Statistical Modeling of Mine Pool Formation in Underground Coal Mines of Ohio

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Overview of Acid Mine Drainage and Mine Pool Formation

- Formation of mine pool and discharge to the surface
- SMCRA requires the estimation of probable hydrologic consequences
- Highest point of mining is not an accurate prediction of post-mining water level
  - Post-mining water level is used to determine areas of a mine that may have post-mining water levels greater than the surface elevation

Statistical Modeling of Mine Pool Formation

- Study hydrogeological parameters of mine pools and create a method to determine if a mine pool will develop and potentially discharge to the surface

- Our hypothesis is that the formation of mine pools depends on hydrogeological parameters and properties of the surrounding rocks and coal

Objectives

- Acquisition of data from mines active in the last 35 years
  - D law permit mines investigated (post-SMCRA)
  - Typically contain more hydrological and geological data
- Creation of a statistical model on mine pool formation
  - Identify key parameters that affect potentiometric head within an underground coal mining area

Task 1: Data Acquisition

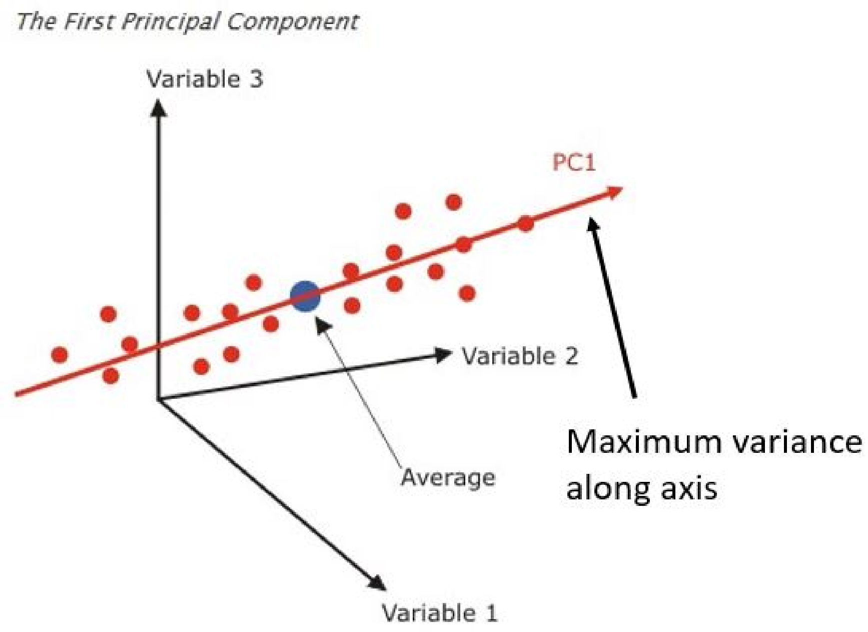
- Data was collected from public sources
- 28 mine permits received from ODNR
- Collected data on boreholes, wells in permits and quarterly monitoring report

Task 2: Multivariate Statistical Analysis

- Performed using the program “The Unscrambler X” by CAMO Software AS
- Principal component analysis (PCA)
- Multiple linear regression (MLR)
- Principal component regression (PCR)
- Partial least squares regression (PLS)

Principal Component Analysis

- Identifies an axis in multidimensional space that better represents the variance of the data (projection of data in axis)



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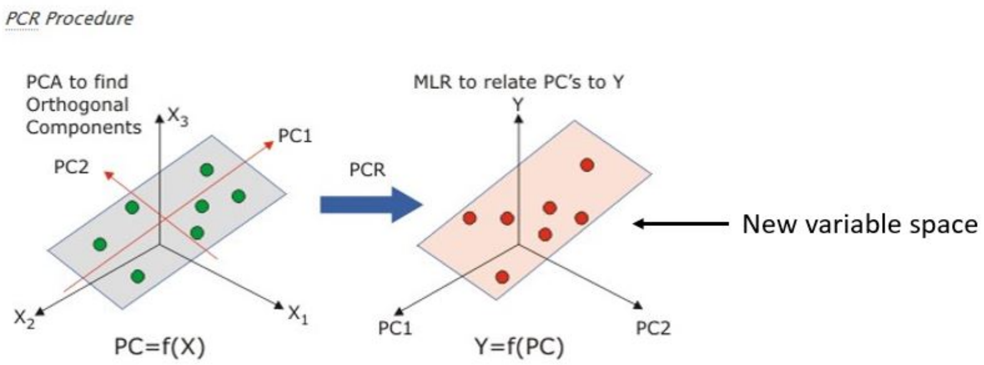
Principal Component Regression

- Relates variance in Y (response) to variance in X (predictor) using the principal components found in PCA as the regressors



