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LAMPIRAN

Lampiran 1. Data Air Sungai

Warna	pH	Suhu	Salinitas	Florida	Phospat	Ammonia
0	7,53	28,5	0,2	0,2434	0,1	0,14
0	7,45	28,2	0,2	0,2723	0,11	0,235
0	9,12	28,7	0,2	0,3685	0,11	0,0169
1	7,81	27,7	0,2	0,3327	0,21	0,2361
1	6,99	26,9	0,3	0,4025	0,29	0,0145
1	7,04	26,6	0,3	0,4135	0,34	0,013
0	7,18	29,8	0,3	0,4167	0,3	0,132
0	7,1	29,6	0,3	0,3667	0,34	0,0075
0	7,28	26,5	0,2	0,3093	0,26	0,0766
0	8,07	26,6	0,2	0,0814	0,24	0,443
1	6,93	26,6	0,2	0,299	0,16	0,137
1	7,71	28	0,2	0,2426	0,21	0,1441
0	3,23	28,1	0,2	0,3869	0,31	0,546
0	8,9	27,9	0,2	0,378	0,35	0,22
1	6,46	26,2	0,2	0,194	0,12	0,03
1	2,98	26,5	0,1	0,385	0,19	0,101
0	7,89	28,3	0,2	0,055	0,15	0,0219
0	4,76	28	0,2	0,2234	0,16	0,0102
0	8,45	28,5	0,2	0,302	0,18	0,0028
1	7,87	27,7	0,2	0,4298	0,22	0,3125
0	9,87	31,2	0,2	0,2159	0,26	0,0068
1	7,26	27,5	0,2	0,4274	0,35	0,2153
1	9,27	26,7	0,2	0,3315	0,34	0,0037
0	7,25	26,6	0,2	0,4265	0,35	0,0037
0	7,38	28,7	0,3	0,1825	0,37	0,0175
0	10,02	29,1	0,3	0,5102	0,5	0,0116
1	7,02	27,4	0,2	1,0386	0,24	0,0027
0	3,55	26,5	0,2	0,2105	0,23	0,0422
0	7,29	27	0,2	0,1711	0,22	0,522
0	6,71	26,8	0,2	0,211	0,14	0,163
1	9,06	27,8	0,2	0,4063	0,2	0,0408

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1	6,98	27,2	0,2	0,4993	0,28	0,062
1	7,28	28	0,2	0,354	0,3	0,016
1	4,32	26,5	0,1	0,416	0,26	0,765
1	6,88	26,2	0,1	0,415	0,22	0,188
0	7,7	28	0,2	0,0028	0,17	0,0172
0	7,81	28,1	0,2	0,1046	0,23	0,0781
0	7,48	28,7	0,2	0,0076	0,16	0,1022
1	8,3	27,8	0,2	0,3988	0,24	0,1634
0	7,09	27,8	0,3	0,377	0,29	0,058
0	4,09	26,8	0,3	0,418	0,28	0,0335
0	7,35	29,1	0,3	0,4255	0,26	0,0071
0	7,13	29	0,3	0,441	0,25	0,0549
1	3,29	27,1	0,2	1,0505	0,24	0,2407
1	7,19	27,7	0,2	0,1416	0,3	0,1787
0	9	28	0,2	0,511	0,25	0,092
0	7,35	28,1	0,2	0,736	0,2	0,0863
1	8,78	28,76	0,3	0,3714	0,3	0,69
1	7,72	27,8	0,2	0,437	0,23	0,062
1	5,26	27,2	0,2	0,4777	0,44	0,441
1	6,99	27	0,2	0,365	0,32	0,132
0	7,88	28,2	0,2	0,2344	0,16	0,0026
0	4,32	28,2	0,2	0,2459	0,16	0,0366
0	7,38	28,8	0,1	0,0076	0,14	0,456
1	7,74	28,1	0,2	0,3172	0,24	0,1002
0	6,87	28,8	0,2	0,4046	0,26	0,0199
0	6,76	28	0,2	0,354	0,24	0,0037
0	8,99	28	0,3	0,322	0,23	0,0245
0	3,07	26,5	0,3	0,202	0,23	0,37
0	6,82	28,4	0,3	0,396	0,25	0,0113
0	7,15	27,2	0,2	0,9442	0,29	0,0027
0	7,25	27,4	0,2	0,2255	0,24	0,584
0	4,65	27	0,2	0,7405	0,21	0,0258
0	7,08	27,5	0,2	0,6196	0,22	0,1285
1	7,09	27,6	0,2	0,335	0,21	0,1085
1	4,67	26,8	0,2	0,4735	0,26	0,0765
1	6,86	26,5	0,2	0,3605	0,15	0,0565
0	7,7	30	0,2	0,05	0,05	0,2367
0	7,8	29	0,2	0,05	0,08	0,2257

