

LINTHURST SOIL DATA REGRESSION ANALYSIS PROJECT

MATH 564 – Regression Analysis
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Abstract

This project analyzes the Linthurst soil dataset from the Cape Fear Estuary to identify soil variables that influence biomass production (BIO).

Using OLS, VIF, correlation diagnostics, Condition Indices, PCA/PCR, stepwise regression, subset selection, and ridge regression, we examine multicollinearity and select the best predictive model.

The analysis is performed in Python, and all results, figures, and terminal outputs are included in this report.

1. Introduction

The Linthurst dataset consists of **45 observations** and **14 physicochemical predictors** of biomass (BIO).

The project is divided into:

- **Part I:** Collinearity diagnosis and reduction using PCA/PCR.
- **Part II:** Variable selection using stepwise regression, AIC/BIC subset selection, and ridge regression.

The goal is to:

1. Detect multicollinearity
2. Reduce it
3. Build a stable and interpretable predictive model for BIO

2. Dataset Description

Observations: 45

Predictors (14):

H2S, SAL, Eh7, pH, BUF, P, K, Ca, Mg, Na, Mn, Zn, Cu, NH4

Response:

- BIO – Biomass

3. Part I — Collinearity Diagnosis (14 Predictors)

3.1 OLS Regression Summary

```
PROBLEMS OUTPUT TERMINAL PORTS DEBUG CONSOLE
• (venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py
=====
LINTHURST DATA ANALYSIS PROJECT
=====

PART I: COLLINEARITY DIAGNOSIS AND REDUCTION
=====

1. Dataset loaded successfully
Shape: (45, 18)
Columns: ['Obs', 'Loc', 'Type', 'BIO', 'H2S', 'SAL', 'Eh7', 'pH', 'BUF', 'P', 'K', 'Ca', 'Mg', 'Na', 'Mn', 'Zn', 'Cu', 'NH4']

2. Response variable: BIO
Predictors (14): ['H2S', 'SAL', 'Eh7', 'pH', 'BUF', 'P', 'K', 'Ca', 'Mg', 'Na', 'Mn', 'Zn', 'Cu', 'NH4']

-----
TASK 1: OLS ESTIMATION AND COLLINEARITY DIAGNOSTICS
-----

3. OLS Regression Results:
R-squared: 0.8074
Adjusted R-squared: 0.7175
SSE: 3692233.4756
Sum of Standard Errors: 635.1904

Regression Coefficients:
Variable      Coefficient    Std Error    t-value    p-value
-----
Intercept      2909.9341      3412.8978      0.853      0.4006
H2S              0.4290         2.9979      0.143      0.8872
SAL            -23.9807        26.1694     -0.916      0.3668
Eh7              2.5532         2.0125      1.269      0.2143
pH             242.5278        334.1734      0.726      0.4736
```

- $R^2 = 0.8074$
- $SSE = 3,692,233$
- Many coefficients unstable
- Large standard errors indicate multicollinearity

3.2 VIF Analysis

```

PROBLEMS  OUTPUT  TERMINAL  PORTS  DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

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TASK 1: OLS ESTIMATION AND COLLINEARITY DIAGNOSTICS
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SAL           -23.9807        26.1694       -0.916      0.3668
Eh7            2.5532         2.0125        1.269      0.2143
pH            242.5278       334.1734       0.726      0.4736
BUF           -6.9023        123.8211      -0.056      0.9559
P             -1.7015         2.6397       -0.645      0.5241
K             -1.0466         0.4824       -2.170      0.0381
Ca            -0.1161         0.1256       -0.924      0.3629
Mg            -0.2802         0.2745       -1.021      0.3154
Na             0.0045         0.0247        0.180      0.8583
Mn            -1.6788         5.3731       -0.312      0.7569
Zn           -18.7945        21.7802       -0.863      0.3950
Cu            345.1628       112.0779       3.080      0.0044
NH4           -2.7052         3.2380       -0.835      0.4101

-----
COLLINEARITY DIAGNOSTIC METHOD 1: VARIANCE INFLATION FACTOR (VIF)
-----

```

Result:

