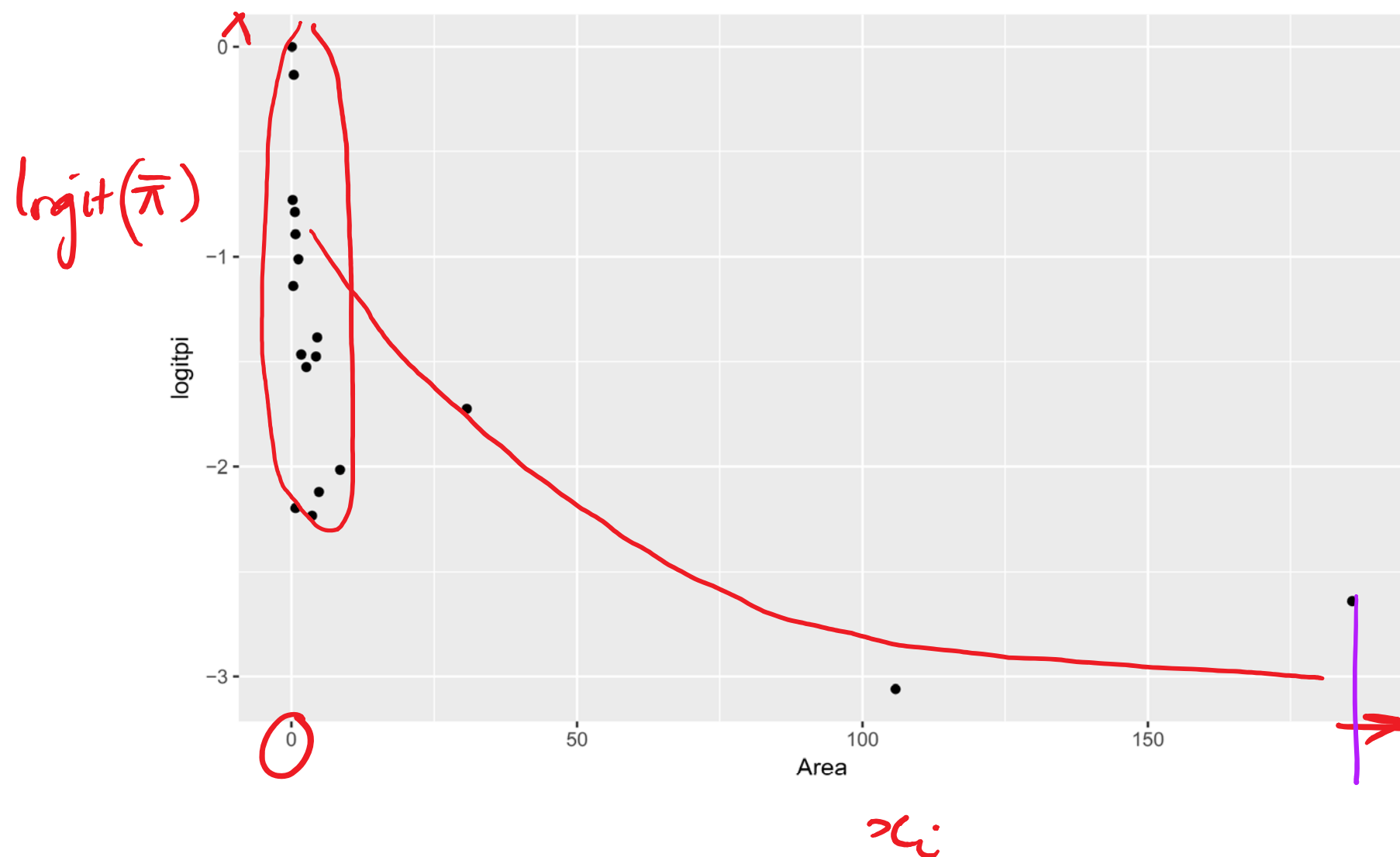
```
NExtinct<-AtRisk-Extinct =  $m_i - y_i$ 
```

```
pis<-Extinct/AtRisk =  $y_i / m_i$ 
```

$$\log\left(\frac{\bar{\pi}_i}{1-\bar{\pi}_i}\right)$$
$$\log\left(\frac{y_i}{m_i - y_i}\right)$$