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1	2,97	28,3	0,2	0,517	0,28	0,339
1	7,06	28,5	0,2	0,456	0,24	0,484
0	6,84	27,8	0,2	0,726	0,25	0,56
1	9,98	31	0,2	0,508	0,2	0,67
1	4,85	27,9	0,2	0,344	0,2	0,2775
1	7,05	29	0,3	0,505	0,33	0,3855

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Lampiran 2. Script Pemrograman

```
library(bayesQR)
library(car)
Air=read.delim("clipboard")
Air

#ANALISIS REGRESI LOGISTIK#
     logit=glm(warna~pH+suhu+salinitas+florida+phospat+ammonia,family
     =binomial(link="logit"),data=Air)
     summary(logit)

#DETEKSI MULTIKOLINEARITAS#
     vif(logit)

#PREDIKSI AKURASI MODEL REGRESI LOGISTIK#
     table(true=Air$warna, pred=round(fitted(logit)))

#ANALISIS REGRESI PROBIT#
     probit=glm(warna~pH+suhu+salinitas+florida+phospat+ammonia,famil
     y=binomial(link="probit"),data=Air)
     summary(probit)

#PENENTUAN PRIOR#
     priorqr=
     prior(warna~pH+suhu+salinitas+florida+phospat+ammonia,data=Air,a
     lasso=TRUE)
     str(priorqr)

#ESTIMASI MODEL REGRESI BINARI KUANTIL DENGAN PENALTI LASSO DAN
MENGGUNAKAN INFORMASI PRIOR#
     out=bayesQR(warna~pH+suhu+salinitas+florida+phospat+ammonia,data
     =Air, quantile=seq(0.05,0.95,0.05), alasso=TRUE,
     ndraw=50000,keep=1,prior=priorqr)
```

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```
#PRINT HASIL ESTIMASI MODEL REGRESI BINARI KUANTIL DENGAN PENALTI
LASSO DAN MENGGUNAKAN INFORMASI PRIOR#
     summary(out,burnin=0)

#PLOT KEKONVERGENAN UNTUK TIAP VARIABEL INDEPENDEN#
plot(out, var=1, plottype="quantile",main=”intercept”)
plot(out, var=”pH”, plottype="quantile",main=”pH”)
plot(out, var=”suhu”, plottype="quantile",main=”suhu”)
plot(out, var=”salinitas”, plottype="quantile",main=”salinitas”)
plot(out, var=”florida”, plottype="quantile",main=”florida”)
plot(out, var=”phospat”, plottype="quantile",main=”phospat”)
plot(out, var=”ammonia”, plottype="quantile",main=”ammonia”)
```

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Lampiran 3. Output Model Regresi Logistik

a. Hasil verifikasi variabel independen

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	pH	-.104	.142	.533	1	.165	.901
	Constant	.425	1.013	.176	1	.675	1.530

a. Variable(s) entered on step 1: pH.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	suhu	-.644	.271	5.652	1	.017	.525
	Constant	17.606	7.516	5.486	1	.019	44264996.206

a. Variable(s) entered on step 1: suhu.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	salinitas	-9.329	5.379	3.008	1	.083	.000
	Constant	1.691	1.160	2.125	1	.145	5.422

a. Variable(s) entered on step 1: salinitas.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	florida	2.683	1.310	4.194	1	.041	14.631
	Constant	-1.289	.541	5.681	1	.017	.276

a. Variable(s) entered on step 1: florida.

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Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	phospat	4.354	3.120	1.948	1	.163	77.822
	Constant	-1.341	.790	2.885	1	.089	.261

a. Variable(s) entered on step 1: phospat.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ammonia	2.010	1.258	2.553	1	.110	7.466
	Constant	-.636	.318	3.985	1	.046	.530

a. Variable(s) entered on step 1: ammonia.

b. Hasil estimasi regresi logistik