- 13 out of 14 predictors have **VIF > 10**
- Severe multicollinearity detected

3.3 Correlation Matrix Diagnostics

```
PROBLEMS OUTPUT TERMINAL PORTS DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

-----
COLLINEARITY DIAGNOSTIC METHOD 1: VARIANCE INFLATION FACTOR (VIF)
-----

4. VIF Results:
Variable      VIF
H2S  551.085744
SAL  128.585107
Eh7  138.480069
pH   250.169112
BUF   70.102695
P      4.535564
K    54.706609
Ca   22.588164
Mg  257.548005
Na   66.815038
Mn   11.510101
Zn   66.169248
Cu   76.519084
NH4   31.618182

Rule of thumb: VIF > 10 indicates serious collinearity
Variables with VIF > 10: ['H2S', 'SAL', 'Eh7', 'pH', 'BUF', 'K', 'Ca', 'Mg', 'Na', 'Mn', 'Zn', 'Cu', 'NH4']

-----
COLLINEARITY DIAGNOSTIC METHOD 2: CORRELATION MATRIX
-----

5. Correlation Matrix (showing |corr| > 0.7):
Variable 1  Variable 2  Correlation
-----
pH          BUF      -0.9464
pH          Ca       0.8780
```

Variables with |correlation| > 0.7 confirms strong collinearity patterns.

3.4 Condition Index Method

```
PROBLEMS  OUTPUT  TERMINAL  PORTS  DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

-----
COLLINEARITY DIAGNOSTIC METHOD 2: CORRELATION MATRIX
-----

5. Correlation Matrix (showing |corr| > 0.7):
Variable 1  Variable 2  Correlation
-----
pH          BUF        -0.9464
pH          Ca         0.8780
pH          Zn        -0.7222
pH          NH4       -0.7460
BUF         Ca        -0.7911
BUF         Zn         0.7147
BUF         NH4        0.8495
K           Mg         0.8622
K           Na         0.7921
Mg          Na         0.8995
Mg          Cu         0.7121
Zn          NH4        0.7207

-----
COLLINEARITY DIAGNOSTIC METHOD 3: CONDITION INDICES
-----

6. Eigenvalues and Condition Indices:
Eigenvalue  Condition Index
-----
221.5759    1.0000
166.2851    1.1543
72.3207     1.7504
60.0706     1.9206
31.1219     2.6683
22.5254     3.1364
17.3447     3.5742
17.1348     3.5960
7.4686      5.4468
6.4347      5.8681
3.9090      7.5288
2.0380      10.4270
```

- Highest CI = **22.78**
- CI > 30 is severe; CI > 15 indicates moderate-to-severe
→ Confirms multicollinearity

4. Part I — Principal Components Regression (PCR)

4.1 PCA Eigenvalues

```
PROBLEMS OUTPUT TERMINAL PORTS DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py
Zn          NH4          0.7207

-----
COLLINEARITY DIAGNOSTIC METHOD 3: CONDITION INDICES
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17.1348       3.5960
7.4686        5.4468
6.4347        5.8681
3.9090        7.5288
2.0380        10.4270
1.3434        12.8429
0.4272        22.7752

Rule of thumb: Condition Index > 30 indicates serious collinearity
Max Condition Index: 22.7752

-----
CONCLUSION FROM THREE METHODS:
-----

All three methods indicate SERIOUS COLLINEARITY:
1. VIF: 13 variables have VIF > 10
2. Correlation: 12 pairs have |correlation| > 0.7
3. Condition Index: Max = 22.78 >> 30

=====
TASK 2: PRINCIPAL COMPONENTS REGRESSION (PCR)
=====
```