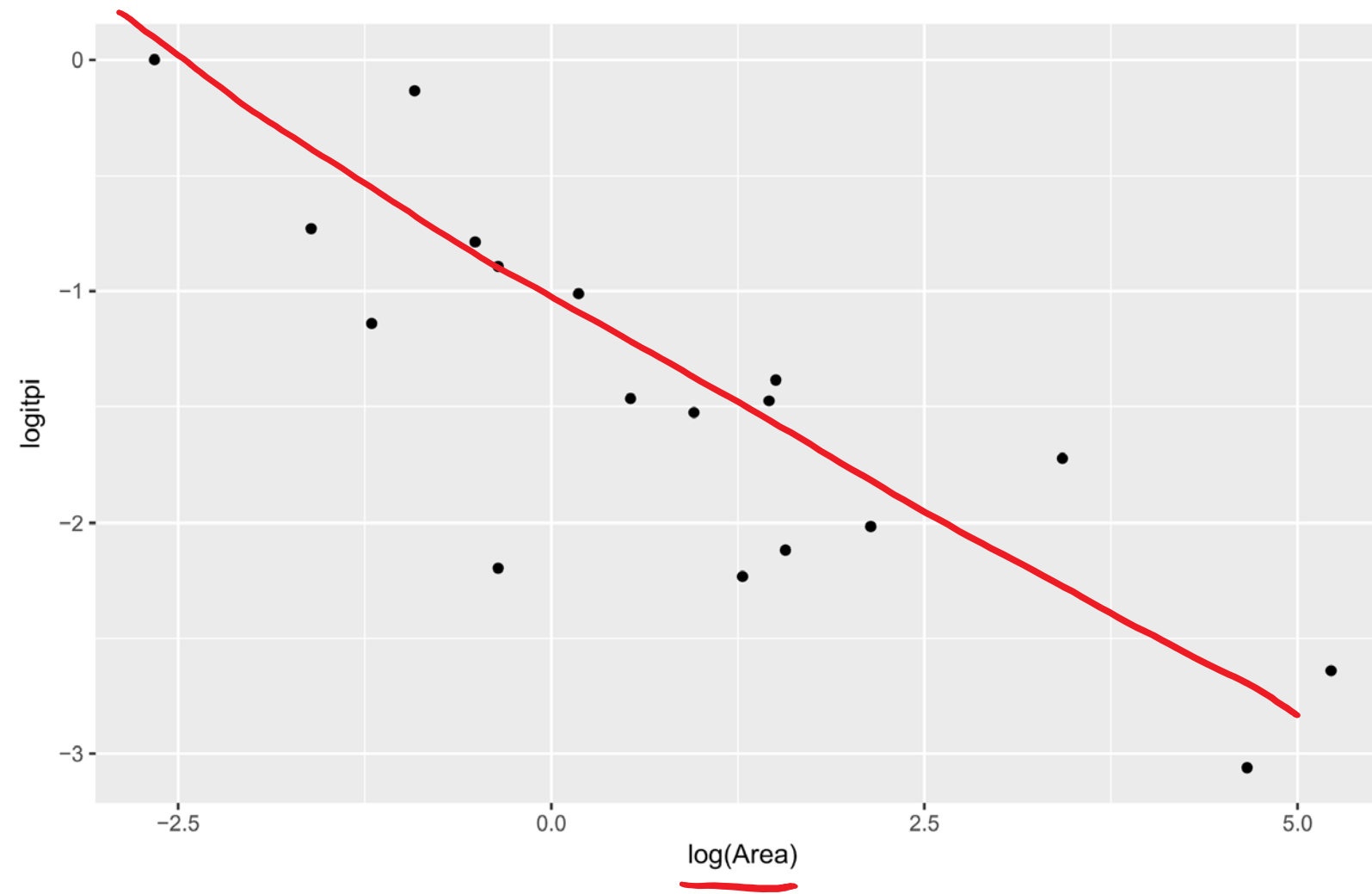
Case Study IV: Visualizing the data

```
library(ggplot2)
ggplot(krunnit, aes(x=Area, y=logitpi))+geom_point()
```