```
Call:
glm(formula = warna ~ pH + suhu + salinitas + florida + phospat +
ammonia, family = binomial(link = "logit"), data = Air)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8907  -0.8302  -0.4860   1.1091   1.4814

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  16.6234     8.3819   1.983   0.0473 *
pH            0.1580     0.1787   0.884   0.3765
suhu         -0.6620     0.3264  -2.028   0.0425 *
salinitas    -9.4160     6.7291  -1.399   0.1617
florida       2.3532     1.4638   1.608   0.1079
phospat       4.6484     4.1628   1.117   0.2641
```

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```
ammonia        2.3488     1.4887    1.578    0.1146
---
Signif.codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

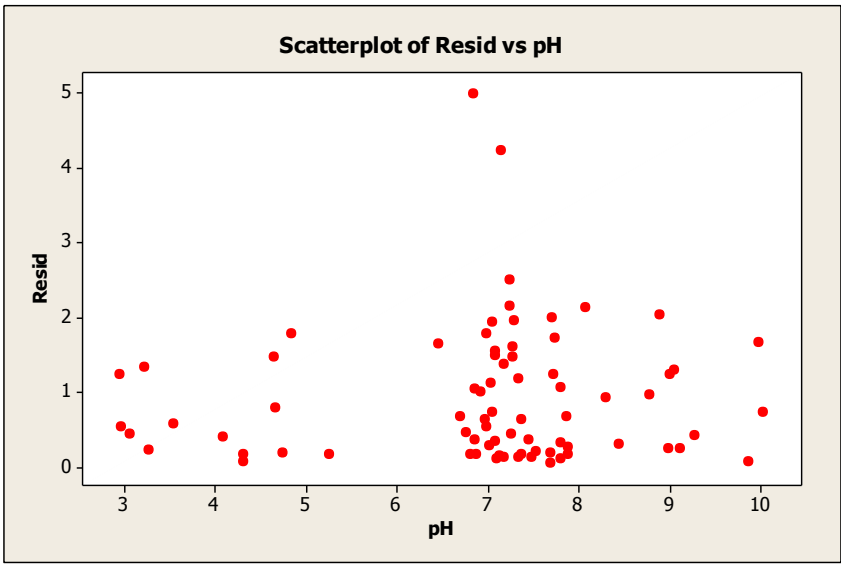
    Null deviance: 102.353  on 74  degrees of freedom
Residual deviance:  84.789  on 68  degrees of freedom
AIC: 98.789

Number of Fisher Scoring iterations: 4
```