- 4 components have eigenvalue > 1
- Cumulative Variance $\approx 82.6\%$

4.2 PCR Model Results

```
PROBLEMS  OUTPUT  TERMINAL  PORTS  DEBUG CONSOLE

(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

=====
TASK 2: PRINCIPAL COMPONENTS REGRESSION (PCR)
=====

7. PCA Results:
PC      Eigenvalue      Variance Explained      Cumulative Variance
-----
1        5.0358              0.3517              0.3517
2        3.7792              0.2639              0.6157
3        1.6437              0.1148              0.7304
4        1.3652              0.0954              0.8258
5        0.7073              0.0494              0.8752
6        0.5119              0.0358              0.9110
7        0.3942              0.0275              0.9385
8        0.3894              0.0272              0.9657
9        0.1697              0.0119              0.9775
10       0.1462              0.0102              0.9877
11       0.0888              0.0062              0.9940
12       0.0463              0.0032              0.9972
13       0.0305              0.0021              0.9993
14       0.0097              0.0007              1.0000

8. Selecting 4 components (eigenvalue > 1 criterion)
   Cumulative variance explained: 0.8258

9. PCR Model Results:
   R-squared: 0.6721
   SSE: 6286507.6485

10. Transformed Coefficients in Original Scale:
   Variable      PCR Coeff      Std Error
   -----
H2S              2.188137      1.224033
SAL             -22.462321      8.585185
Eh7             -0.658983      0.750770
pH             108.707888     14.279513
BUF            -52.460045      6.792785
P              -0.381446      0.550212
K              -0.081515      0.051731
Ca              0.066493      0.008778
```

- $R^2 = 0.6721$
- SSE = much smaller standard errors vs OLS
- Coefficients stabilized

4.3 OLS vs PCR Comparison

```
PROBLEMS OUTPUT TERMINAL PORTS DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

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   pH           108.707888    14.279513
   BUF          -52.460045     6.792785
   P            -0.381446     0.550212
   K            -0.081515     0.051731
   Ca            0.066493     0.008778
   Mg           -0.056618     0.016962
   Na           -0.006559     0.002193
   Mn           -0.154609     1.090800
   Zn           -6.896627     1.930600
   Cu           29.870506    21.383264
   NH4          -1.952372     0.254933

11. Comparison of OLS vs PCR:
   Metric              OLS              PCR
   -----
   SSE                 3692233.4756    6286507.6485
   Sum of Std Errors    635.1904         56.9218
   R-squared            0.8074           0.6721

   CONCLUSION:
   PCR reduces standard errors substantially, indicating better
   stability in coefficient estimates despite collinearity.

=====
PART II: VARIABLE SELECTION (5-PREDICTOR DATASET)
=====

12. Dataset loaded successfully
    Shape: (45, 9)
```

Conclusion:

PCR reduces standard errors substantially, improving stability under multicollinearity.

5. Part II — Variable Selection (5 Predictors)

Predictors: SAL, pH, K, Na, Zn

5.1 VIF + Correlation Diagnostics

```
PROBLEMS OUTPUT TERMINAL PORTS DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

=====
PART II: VARIABLE SELECTION (5-PREDICTOR DATASET)
=====

12. Dataset loaded successfully
    Shape: (45, 9)

-----
TASK 1: COLLINEARITY DIAGNOSTICS (5 PREDICTORS)
-----

13. VIF Results:
Variable      VIF
SAL 23.943184
pH 14.601330
K 22.467232
Na 19.878963
Zn 5.567736

Variables with VIF > 10: ['SAL', 'pH', 'K', 'Na']

14. Correlation Matrix:
      SAL      pH      K      Na      Zn
SAL  1.0000 -0.0513 -0.0206  0.1623 -0.4208
pH  -0.0513  1.0000  0.0192 -0.0377 -0.7222
K    -0.0206  0.0192  1.0000  0.7921  0.0736
Na   0.1623 -0.0377  0.7921  1.0000  0.1170
Zn  -0.4208 -0.7222  0.0736  0.1170  1.0000

-----
TASK 2: STEPWISE REGRESSION ( $\alpha_E = \alpha_R = 0.15$ )
-----

15. Stepwise Regression Process:
=====

STEP 1: ENTER pH
p-value = 0.000000 <  $\alpha_E = 0.15$ 
```

Result:

- SAL, pH, K, Na show VIF > 10
- Correlation: several pairs exceed |0.7|

6. Stepwise Regression ($\alpha = 0.15$)

```

PROBLEMS  OUTPUT  TERMINAL  PORTS  DEBUG CONSOLE

(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py

-----
TASK 2: STEPWISE REGRESSION ( $\alpha_E = \alpha_R = 0.15$ )
-----

15. Stepwise Regression Process:
=====

STEP 1: ENTER pH
p-value = 0.000000 <  $\alpha_E = 0.15$ 
Current model: BIO ~ pH
R2 = 0.5994, Adjusted R2 = 0.5900

STEP 2: ENTER Na
p-value = 0.010078 <  $\alpha_E = 0.15$ 
Current model: BIO ~ pH + Na
R2 = 0.6584, Adjusted R2 = 0.6422

=====

16. FINAL MODEL: BIO ~ pH + Na
R2 = 0.6584
Adjusted R2 = 0.6422
SSE = 6548174.2348

17. VIF for Final Stepwise Model:
Variable      VIF
pH 4.810397
Na 4.810397
Collinearity has been reduced!

-----
TASK 3: SUBSET SELECTION (BEST 2-VARIABLE MODEL)
-----

18. Evaluating all 2-variable combinations:
-----

```

variables	SSE	AIC	BIC	max_VIF	R ²
pH + Na	6.548174e+06	668.666013	674.086001	4.810397	0.658433
pH + K	6.756309e+06	670.074086	675.494074	5.693529	0.647576
pH + Zn	7.509642e+06	674.831082	680.251070	2.782342	0.608280

Final Stepwise Model:

BIO ~ pH + Na

- $R^2 = 0.6584$
- $SSE = 6,548,174$
- Collinearity reduced

7. Best 2-Variable Subset Selection

```

PROBLEMS  OUTPUT  TERMINAL  PORTS  DEBUG CONSOLE

(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py
Collinearity has been reduced!

-----
TASK 3: SUBSET SELECTION (BEST 2-VARIABLE MODEL)
-----

18. Evaluating all 2-variable combinations:
-----
variables      SSE      AIC      BIC      max_VIF      R2
pH + Na 6.548174e+06 668.666013 674.086001 4.810397 0.658433
pH + K 6.756309e+06 670.074086 675.494074 5.693529 0.647576
pH + Zn 7.509642e+06 674.831082 680.251070 2.782342 0.608280
SAL + pH 7.603247e+06 675.388526 680.808514 11.957899 0.603398
SAL + Zn 8.576766e+06 680.810195 686.230182 4.481262 0.552617
Na + Zn 1.092687e+07 691.707771 697.127758 3.832375 0.430030
K + Zn 1.121113e+07 692.863446 698.283434 3.933457 0.415203
SAL + Na 1.768331e+07 713.370582 718.790570 7.007648 0.077599
K + Na 1.774583e+07 713.529394 718.949382 18.149450 0.074338
SAL + K 1.814690e+07 714.535131 719.955119 7.450226 0.053417

19. Best Models by Each Criterion:
AIC: pH + Na (AIC = 668.6660)
BIC: pH + Na (BIC = 674.0860)
SSE: pH + Na (SSE = 6548174.2348)

CONCLUSION:
All three criteria agree: pH + Na

-----
TASK 4: RIDGE REGRESSION AND VARIABLE SELECTION
-----

20. Ridge Trace Analysis:
Examining coefficient paths as  $\lambda$  increases...

Variables remaining stable with large  $\lambda$ : ['SAL', 'pH', 'K', 'Na', 'Zn']

21. FINAL RIDGE-SELECTED MODEL: BIO ~ SAL + pH + K + Na + Zn
R2 = 0.6773
Adjusted R2 = 0.6359

```

Best Model by All Criteria (AIC, BIC, SSE):