Case Study IV: Visualizing the data

```
ggplot(krunit, aes(x=log(Area), y=logitpi))+geom_point()
```



Case Study IV/ Logistic Model with logged explanatory variable

```
fitbl<-glm(cbind(Extinct,NExtinct)~log(Area), family=binomial, data=krunit)  
summary(fitbl)
```

```
##  
## Call:  
## glm(formula = cbind(Extinct, NExtinct) ~ log(Area), family = binomial,  
##      data = krunit)
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -1.71726 -0.67722  0.09726  0.48365  1.49545
```

```
## Coefficients:
```

```
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -1.19620    0.11845 -10.099  < 2e-16 ***  
## log(Area)    -0.29710    0.05485  -5.416  6.08e-08 ***
```

```
## ---
```

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

```
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
```

```
##      Null deviance: 45.338  on 17  degrees of freedom
```

```
## Residual deviance: 12.062  on 16  degrees of freedom
```

```
## AIC: 75.394
```

```
##
```

```
## Number of Fisher Scoring iterations: 4
```

response
predictor
 y_i
 $m_i - y_i$

logistic regression

$\frac{\hat{\beta}}{se(\hat{\beta})}$ *Wald*

$\Rightarrow p \approx 0$ or $p < 0.0001$

Deviance (Fitted vs Sat.)

Case IV: Deviance test and Estimated Var-Cov of β

```
anova(fitbl, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: cbind(Extinct, NExtinct)
##
## Terms added sequentially (first to last)
##
##
```

	Df	Deviance	Resid. Df	<u>Resid. Dev</u>	Pr(>Chi)
## NULL			17	45.338	
## log(Area)	1	33.277	16	<u>12.062</u>	7.994e-09 ***

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

✓ LRT

```
print(vcov(fitbl))
```

```
##           (Intercept)      log(Area)
## (Intercept) 0.014029452 -0.002602237
## log(Area)   -0.002602237 0.003008830
```

$$0.003 = (0.05485)^2$$

$$\text{Var}(\hat{\beta}_1) = (\text{se}(\hat{\beta}_1))^2$$

Case IV: Wald tests in R

```
library(aod) # Analysis of Overdispersed Data  
wald.test(Sigma=vcov(fitbl), b=coef(fitbl), Terms=2)
```

```
## Wald test:  
## -----  
##  
## Chi-squared test:  
## X2 = 29.3, df = 1, P(> X2) = 6.1e-08
```

$$=(-5.416)^2 = 29.3$$

Case IV: Confidence Intervals for β 's

```
CL=cbind(bhat=coef(fitbl), confint.default(fitbl)) # 95% CI for betas
CL
```

```
##              bhat      2.5 %      97.5 %
## (Intercept) -1.1961955 -1.4283454 -0.9640456
## log(Area)    -0.2971037 -0.4046132 -0.1895942
```

```
2^(CL) # doubling Area
```

```
##              bhat      2.5 %      97.5 %
## (Intercept)  0.4364247  0.3715568  0.5126174
## log(Area)    0.8138847  0.7554388  0.8768524
```