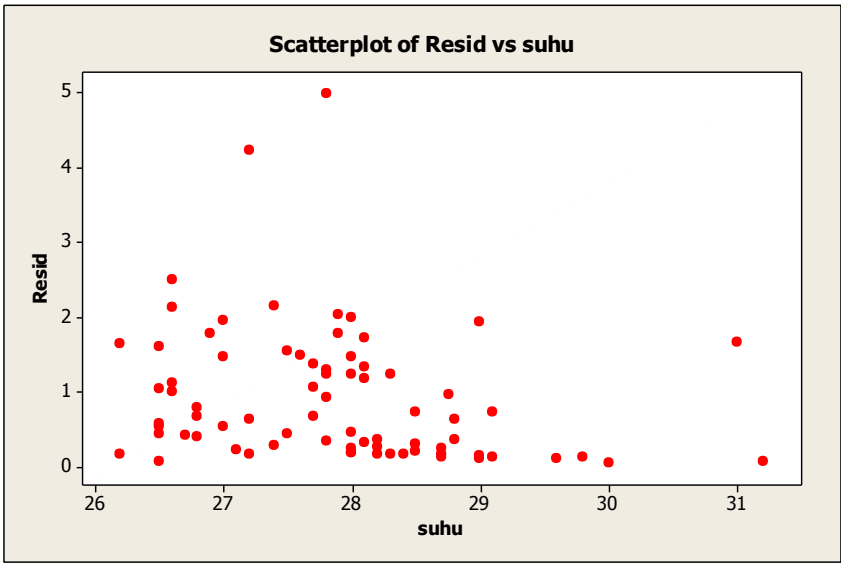
c. Hasil pengujian asumsi No Multikolinearitas

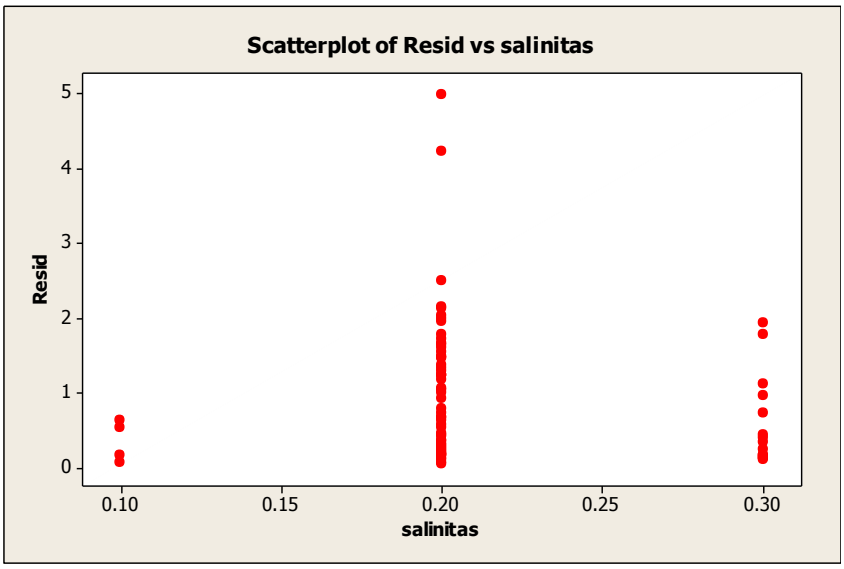
pH	suhu	salinitas	florida	phospat	ammonia
1.289718	1.380156	1.337382	1.137657	1.388754	1.139642