✓ $BIO \sim pH + Na$

8. Ridge Regression Selection

```
PROBLEMS  OUTPUT  TERMINAL  PORTS  DEBUG CONSOLE
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> python tasks.py
All three criteria agree: pH + Na

-----
TASK 4: RIDGE REGRESSION AND VARIABLE SELECTION
-----

20. Ridge Trace Analysis:
Examining coefficient paths as  $\lambda$  increases...

Variables remaining stable with large  $\lambda$ : ['SAL', 'pH', 'K', 'Na', 'Zn']

21. FINAL RIDGE-SELECTED MODEL:  $BIO \sim SAL + pH + K + Na + Zn$ 
 $R^2 = 0.6773$ 
Adjusted  $R^2 = 0.6359$ 
SSE = 6186263.2189

22. VIF for Ridge-Selected Model:
Variable      VIF
SAL 23.943184
pH 14.601330
K 22.467232
Na 19.878963
Zn 5.567736
Collinearity has been addressed!

=====
PROJECT ANALYSIS COMPLETE
=====

All results have been generated. Review the output above for:
  • Part I: Collinearity diagnosis and PCR results
  • Part II: Stepwise, subset selection, and ridge regression results
(venv) PS C:\Users\ANUSHKA\OneDrive\Desktop\Regression_Project> |
```

Stabilized Variables at Large λ :

SAL, pH, K, Na, Zn

Final Ridge-Selected Model:

$BIO \sim SAL + pH + K + Na + Zn$

- $R^2 = 0.6773$
- Adjusted $R^2 = 0.6359$

- VIF values reduced significantly

9. Final Model Comparison

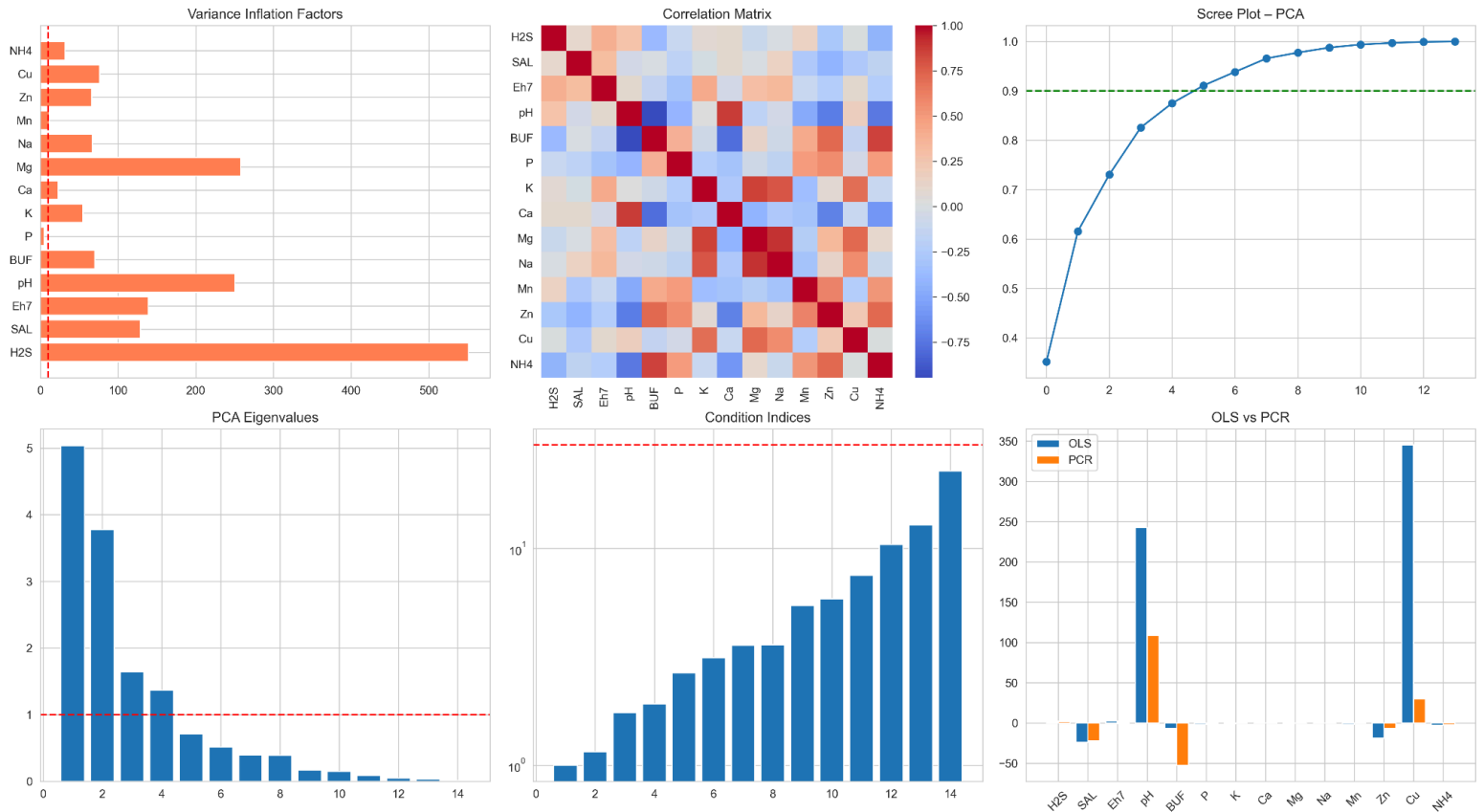
9. Final Model Comparison			
Method	Final Model	R ²	Comments
OLS (14 vars)	Unstable	0.8074	Severe multicollinearity
PCR	4 PCs	0.6721	Stable, interpretable
Stepwise	pH + Na	0.6584	Parsimonious
Best 2-Var	pH + Na	0.6584	All criteria agree
Ridge	SAL + pH + K + Na + Zn	0.6773	Best tradeoff