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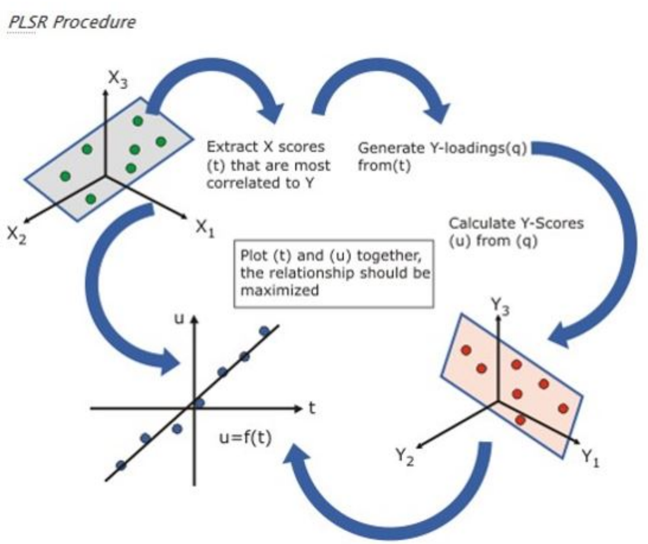
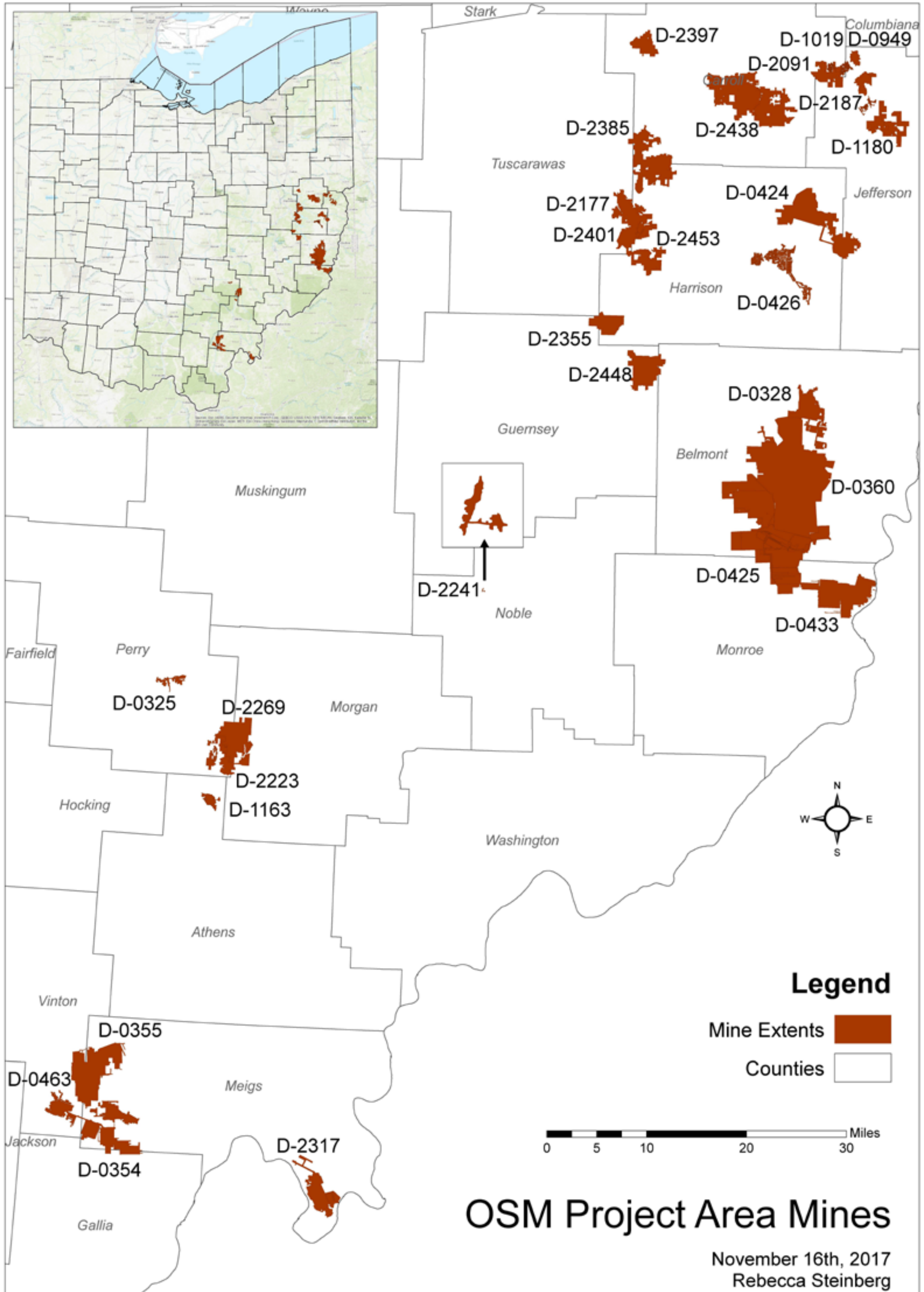
Partial Least Squares Regression



This diagram considers the generalized case of having multiple Y and X variables

(after CAMO Software AS, 2018)

- Finds the multidimensional direction in the X space that explains the maximum multidimensional variance direction in the Y space
- Represented by a linear regression model



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Multi-Mine Multivariate Statistical Analysis

- Multi-mine without water withdrawal
  - 11 mines analyzed (9 unique mines)
    - Two mines mined two seams so they were treated as four different mines
  - Data from 381 wells was compiled
    - 22 outliers were removed
    - 322 wells were used as predictors
    - 38 wells were used as validators

Multi-Mine Multivariate Statistical Analysis

- Multi-mine with NPDES withdrawal
  - 7 mines analyzed
  - Wells with data sometime between 2007-2017
  - Data from 111 wells was compiled
    - 13 outliers were removed
    - 88 wells were used as predictors
    - 10 were used as validators