d. Hasil pengujian asumsi Homoskedastisitas

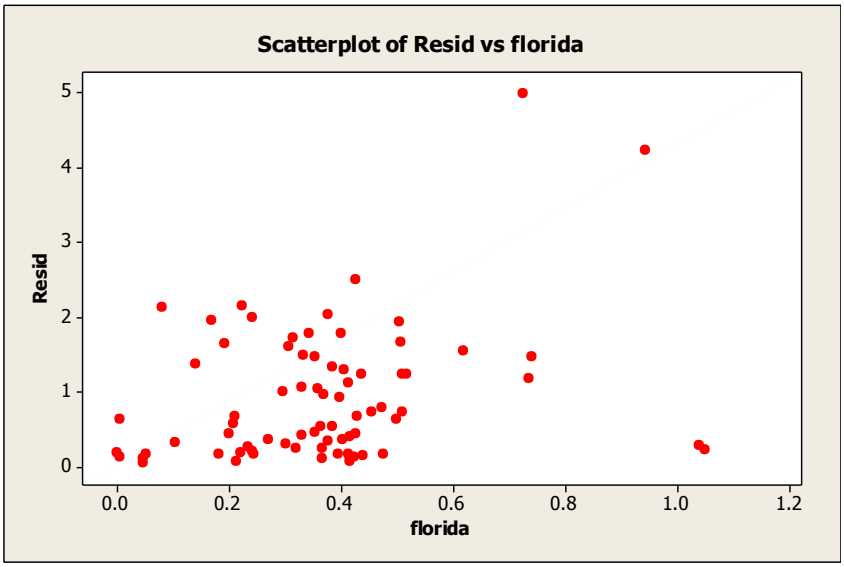


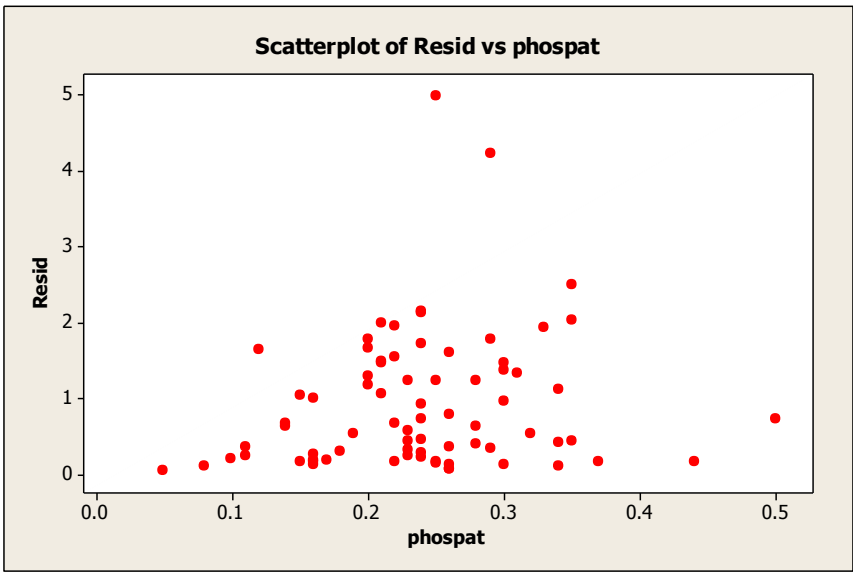
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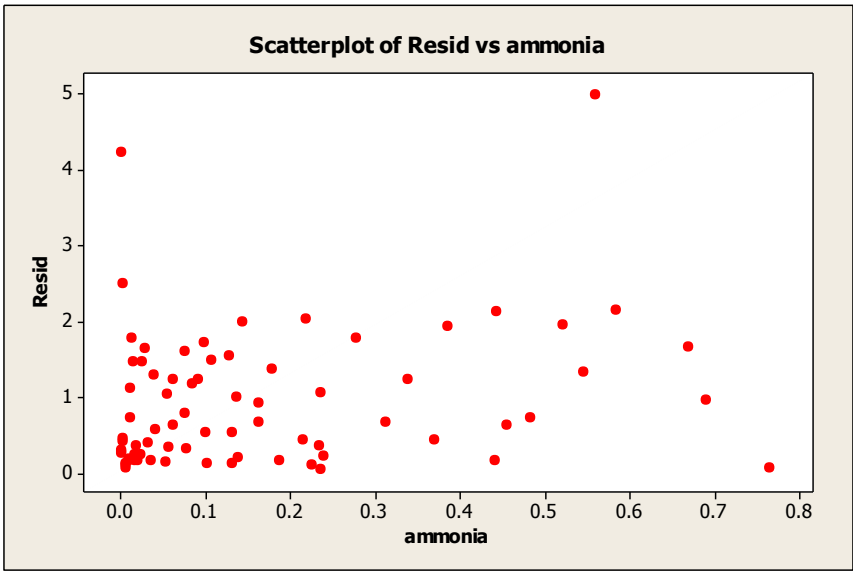


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e. **Hasil akurasi model regresi logistik**

```
pred

true   0  1
 0    30 13
 1    17 15
```