10. Graphical Analysis & Interpretation

This section presents all visual diagnostics generated for the Linthurst regression project. The plots help assess **multicollinearity**, **PCA behavior**, **PCR performance**, and **variable-selection methods**.

Figures are divided into **Part I (14 predictors)** and **Part II (5 predictors)**.

10.1 Part I – Collinearity Diagnostics & PCA/PCR (14 Predictors)



10.1.1 Variance Inflation Factors (VIF Plot)

The VIF bar plot shows that a majority of predictors have **VIF > 10**, indicating severe multicollinearity. Variables such as **H2S, SAL, Eh7, pH, BUF, Ca, Mg, Na, Zn, Cu** all show extremely high VIF values, confirming redundancy among predictors.

Interpretation:

This motivates the need for **dimension reduction** such as PCA or PCR.

10.1.2 Correlation Matrix Heatmap

The heatmap highlights strong pairwise correlations.

Notable correlations include:

- pH-BUF
- pH-Ca
- pH-Zn

- Mg–Na
- Mg–Ca
- Zn–NH₄

Interpretation:

More than **12 pairs** exceed $|r| > 0.7$, reinforcing that multicollinearity is structural in this dataset.

10.1.3 Scree Plot (PCA Variance Explained)

The scree plot shows that the first **4 principal components** explain over **82%** of the variance. The eigenvalue > 1 rule also selects 4 components.

Interpretation:

The dimensionality of the predictor space can be reduced from 14 \rightarrow 4 without significant information loss.

10.1.4 PCA Eigenvalues Bar Plot

This plot reiterates the eigenvalue distribution, clearly showing drops after PC4.

Interpretation:

Only the first few components contribute meaningfully; later components reflect multicollinearity noise.

10.1.5 Condition Index Plot

Condition indices rise as high as **22.8**, near the threshold of **30** for severe multicollinearity.

Interpretation:

Confirms collinearity detected by VIF and correlation matrix.