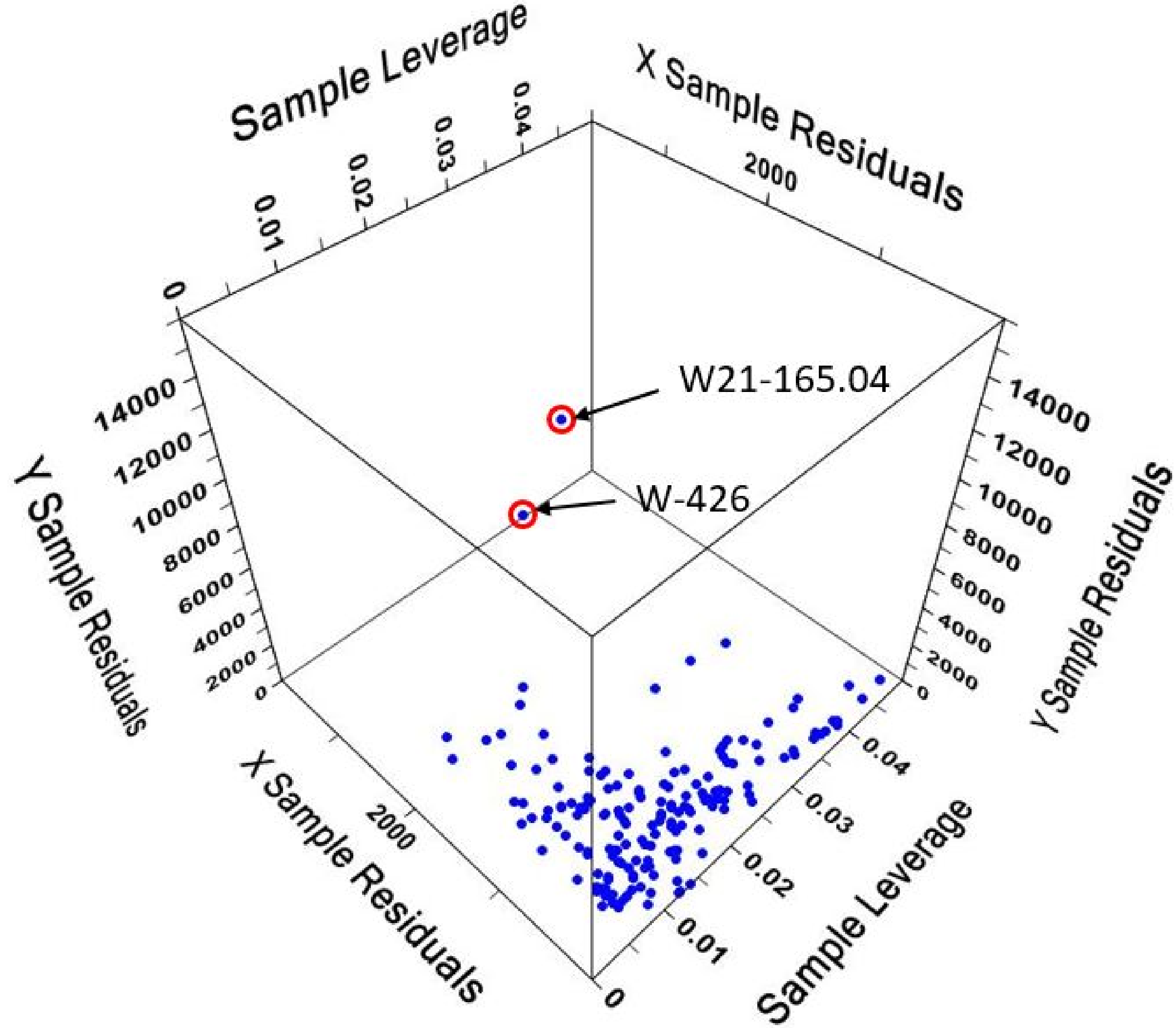
X Variables Analyzed

- Surface elevation of well (msl)
- Bottom of well elevation (msl)
- Overburden thickness (ft)
- Thickness of mined coal seam (ft)
- Thickness of shale + clay (ft)
- Thickness of sandstone (ft)
- Thickness of limestone (ft)
- Accumulative coal volume (Mm^3)
- Area of underground mines within a 4 mile buffer (acres)
- Average annual precipitation (in)