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Lampiran 4. Output Model Regresi Probit

```
Call:
glm(formula = warna ~ pH + suhu + salinitas + florida + phospat +
ammonia, family = binomial(link = "probit"), data = Air)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8872  -0.8182  -0.4437   1.1199   1.4920

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 10.33613    4.97646   2.077   0.0378 *
pH           0.09539    0.10827   0.881   0.3783
suhu        -0.41060    0.19369  -2.120   0.0340 *
salinitas   -5.99604    4.02822  -1.489   0.1366
florida      1.41773    0.85876   1.651   0.0988 .
phospat      2.99437    2.49050   1.202   0.2292
ammonia      1.44195    0.89122   1.618   0.1057
---
Signif.codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 102.353  on 74  degrees of freedom
Residual deviance:  84.318  on 68  degrees of freedom
AIC: 98.318

Number of Fisher Scoring iterations: 5
```

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Lampiran 5. Output Model Regresi Binari Kuantil Bayesian Terpenalti

```
List of 3
 $ c     : num 0.01
 $ d     : num 100
 $ method: chr "QRb.AL"
 - attr(*, "class")= chr "bayesQR.prior"
```

a. Hasil estimasi regresi binari kuantil Bayesian terpenalti dengan $\theta = 0,05$ sampai $\theta = 0,95$

```
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.05
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate  lower  upper
(Intercept)        0.00287 -44.94 38.612
pH                -0.26617  -3.15  2.840
suhu              -0.75488  -2.35  0.984
salinitas         -5.00891 -35.95 22.567
florida           10.69421  -5.03 27.804
phospat            5.35165 -23.22 35.979
ammonia            8.53314  -7.22 27.600

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.1
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate  lower upper
(Intercept)          8.391 -39.93 37.93
pH                   0.140  -1.39  2.11
suhu                -0.793  -2.11  0.98
salinitas           -6.758 -36.68 16.22
florida              6.862  -2.11 16.06
phospat              8.213 -11.02 32.70
ammonia              6.270  -3.62 16.62

****************************************
Type of dependent variable: binary
```

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```
Lasso variable selection: yes
Estimated quantile:  0.15
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate  lower  upper
(Intercept)         0.9558 -25.31 21.123
pH                 -0.0546  -1.16  0.916
suhu               -0.2807  -1.04  0.823
salinitas         -10.4216 -43.93 12.132
florida             4.7618  -1.97 10.943
phospat             6.8452  -9.07 25.833
ammonia             4.1740  -3.10 11.592

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.2
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower upper
(Intercept)        11.6618 -36.401 35.59
pH                  0.0749  -0.778  1.12
suhu               -0.6247  -1.592  1.19
salinitas          -9.6850 -33.733 10.84
florida             4.2024  -1.020  9.33
phospat             5.3600  -8.699 20.35
ammonia             3.5884  -2.111  9.53
****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.25
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         9.1695 -15.021 37.526
pH                  0.0731  -0.606  0.777
suhu               -0.4809  -1.563  0.266
salinitas         -10.1125 -39.363  8.119
florida             3.6006  -0.901  8.489
phospat             5.2329  -7.204 18.812
```

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```
ammonia             3.0209  -2.094  8.352

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.3
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         7.4982 -22.444 44.249
pH                  0.0249  -0.639  0.659
suhu               -0.3812  -1.779  0.819
salinitas         -10.2216 -32.742  5.723
florida             3.2693  -0.673  7.563
phospat             5.6667  -5.288 18.351
ammonia             2.7602  -1.692  7.585

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.35
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         3.6985 -22.178 14.919
pH                  0.0567  -0.472  0.565
suhu               -0.2333  -0.676  0.765
salinitas          -9.7500 -29.499  4.762
florida             3.3210  -0.576  7.471
phospat             5.3587  -3.686 16.634
ammonia             2.7483  -1.469  7.154
****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.4
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         4.2772 -20.116 26.037
pH                  0.0245  -0.501  0.532
```

