Productivity Equation for Reclaiming Surface Mines

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ABSTRACT / This article addresses the development of an agricultural productivity equation for predicting new soil (neo-sol) plant growth potential in Clay County, Minnesota, USA. Soil factors examined in the study include percent organic matter, percent slope, percent rock fragments, hydraulic conductivity, electrical conductivity, pH, topographic position, available water-holding capacity, bulk density, and percent clay. Squared terms and two-factor interaction terms were also examined as possible regressors. A best equation was selected that had a multiple coefficient of determination of 0.7399 and has five significant regressors and intercept with $P < .0001$. The regressors are hydraulic conductivity, percent slope squared, bulk density times percent rock fragments, electrical conductivity times percent rock fragments, and electrical conductivity times percent organic matter. The regressors predict soil suitability for a general crop model. The crops included in the model are wheat, oats, barley, soybeans, sugar beets, sunflowers, and grasses/legumes.

This article presents a mathematical equation to predict the degree of success in reclaiming gravel pits within Clay County, Minnesota, USA, for agricultural purposes.

Literature Review

To reclaim surface mined lands, predictive reclamation modeling has been suggested as a tool to assist in postmining landscape planning (Doll 1985). This premining process can assist in the avoidance of rendering the postmining landscape unsuitable for many postmining land uses.

In the past, predicting these postmining soil productivity levels has been difficult because the reclaimed landscape contains new soil profiles. These new soils (neo-sols) have unknown vegetation production potential. In an attempt to understand the problems associated with reconstructing soils, Plotkin (1986) reviewed the technical issues and difficulties concerning neo-sols. During reconstruction, the reclamation specialist can manipulate the physical and chemical attributes of these neo-sols; however, there are only a few general guidelines for building productive neo-sols. The reclamation specialist is confronted with generating neo-sols in a situation where the neo-sol prescriptions are unspecific. In addition, regulatory agencies are requiring that the neo-sol be equal in productivity to the premining soil at a 90% confidence level.

The traditional method to obtain neo-sol productivity performance and evaluation is to grow crops on the neo-sols and compare the results to reference areas. Doll and Wollenhaupt (1985) suggested that comparing reclaimed land productivity levels to reference areas is unreliable and expensive. Walsh (1985) recommended the development of better quantitative models. He stated that there needs to be a high-quality baseline study, better soil overburden evaluation criteria, and better monitoring data. Further, he believes these improvements would lead to a more reliable predictive model. To develop a more reliable evaluation, Vories (1985) described the current research required, and he suggested: (1) that a standard must be established to evaluate crop productivity, (2) statistical validation of indirect tests, and (3) determination of which crops should be used to assess productivity potential.

These suggestions have led to a different soil evaluation approach. Doll and others (1984) suggest that neo-sol productivity must be determined from the actual physical and chemical properties of the neo-sol. Based upon this concept, Doll and Wollenhaupt (1985) have presented a numerical productivity index to assess the postmining productivity level of neo-sols. The index attempts to predict mathematically the soil productivity potential.

KEY WORDS: Landscape architecture; Environmental planning; Postmine land-use design

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Neill (1979) proposed one of the first productivity index models; this model was later modified by Pierce and others (1983). Lohse and others (1985) described a land productivity formula for Illinois agricultural areas.

Based upon models of Pierce and others and of Neill, plus experience and extensive research, Doll (1985) and Doll and Wollenhaupt (1985) proposed the following preliminary productivity equation for the western North Dakota coal mining region (equation 1). The units of measurement for the independent variables are not specified in this equation.

$$PI = 100\,TOP \sum_{i=1}^{n} (AWC_i \times SAR_i \times EC_i \times BD_i \times HC_i \times Wf_i) \qquad (1)$$

where PI = productivity index, TOP = topographic position, AWC = available water-holding capacity, SAR = sodium absorption ratio, EC = electrical conductivity, BD = bulk density, HC = hydraulic conductivity, WF = rooting depth weighting factor, and i = soil depth.

The equation attempts to predict soil productivity potential by assessing specific soil attributes. In the equation of Doll and Wollenhaupt (1985), these measurable properties were selected based upon the experimentation and experience of the authors. Other soil properties could be selected; however, soil factors not found in the equation were considered insignificant for western North Dakota soils.

Only root zone factors were considered for the equation. Soil productivity equations examine the portion of the landscape that is actually being disturbed. The portion being disturbed is the rooting zone (soil). These soil productivity equations are attempts to predict the agricultural potential of only the rooting zone. See Burley and Thomsen (1987) for further elaboration on the selection of independent variables.

Doll's equation is strictly hypothetical and is presently in the development process. For instance, the measuring scale and standardization of the soil properties have not yet been established. In addition, the equation-building process to determine the best mathematical equation with a predicted statistical reliability has not been conducted. Therefore, the model cannot yet be mathematically applied to a real situation. This article describes the first statistically reliable productivity equation to be published.