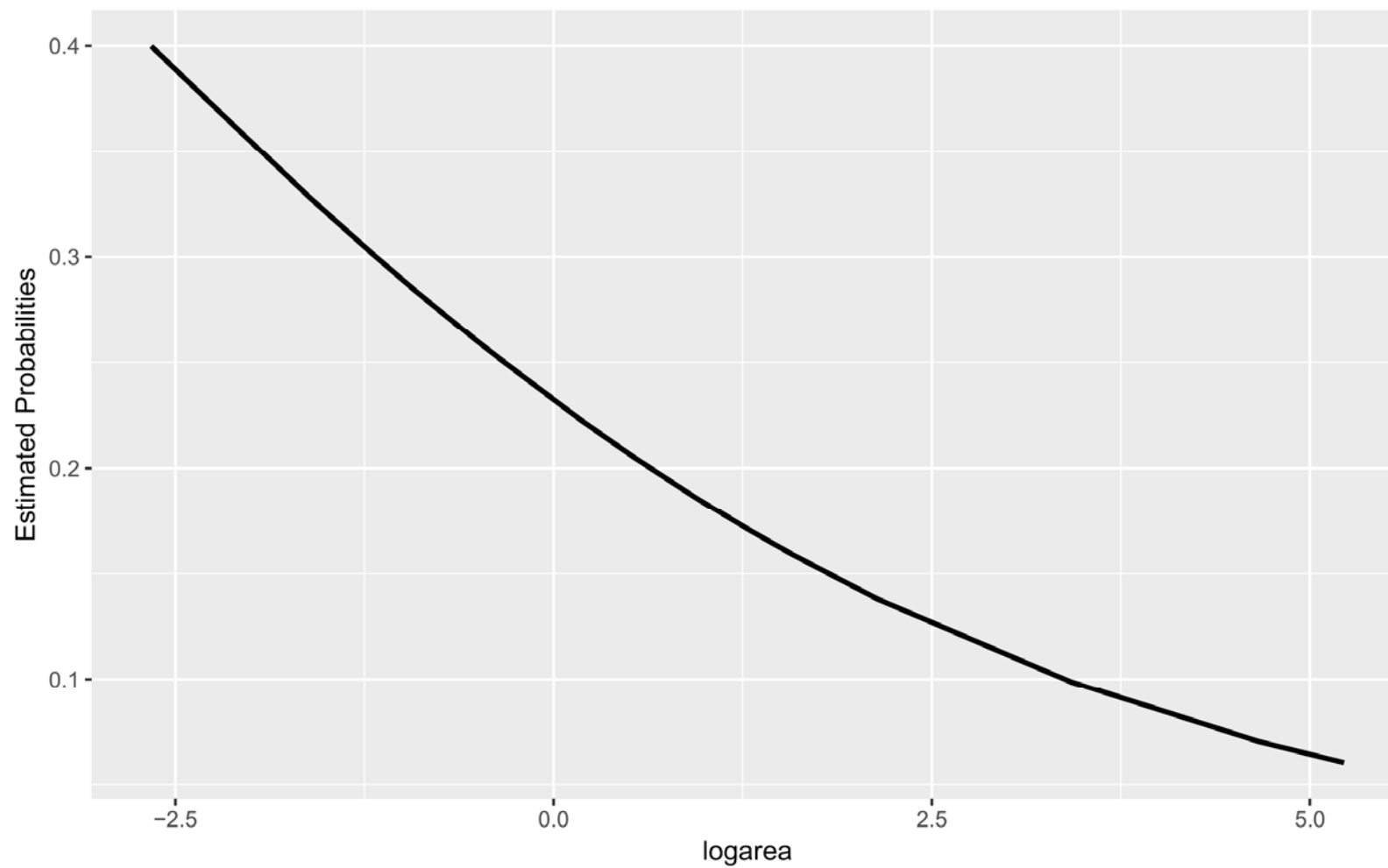
```
.5^(CL) # halving Area
```

```
##              bhat      2.5 %      97.5 %
## (Intercept)  2.291346  2.691379  1.950773
## log(Area)    1.228675  1.323734  1.140443
```

$$\hat{\beta}_1 \pm 1.96 (se(\hat{\beta}_1))$$
$$-0.297 \pm 1.96 (0.05485)$$

Case IV Effect Plot

```
ggplot(krunnit, aes(x=logarea, y=phats))+ylab("Estimated Probabilities")+  
  geom_line(size=1)
```



$\hat{\pi}_{m,c}$

As logarea ↑
 $\hat{\pi}_{m,i}$ ↓
⇓
Larger preserves
associated with
lower extinction.