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```
suhu               -0.2255  -1.030  0.669
salinitas         -10.3549 -29.240  4.463
florida             3.3357  -0.285  7.785
phospat             5.4349  -3.778 17.120
ammonia             2.5935  -1.383  6.954

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.45
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         10.831 -25.506 31.613
pH                   0.115  -0.432  0.592
suhu                -0.480  -1.286  0.921
salinitas           -8.878 -25.182  4.750
florida              3.660  -0.239  8.783
phospat              4.579  -5.059 17.155
ammonia              2.864  -1.132  7.230

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.5
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate    lower  upper
(Intercept)          9.950 -17.8547 28.466
pH                   0.153  -0.3259  0.652
suhu                -0.453  -1.1916  0.636
salinitas           -8.463 -23.4015  4.408
florida              3.997  -0.0206  9.394
phospat              4.611  -4.3662 15.411
ammonia              2.951  -0.8557  7.282
****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.55
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000
```

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```
Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         30.434 -11.002 57.073
pH                   0.327  -0.299  0.905
suhu                -1.241  -2.276  0.359
salinitas           -7.733 -24.767  6.172
florida              4.384  -0.189 10.524
phospat              4.623  -4.945 16.187
ammonia              4.350  -0.296 10.077

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.6
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate    lower upper
(Intercept)          9.748 -34.1500 27.47
pH                   0.137  -0.4152  0.67
suhu                -0.418  -1.1159  1.14
salinitas          -10.108 -29.3384  3.62
florida              4.521  -0.0656 10.08
phospat              4.942  -4.6627 17.87
ammonia              3.309  -0.6563  8.15

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.65
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         14.111  -9.023 32.341
pH                   0.183  -0.399  0.757
suhu                -0.586  -1.289  0.380
salinitas          -10.242 -27.140  3.744
florida              5.124   0.295 11.265
phospat              5.277  -5.042 17.574
ammonia              3.737  -0.524  9.025
****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.7
Lower credible bound:  0.025
```

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```
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         14.389 -22.388 28.695
pH                   0.181  -0.411  0.756
suhu                -0.591  -1.215  0.768
salinitas          -10.181 -29.005  4.043
florida              5.609   0.375 12.200
phospat              5.223  -5.010 17.675
ammonia              4.121  -0.407  9.608

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.75
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         11.876 -15.451 30.493
pH                   0.161  -0.526  0.773
suhu                -0.487  -1.195  0.569
salinitas          -11.392 -29.867  3.373
florida              6.601   0.460 14.116
phospat              5.354  -5.104 18.832
ammonia              4.581  -0.671 10.974