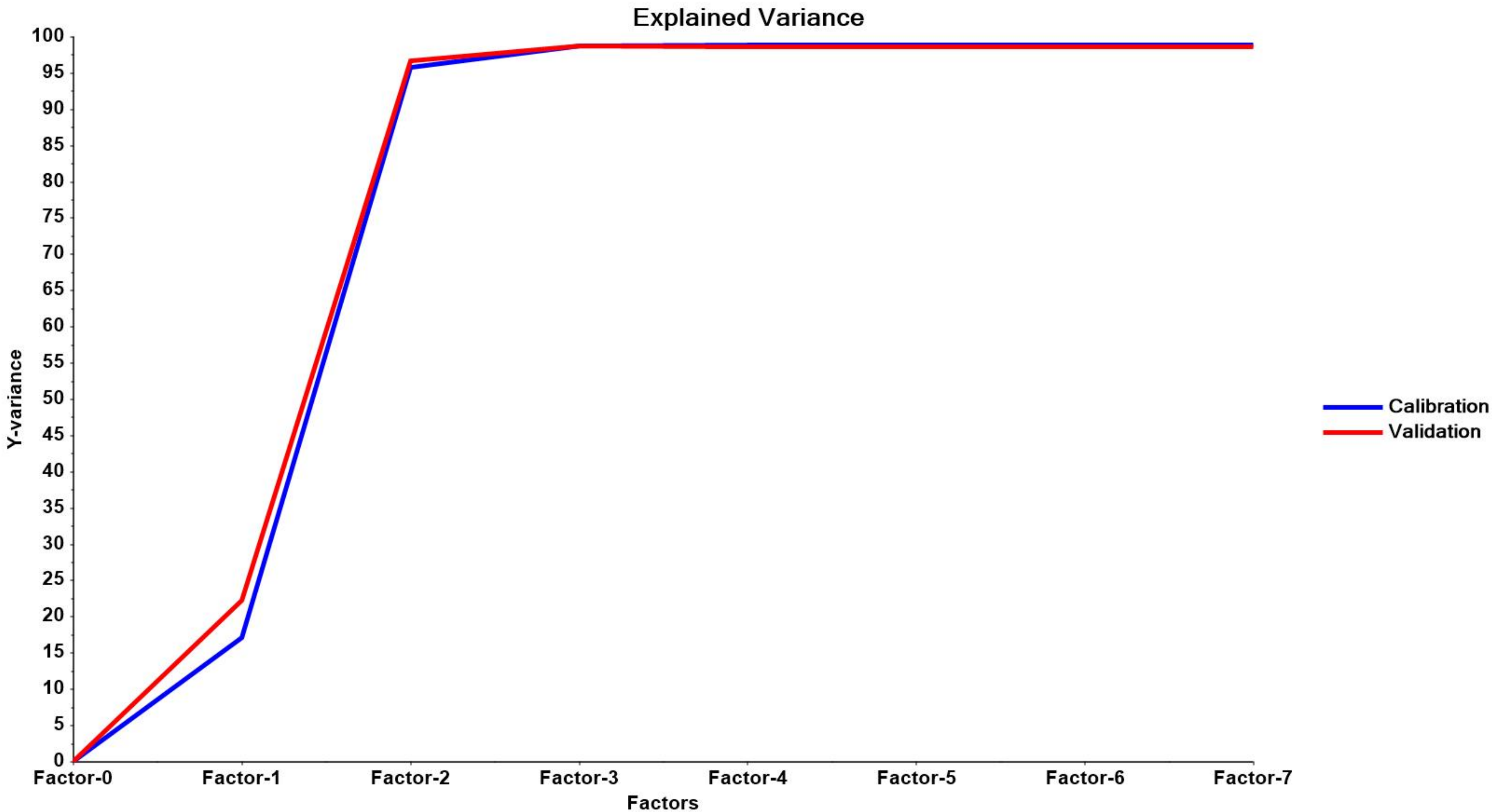
Y Variables analyzed

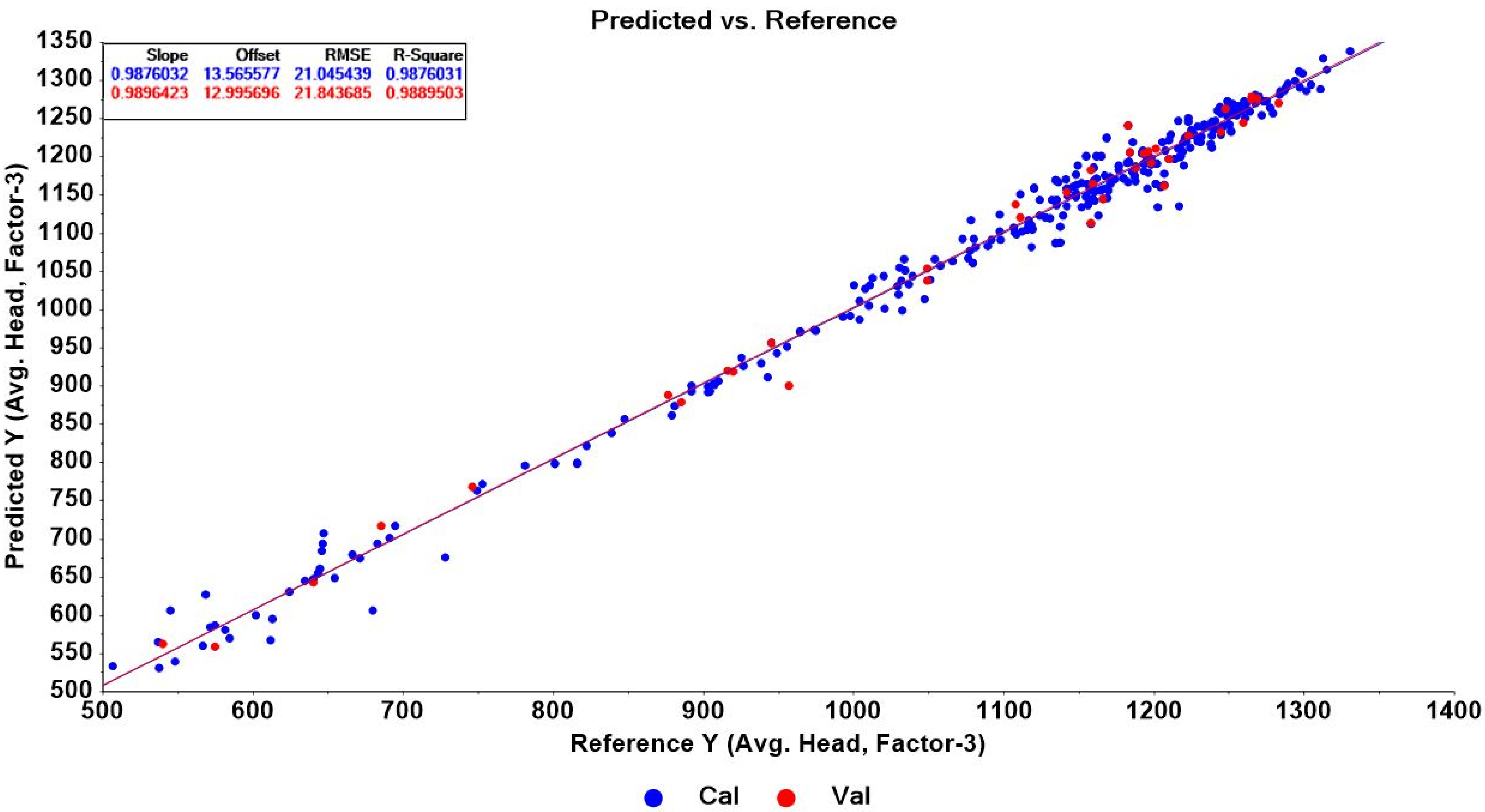
- Average potentiometric head (msl)
- Maximum potentiometric head (msl)
- Minimum potentiometric head (msl)

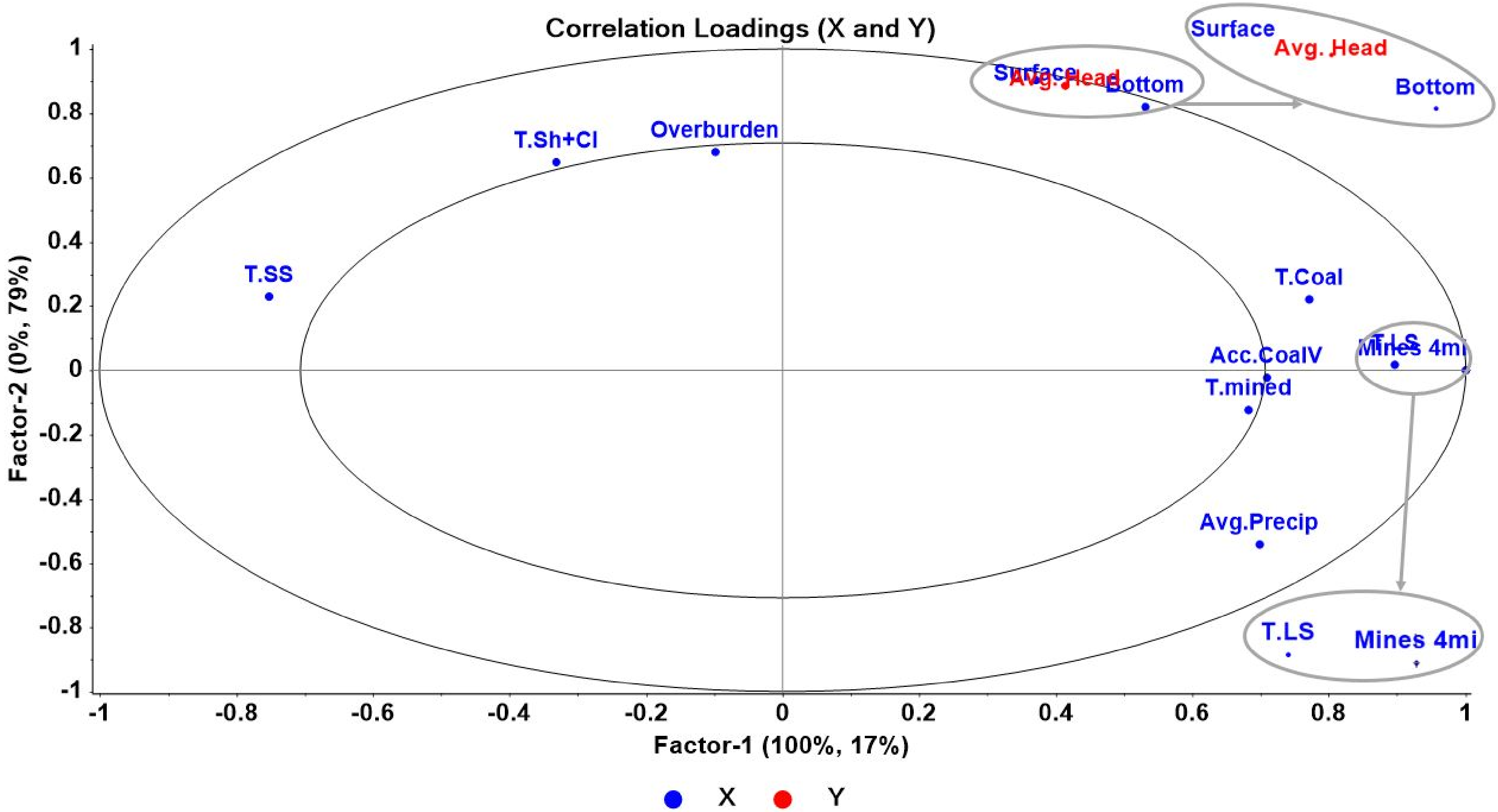
Influence



Sample Leverage
X Sample Residuals
Y Sample Residuals
W21-165.04
W-426
0
0.01
0.02
0.03
0.04
2000
14000
12000
10000
8000
6000
4000