Case IV: Deviance test and Estimated Var-Cov of β

```
anova(fitbl, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: cbind(Extinct, NExtinct)
##
## Terms added sequentially (first to last)
##
##
##              Df Deviance Resid. Df Resid. Dev Pr(>Chi)
## NULL                      17         45.3
## log(Area)    1      33.3      16      12.1    8e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
1-pchisq(12.062, 16)
```

```
## [1] 0.7397
```

$\text{logit}(\hat{\pi}) = \hat{\beta}_0 + \hat{\beta}_1 \text{log(Area)}$
was adequate

0.74

Case IV: Estimated probabilities of extinction per island

```
phats<-predict.glm(fitbl, type="response") # estimated probability of extinction
options(digits=4)
rbind(Extinct, NExtinct, pis,phats)
```

π_i

##		1	2	3	4	5	6	7	
## Extinct		5.00000	3.00000	10.00000	6.0000	3.0000	4.000	8.0000	
## NExtinct		70.00000	64.00000	56.00000	45.0000	25.0000	16.000	35.0000	
## pis		0.06667	0.04478	0.15152	0.1176	0.1071	0.200	0.1860	
## phats		0.06017	0.07036	0.09854	0.1380	0.1595	0.162	0.1639	
##		8	9	10	11	12	13	14	15
## Extinct		3.00000	5.0000	6.0000	8.0000	2.0000	9.0000	5.0000	7.0000
## NExtinct		28.00000	23.0000	26.0000	22.0000	18.0000	22.0000	11.0000	8.0000
## pis		0.09677	0.1786	0.1875	0.2667	0.1000	0.2903	0.3125	0.4667
## phats		0.17125	0.1854	0.2052	0.2226	0.2516	0.2516	0.2603	0.2842
##		16	17	18					
## Extinct		8.0000	13.0000	3.0000					
## NExtinct		25.0000	27.0000	3.0000					
## pis		0.2424	0.3250	0.5000					
## phats		0.3019	0.3278	0.3998					

Case IV Fit Statistics

```
AIC(fitb1)
```

```
## [1] 75.39
```

```
BIC(fitb1)
```

```
## [1] 77.17
```