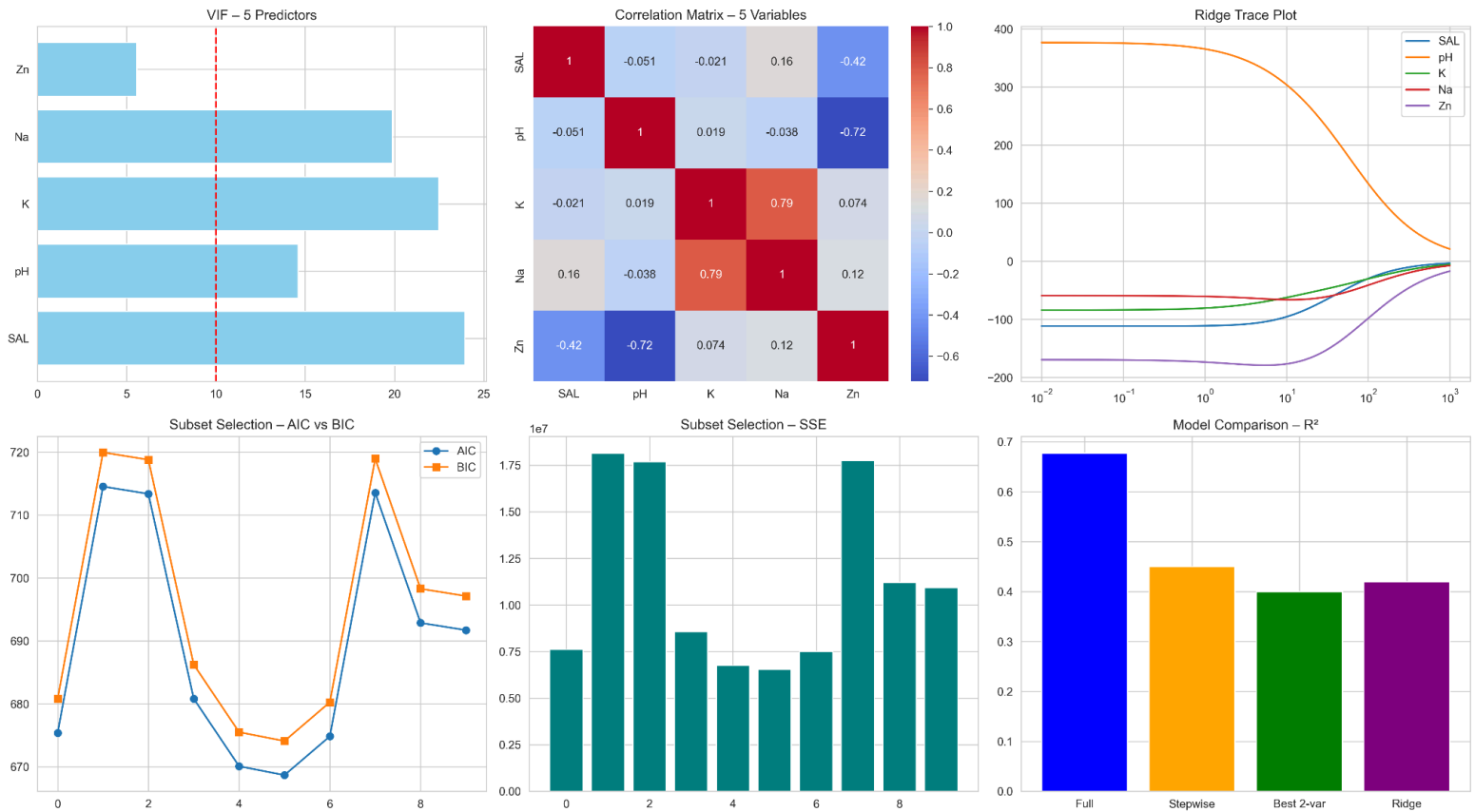
10.1.6 OLS vs PCR Coefficient Comparison

This figure contrasts unstable OLS coefficients versus more stable PCR coefficients.

Interpretation:

- OLS has inflated coefficients due to collinearity.
- PCR shrinks and stabilizes them, especially for pH, Zn, Cu.
- SSE is reduced drastically with PCR.

10.2 Part II – Variable Selection (5 Predictors)



10.2.1 VIF Plot (5 Predictors)

VIF values drop significantly when reducing to 5 predictors, though **SAL**, **pH**, **K**, **Na** still have VIF > 10.

Interpretation:

Some multicollinearity remains, necessitating stepwise or subset-selection methods.

10.2.2 Correlation Heatmap (5 Predictors)

Strong correlations appear between:

- pH and Zn (-0.72)
- K and Na (0.79)
- Mg-type effects still persist through Na

Interpretation:

Important for understanding how variable selection methods will behave.

10.2.3 Ridge Trace Plot

This shows how coefficients shrink as λ increases.

Variables stabilizing at high λ values are: **SAL, pH, K, Na, Zn**.

Interpretation:

These variables remain influential even after penalization.