Explained Variance
Y-variance
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
Factor-0
Factor-1
Factor-2
Factor-3
Factor-4
Factor-5
Factor-6
Factor-7
Factors
Calibration
Validation


Predicted vs. Reference
Slope Offset RMSE R-Square
0.9876032 13.565577 21.045439 0.9876031
0.9896423 12.995696 21.843685 0.9889503
Predicted Y (Avg. Head, Factor-3)
Reference Y (Avg. Head, Factor-3)
Cal
Val



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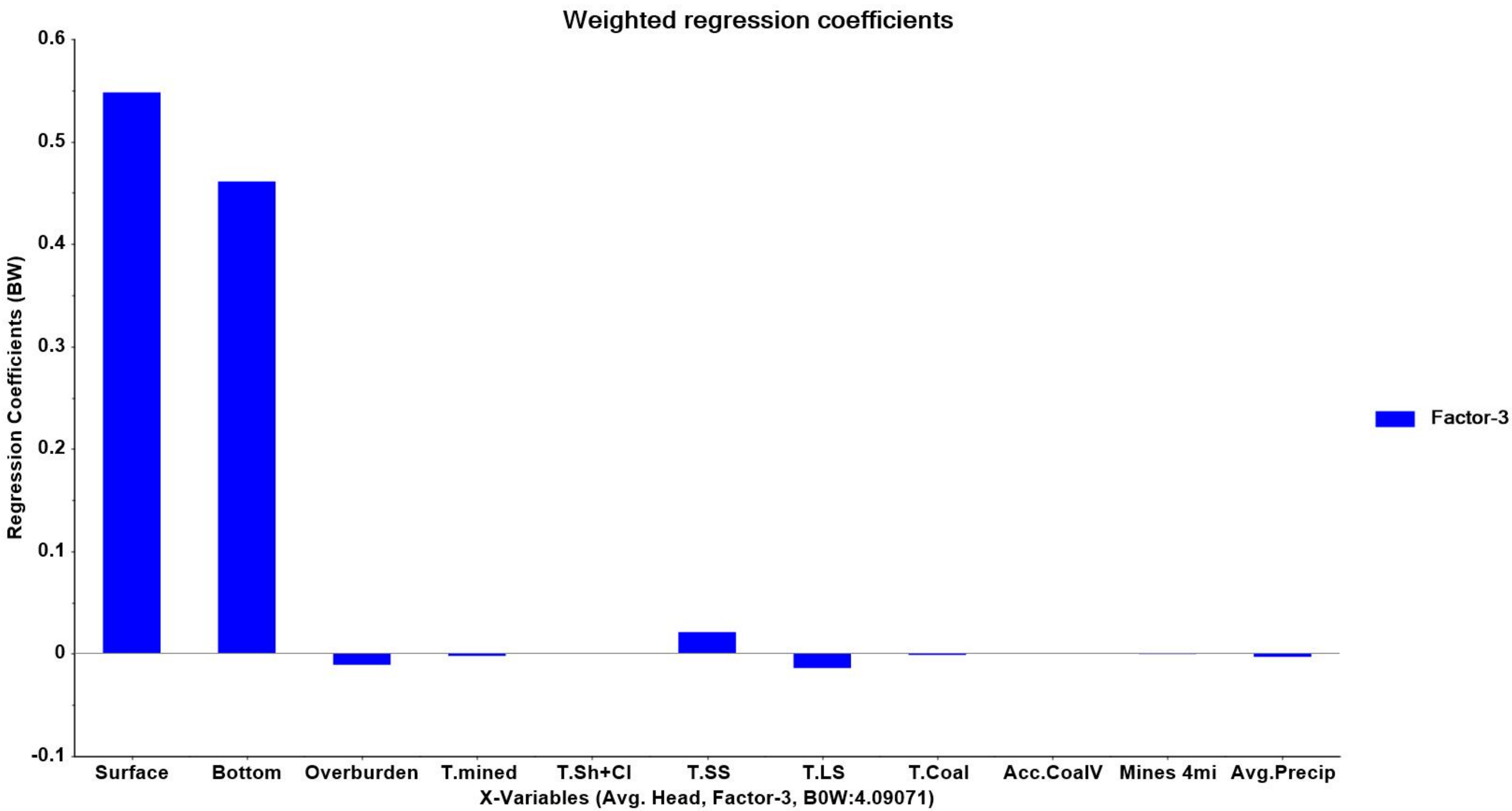

Weighted regression coefficients
Regression Coefficients (BW)
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
Factor-3
Surface
Bottom
Overburden
T.mined
T.Sh+Cl
T.SS
T.LS
T.Coal
Acc.CoalV
Mines 4mi
Avg.Precip
X-Variables (Avg. Head, Factor-3, B0W:4.09071)

Coefficients For Multivariate Linear Equation

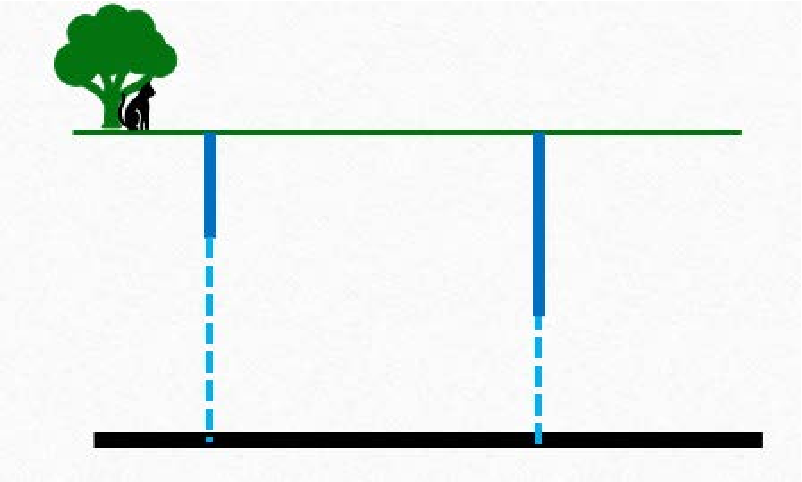
Variable	PCR	PLS
β0	4.37929	4.09071
Surface elevation (msl)	0.53517	0.54799
Bottom elevation (msl)	0.47516	0.46126
Overburden thickness (ft)	-0.0077	-0.0107
Thickness of the mined coal seam (ft)	-0.0019	-0.0021
Thickness of shale + clay (ft)	-0.0018	0.00069
Thickness of sandstone (ft)	0.02148	0.02124
Thickness of limestone (ft)	-0.0104	-0.0138
Total thickness of coal (ft)	-0.0009	-0.0012
Accumulative coal volume (Mm^3)	0.00204	0.00041
Area of underground mines in a 4mile buffer (acres)	-0.0001	-0.0001
Average precipitation (in)	-0.0027	-0.003