Case IV Residuals

Fitted Model *type of residuals.*

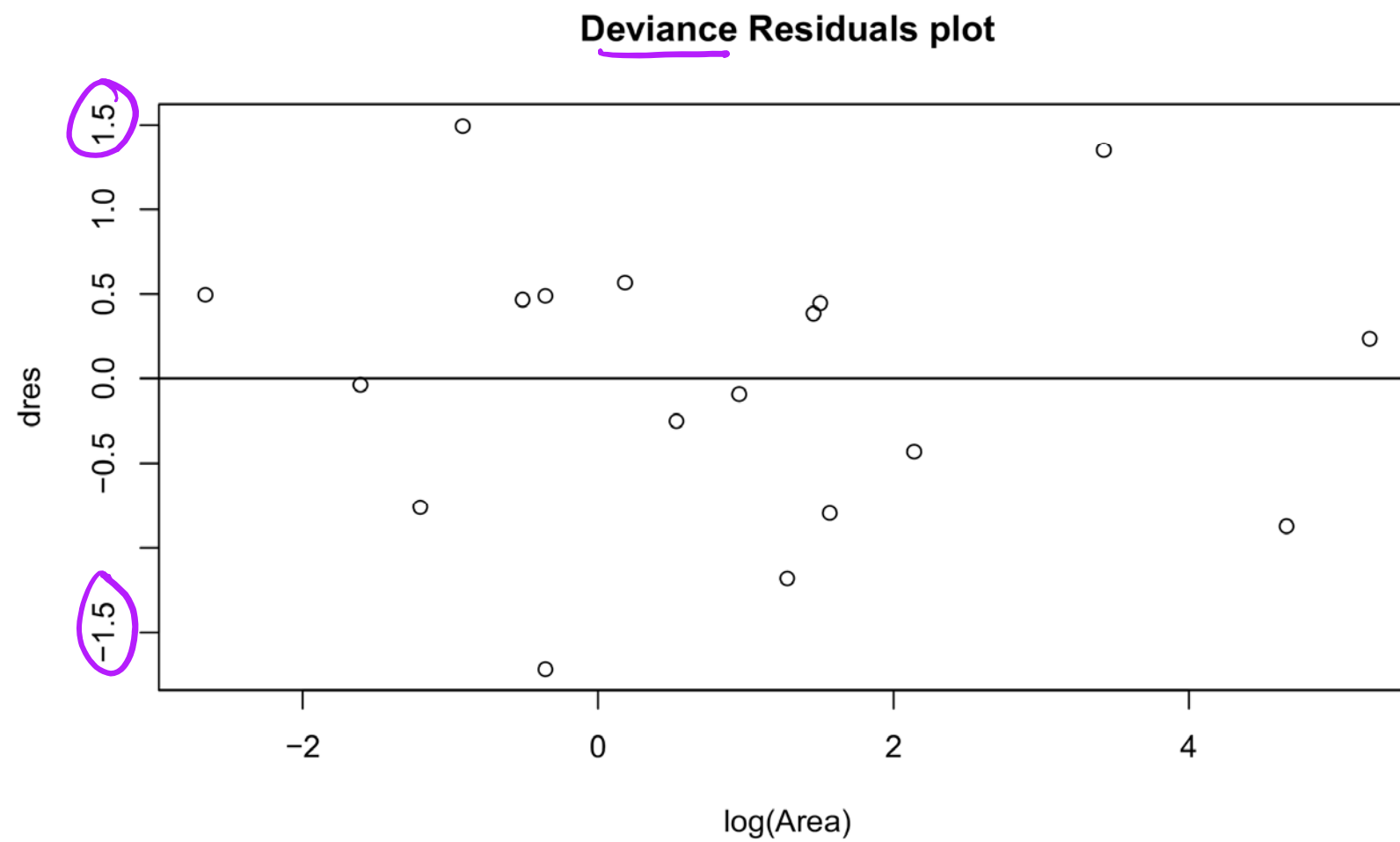
```
rres<-residuals(fitbl, type=c("response"))
pres<-residuals(fitbl, type=c("pearson"))
dres<-residuals(fitbl, type=c("deviance"))
rbind(pis,phats,rres, pres,dres)
```

$\pi_i - \hat{\pi}_i$

##		1	2	3	4	5	6	7	8
##	pis	0.066667	0.04478	0.15152	0.11765	0.10714	0.20000	0.18605	0.09677
##	phats	0.060173	0.07036	0.09854	0.13800	0.15946	0.16205	0.16389	0.17125
##	rres	0.006493	-0.02558	0.05298	-0.02035	-0.05232	0.03795	0.02216	-0.07448
##	pres	0.236464	-0.81883	1.44400	-0.42139	-0.75619	0.46058	0.39247	-1.10075
##	dres	0.232656	-0.87369	1.34958	-0.43071	-0.79584	0.44746	0.38577	-1.18097
##		9	10	11	12	13	14	15	16
##	pis	0.178571	0.18750	0.26667	0.1000	0.29032	0.3125	0.4667	0.24242
##	phats	0.185415	0.20524	0.22264	0.2516	0.25158	0.2603	0.2842	0.30185
##	rres	-0.006844	-0.01774	0.04403	-0.1516	0.03875	0.0522	0.1825	-0.05943
##	pres	-0.093181	-0.24850	0.57969	-1.5622	0.49717	0.4759	1.5673	-0.74367
##	dres	-0.093632	-0.25127	0.56727	-1.7173	0.48934	0.4666	1.4954	-0.75939
##		17	18						
##	pis	0.325000	0.5000						
##	phats	0.327828	0.3998						
##	rres	-0.002828	0.1002						
##	pres	-0.038101	0.5008						
##	dres	-0.038129	0.4957						

Case IV Residuals Plot

```
plot(log(Area), dres, main="Deviance Residuals plot")  
abline(h=0)
```



Case IV Residuals Plot

```
plot(log(Area), pres, main="Pearson Residuals plot")  
abline(h=0)
```