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.8
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)          35.03 -13.461 64.212
pH                    0.36  -0.421  1.124
suhu                 -1.37  -2.688  0.429
salinitas           -12.70 -35.958  4.871
florida               7.84   0.614 16.886
phospat               6.55  -5.648 21.061
ammonia               7.10   0.157 15.141
****************************************
```

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```
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.85
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower  upper
(Intercept)         23.811 -12.383 55.478
pH                   0.285  -0.711  1.262
suhu                -0.945  -2.280  0.439
salinitas          -12.413 -36.237  7.476
florida              9.795   0.921 20.738
phospat              6.284  -7.601 23.761
ammonia              7.466  -0.933 18.249

****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.9
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower upper
(Intercept)         5.7910 -25.067 33.35
pH                  0.0397  -1.511  1.31
suhu               -0.2102  -1.381  1.23
salinitas         -12.1524 -44.422 10.10
florida            13.3493   0.709 25.83
phospat             6.1945 -10.396 27.51
ammonia             7.5768  -2.877 21.92

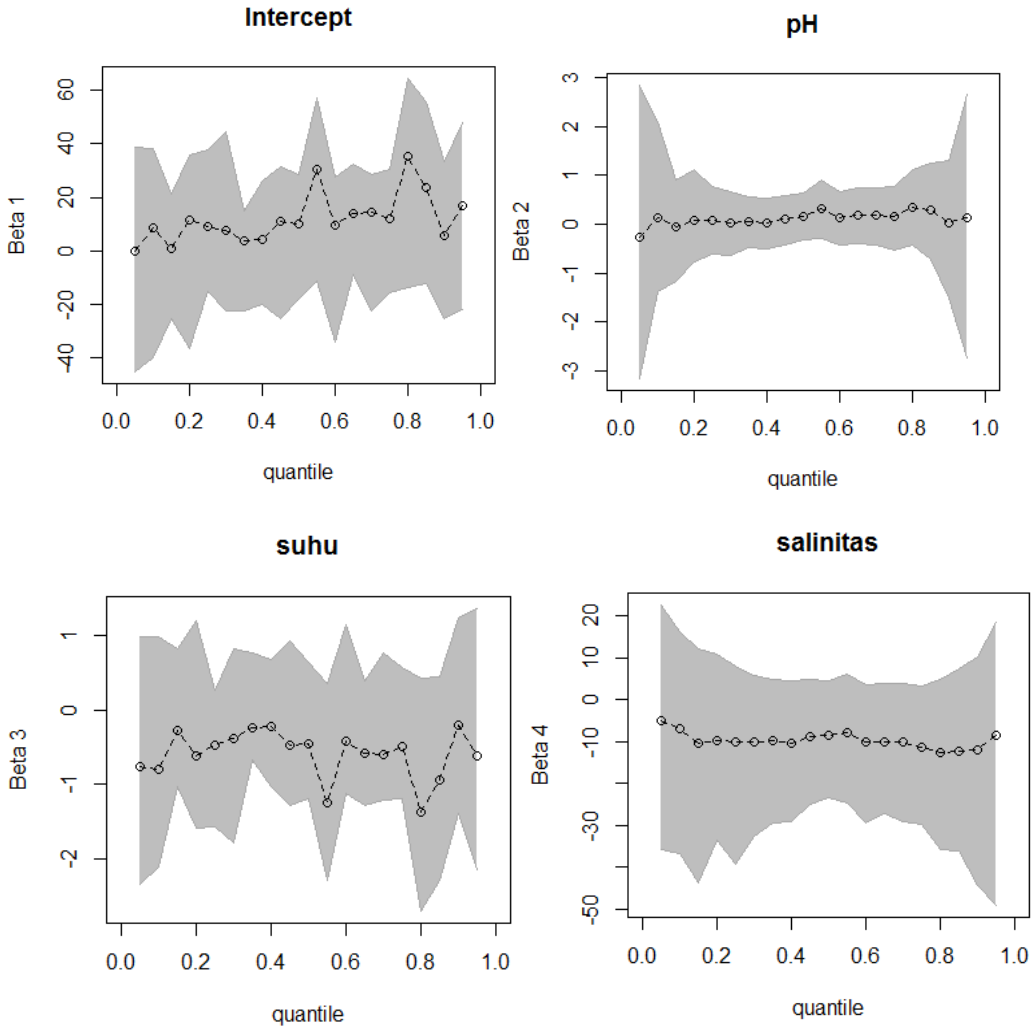
****************************************
Type of dependent variable: binary
Lasso variable selection: yes
Estimated quantile:  0.95
Lower credible bound:  0.025
Upper credible bound:  0.975
Number of burnin draws:  0
Number of retained draws:  50000

Summary of the estimated beta:
            Bayes Estimate   lower upper
(Intercept)         16.746 -21.736 47.96
pH                   0.132  -2.739  2.67
suhu                -0.608  -2.133  1.35
salinitas           -8.377 -49.036 18.59
```

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```
florida              21.451    0.118 45.51
phospat               8.452 -14.764 39.72
ammonia              11.379  -5.096 34.70
```

b. Quantile plot estimasi beta pada regresi binari kuantil Bayesian terpenalti



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