Goodness-of-fit Indexes

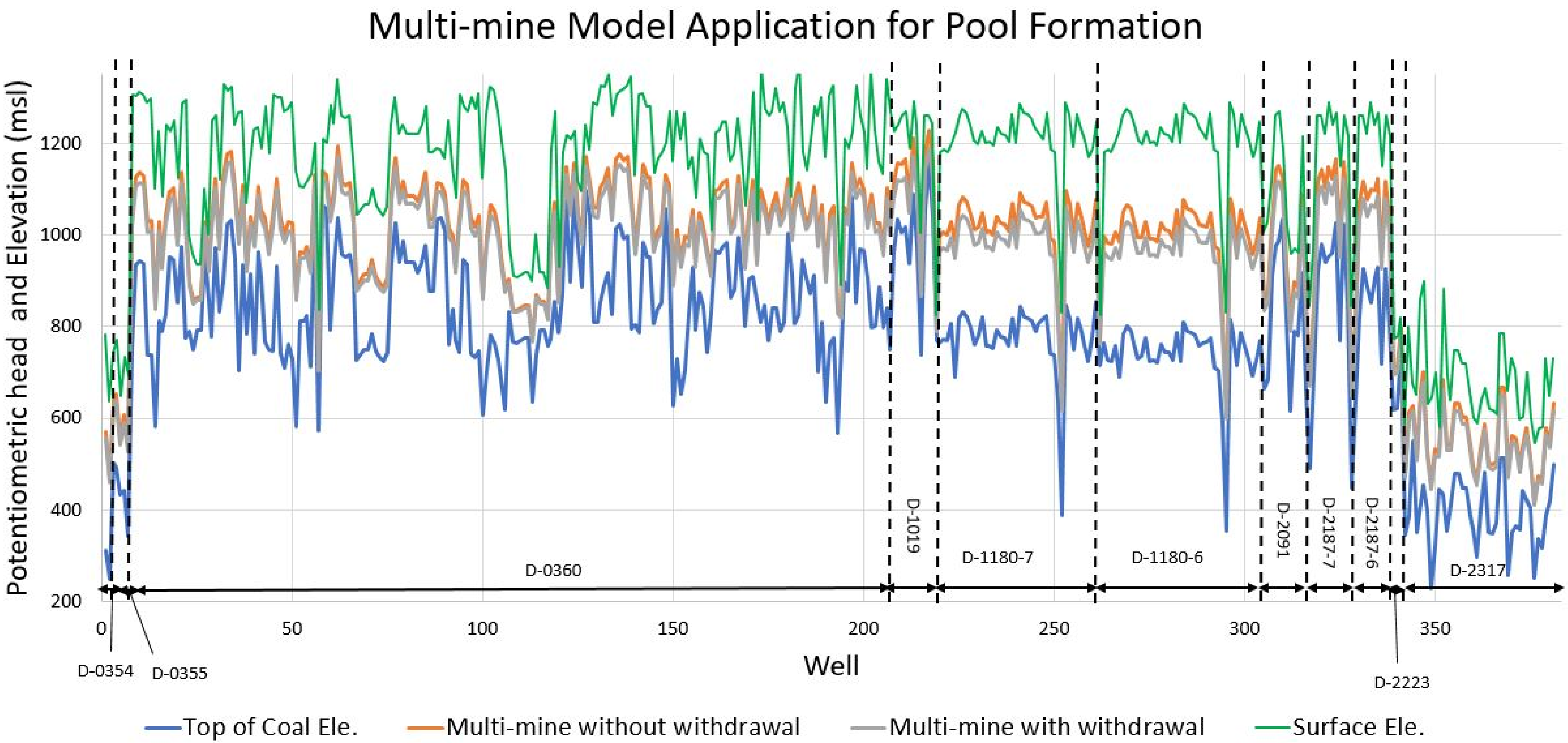
	Nash-Sutcliffe Efficiency	Percent Bias (%)	Mean Absolute Error (ft)	Volumetric Efficiency	Root Mean Square Error (ft)	Relative Index of Agreement
Ideal value	**1**	**0**	**0**	**1**	**0**	**1**
PCR	0.9873	4.50E-07	0.029	1	21.271	0.9958
PLS	0.9876	1.48E-06	0.024	1	21.045	0.9959