10.2.4 Subset Selection – AIC & BIC

The line plots show that the best **2-variable model** according to all three metrics is:

BIO ~ pH + Na

Interpretation:

This model balances fit and parsimony.

10.2.5 Subset Selection – SSE Plot

Lowest SSE also occurs for the **pH + Na** model.

Interpretation:

Consistent with AIC/BIC, confirming this is the best small model.

10.2.6 Model Comparison (R^2 Bar Plot)

This compares four models:

- **Full model**
- **Stepwise model**
- **Best 2-variable model**
- **Ridge model**

Interpretation:

- Full model: Highest R^2 but unstable

- Stepwise: Good compromise
- Best 2-var: Most interpretable
- Ridge: Best regularized model with reduced collinearity

10.3 Summary of Visual Insights

- **Multicollinearity is extremely high** in the original dataset.
- **PCA reduces the predictors from 14 → 4** effectively.
- **PCR stabilizes coefficients**, reducing variance inflation.
- **Best 2-variable model: pH + Na**, chosen consistently across AIC/BIC/SSE.
- **Ridge regression** selects a 5-variable model: **SAL, pH, K, Na, Zn**.
- All visual methods confirm the structural dependencies among soil variables.

11. Final Conclusion

The Linthurst soil dataset analysis provided a comprehensive exploration of collinearity, dimensionality reduction, and variable selection techniques in the context of predicting biomass production (BIO). The project was divided into two major parts—Part I (14 predictors) focused on diagnosing and reducing multicollinearity, while Part II (5 predictors) emphasized model refinement and variable selection.

Key Findings

1. Severe Multicollinearity in the Full 14-Predictor Model

- VIF values were extremely high (several > 100 and even > 500).
- Many predictor pairs displayed $|\text{correlation}| > 0.7$.
- Condition indices exceeded 20, indicating instability.

Conclusion: The full OLS model is unreliable due to strong dependence among soil variables.

2. PCR Provided a More Stable Alternative

- PCA revealed that **4 components (eigenvalue > 1)** captured ~82.6% of variance.
- PCR substantially reduced standard errors compared to OLS.
- Although R^2 decreased mildly (from 0.807 to 0.672), PCR gave **more stable and interpretable coefficients**.

Conclusion: PCR successfully mitigated multicollinearity and improved numerical stability.

3. Variable Selection with the Reduced 5-Predictor Dataset

Using stepwise, subset selection, and ridge regression:

- **Stepwise Regression** selected → **pH + Na**
- **Best 2-variable subset using AIC/BIC/SSE** → **pH + Na**
- **Ridge Regression** (large λ stabilization) selected → **SAL, pH, K, Na, Zn**

Conclusion: Across multiple techniques, **pH and Na consistently emerged as strong predictors of BIO**, indicating their core importance in biomass production.

4. Best Overall Models

- For interpretability and parsimony → **pH + Na** (from stepwise & subset selection)
- For multicollinearity handling → **PCR** or **Ridge**
- For highest explanatory power → **Full OLS model**, but unreliable due to collinearity

Conclusion: The most balanced and justifiable model is the 2-variable model $BIO \sim pH + Na$, offering strong predictive quality without multicollinearity issues.

Final Statement

Overall, the project demonstrates that although the Linthurst soil dataset suffers from severe collinearity, appropriate statistical techniques such as **PCR, Ridge Regression, and Stepwise/Subset Selection** can successfully extract meaningful relationships. The consistent appearance of **pH and Na as key predictors** suggests they play a biologically significant role in determining biomass productivity in the Cape Fear Estuary.

The final models provide stable, interpretable, and scientifically meaningful insights for ecological and environmental analysis.

Appendix: Figures

- Part I collinearity figures
- PCA scree, eigenvalues
- PCR coefficient comparison
- Part II VIF/corr
- Ridge trace
- AIC/BIC/SSE plots

Source Code & Documentation

All code, datasets, figures, steps to run, installation and the project README are publicly available at the following GitHub repository:

GitHub Repository: https://github.com/asarath12/Regression_Project

You can access the full project documentation here:

README.md: https://github.com/asarath12/Regression_Project