Applying The Model

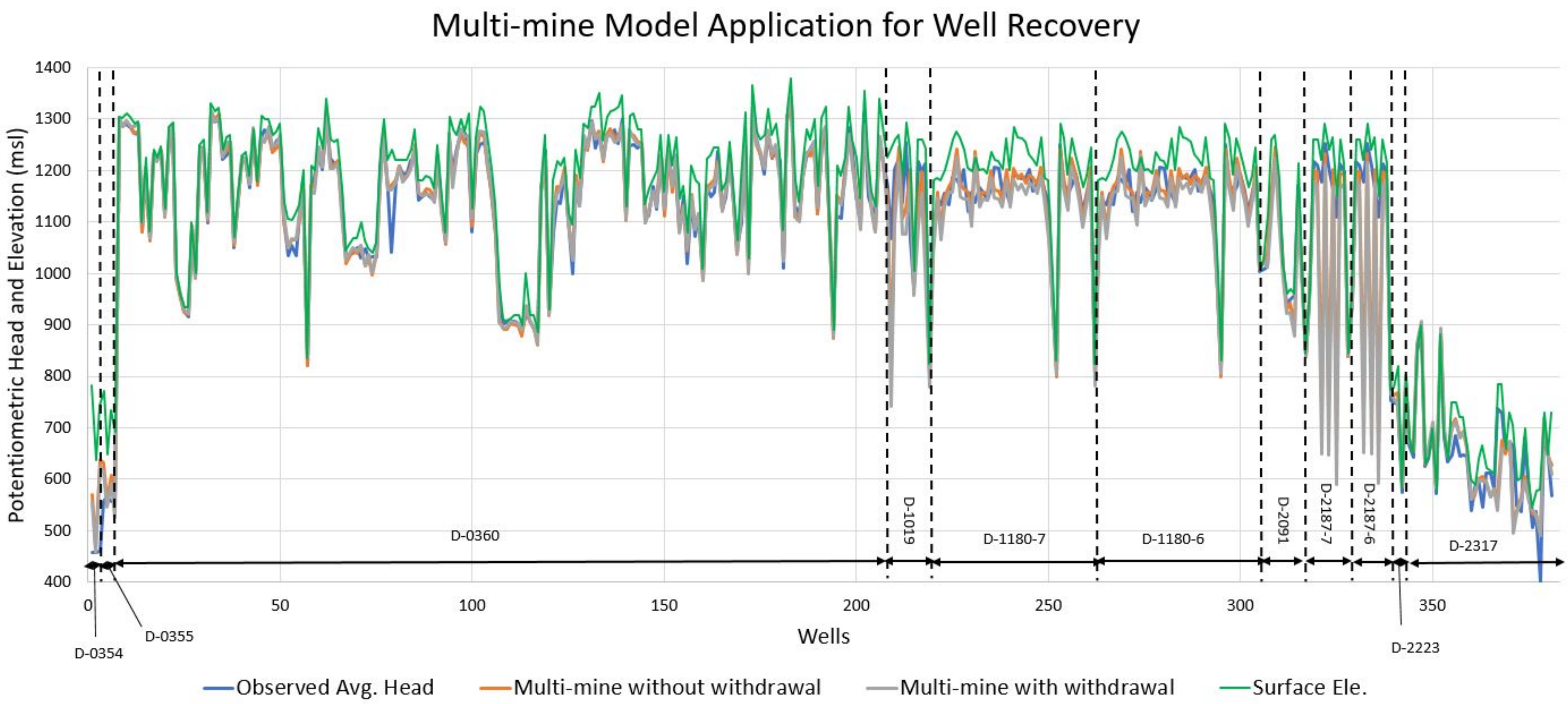
- What will the potentiometric head be with respect to the mined coal seam after mining?
  - Extrapolate bottom of well elevation to bottom of mined coal seam elevation
  - Maximum accumulative coal volume
  - No water withdrawal



$$y = f(surface\ elevation, bottom\ elevation \ldots etc.)$$



All modeled mines will be flooded

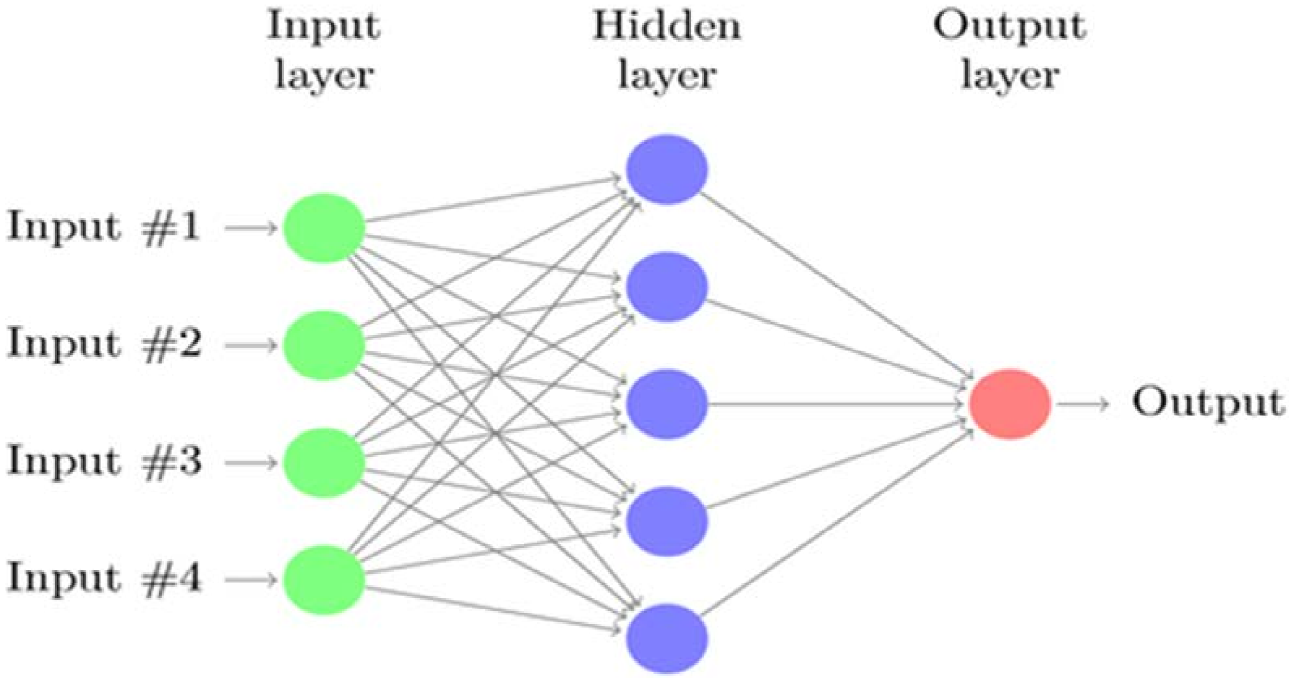


48% of mines will have water levels higher than the observed heads before closing, 52% will have water levels lower than the observed heads before closing

Another method: Artificial Neural Network

- Artificial Neural Network was used to build predictive models for mine pool development finding relationships between mine parameters and the development of mine pools.

- Artificial Neural Networks are computational method formed by individual cells that perform computational calculations similar to the way the human brain works, learning from training data.



- 10% of data was used for validation.

- Group Method of Data Handling in NeuroShell 2 was used to produce various polynomial regressions.

Artificial Neural Network

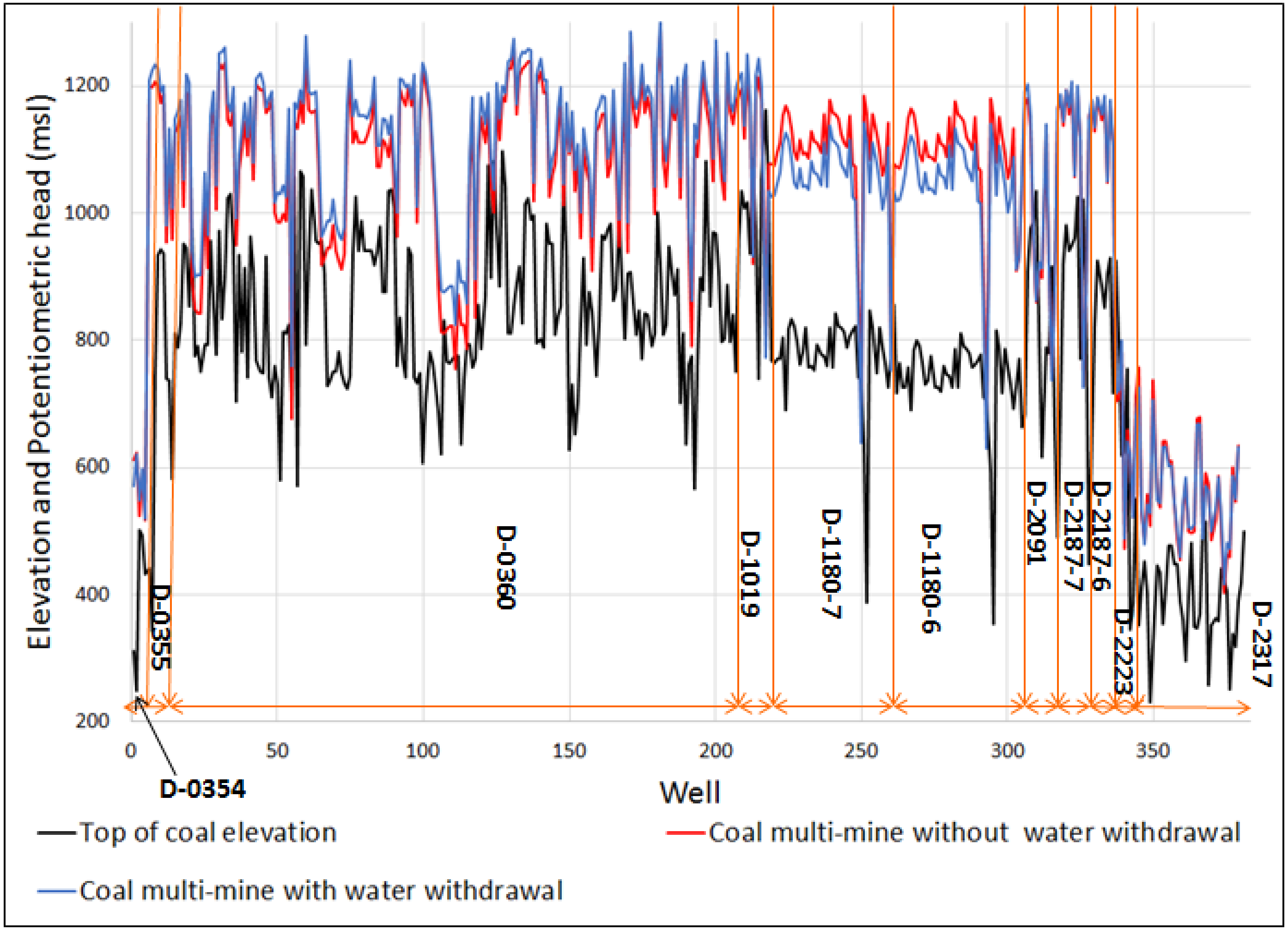
- Three polynomial were modeled:
  - linear
  - second degree polynomial
  - third degree polynomial
- The table shows the second degree polynomial equation, most significant variables, and least significant variables for the average head.

Best formula:	Y=-1.7E-002*X11+4.5E-004*X10-2.3E-002*X4+1.6E-002*X5-8.3E-002-1.5E-002*X7-1.4E-002*X6-4.9E-002*X9+0.73*X1+0.37*X2+0.2*X1^2+0.24*X2^2-0.52*X1*X2+4.7E-002*X1*X9+2.3E-002*X2*X9+1.4E-002*X1^2*X9+1.5E-002*X2^2*X9-3.3E-002*X1*X2*X9-4.3E-002*X11^2-1.8E-002*X7^2-1.6E-002*X5^2+9.5E-002*X10^2
Legend:	X1=2.*(Surface Elevation for Sampling Station (msl)-545.)/835.-1.
	X2=2.*(Bottom of well elevation (msl)-80.)/1220.-1.
	X3=2.*(Overburden thickness (ft)-56.)/506.6-1.
	X4=2.*(Thickness of mined coal seam (ft)-1.17)/10.59-1.
	X5=2.*(Thickness Shale + Clay (ft)-13.9)/452.53-1.
	X6=2.*Thickness Sandstone (ft)/258.71-1.
	X7=2.*Thickness Limestone (ft)/204.97-1.
	X8=2.*Thickness Coal (ft)/33.23-1.
	X9=2.*Accumulative Coal Volume (Mm^3)/146.18-1.
	X10=2.*(Underground Mine Area 4mi (acres)-617.98)/110430.52-1.
	X11=2.*(Average Annual Precipitation (in)-37.)/4.-1.
	Y=2.*(Average Head (msl)-400.)/930.67-1.
Most significant variables:	Surface Elevation for Sampling Station (msl)
	Bottom of well elevation (msl)
	Thickness of mined coal seam (ft)
	Thickness Shale + Clay (ft)
	Thickness Sandstone (ft)
	Thickness Limestone (ft)
	Accumulative Coal Volume (Mm^3)
	Underground Mine Area 4mi (acres)
	Average Annual Precipitation (in)
Less significant variables:	Thickness Coal (ft)

Application of Artificial Neural Network

- For this simulation, in the polynomial equations, the bottom of coal elevation was used to simulate the potentiometric head at the bottom of the mined coal layer after mine closure. Maximum coal extraction was also assumed.

- For the equation that contains water withdraw, zero water withdraw was simulated because free recovery of the water in the system is assumed and pumping is expected to cease.



Average calculated heads at the bottom of the mined coal layer after mine closure using the two modeling approaches and the top of the coal layer.

	Parameters without water withdraw			
		Maxinum	Average	Mininum
Polynomial 1	Mean square error	0.01	0.01	0.01
	R squared	0.97	0.96	0.94
	Correlation coefficient	0.98	0.98	0.97
	Norm. mean square error	0.01	0.02	0.03
Polynomial 2	Mean square error	0.003	0.003	0.006
	R squared	0.98	0.98	0.97
	Correlation coefficient	0.99	0.99	0.98
	Norm. mean square error	0.01	0.01	0.02
Polynomial 3	Mean square error	0.002	0.002	0.004
	R squared	0.99	0.99	0.98
	Correlation coefficient	1.00	0.99	0.99
	Norm. mean square error	0.004	0.005	0.01

Conclusions

- Multivariate analysis and ANN are effective in the identification of important parameters
  - Thickness of the mined coal seam and total thickness of coal are not significant parameters
- Identified parameters that should be collected before, during and after mining
  - Water withdrawal from the mine
- This work is an initial effort to construct a model to predict the formation of mine pools
  - Should be improved with future research

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- **Sponsors:**
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