The importance of this approach lies in its ability to accurately and reliably predict the influences of soil disturbance and crop productivity. By predicting postmining agricultural productivity during the premining process, numerous postmining site-plan iterations can be generated to determine the optimum soil configuration. The landscape engineer can test various hypothetical neo-sol profiles and develop a postmining reclamation plan that produces the most productive neo-sol possible. This means the effectiveness of reclamation activities can be improved. Typically, many postmining reclamation plans treat the mining operation as one distinct process and the reclamation operation as another. Overburden, topsoil, excess sand, and flumed fines are often handled twice, once during the mining operation itself and again during reclamation. Bauer (1982) suggests that much of this double handling can be avoided. Theoretically, the optimum soil configuration can be incorporated into the actual mining operation, leading to cost savings by eliminating the second soil handling.

Research Objectives and Assumptions

The objectives of this paper are: (1) to review the development of neo-sol productivity models; and (2) to report on the development of a neo-sol productivity model for Clay County, Minnesota.

The assumptions necessary to produce the results reported in this paper are: (1) the necessary field data to develop the model have already been collected (Note: The data cannot be productivity values derived from an index. The data must be actual field data. Data derived from an index will only reveal an equation that approximates the index); (2) a multiple regression model is the type of model desired; (3) a multiple regression model will yield significant results ($P < .05$ for factors in model); and (4) a significant multiple regression model can be used to demonstrate the development of a surface mining site in Clay County.

Research Methodology

The general approach described in this paper is as follows:

1. Review literature to understand the current body of knowledge concerning predictive reclamation modeling for neo-sols
2. Describe study area
3. Input relevant dependent and independent variables from study area into the Higher Education Computer Network (HECN) of the state of North Dakota
4. Standardize all variables

5. Perform principal component analysis upon the dependent variables to search for a linear combination of variables that can be expressed in univariate form
6. Eliminate unlikely regressors through the RSReg procedure (a multiple regression procedure) in SAS (Statistical Analysis System) (cutoff value $P < .25$)
7. Perform maximum R-squared improvement analysis to select the best combination of regressors to predict crop productivity
8. Perform multicollinearity and C-plot checks of the best model(s)
9. Plot observed versus predicted productivity scores of best model
10. State conclusions

Figure 1 is a flowchart describing the flow of the data through the process. In the flowchart, one critical decision point is highlighted. At this point, the model is rejected or accepted. If the model is rejected, the next best equation is selected from diagnostics and C-plot criteria. A description of the logic and basis for the methodology is specified by Burley and Thomsen (1987).

Study Area

In Clay County, surface mining and agriculture are closely related land uses. By examining the geological formations, surface mining history, and agricultural patterns, one can develop a clear relationship between sand and gravel surface mining and postmining agricultural land uses.

Location

The study area is Clay County, Minnesota (Figure 2), located in the upper Midwest along the west-central boundary of Minnesota adjacent to North Dakota. The county is approximately 1693 km^2 (1052 mi^2) in area with about 8 km^2 (5 mi^2) of surface water (Jacobson 1982).

Climate and Agricultural Crop Selection

Clay County is in the humid continental–cool summer climatic region (Espenshade 1974). This means that the summer has occasionally cool days and the winter is very cold with arctic air surging over the county (Jacobson 1982).

Cool temperatures limit the selection of possible crops grown in Clay County. For example, there are only 4062 average growing degree-days in Hawley, Minnesota (Jacobson 1982). This cool and relatively dry climate allows the production of wheat, barley, oats, potatoes, sunflowers, soybeans, sugar beets, and native prairie grass hay.

The crops selected for 1977 production within the county included wheat (217,300 acres), sugar beets (46,800 acres), sunflowers (52,000 acres), corn (25,000 acres), potatoes (7800 acres), soybeans (26,500 acres), other small grains (124,500 acres), and hay (24,000 acres) (Jacobson 1982). While most of the native vegetation in the county has been eliminated, Clay County remains primarily a rural region producing agronomic crops.

Clay County Surface Mining History

The demand for sand and gravel is primarily in the Fargo–Moorhead urban center and in the glacial lake plain. To support this demand, sand and gravel is mined. Since the surface of the glacial lake plain is composed of clay, sand and gravel had to be obtained elsewhere. The beach ridges of glacial Lake Agassiz contained an abundance of sand and gravel.

Beginning in the 1920s, the beach ridges were mined to support a growing Fargo–Moorhead urban center and to build an extensive roadway system in the glacial lake plain. In the 1960s the beach ridge sand and gravel deposits near Fargo–Moorhead were being exhausted by constructing an interstate highway system, improving federal highways, and developing North Dakota's largest metropolitan area (Fargo–Moorhead). Some beach ridge deposits could not be utilized by the sand and gravel industry, since they were contaminated with Cretaceous shale. This forced operators to consider sand and gravel deposits in the glacial moraine. Both contaminated deposits and exhausted deposits led to the development of the Alexandria Moraine surface mines.

The major market for the sand and gravel is to the west in the glacial lake plain. Unlike many sand and gravel operations, which are very close to urban land, sand and gravel operations in Clay County are relatively far away. Thus the postmining land use for most reclaimed mining sites will probably not be urban, but rural. In the rural landscape, agriculture is the predominant land use. Thus, reclaiming the landscape for agriculture can be considered a logical postmining land-use decision. The development of a predictive equation could assist in constructing neo-sols for productive cropland.

Methods

Required Baseline Data

To develop the model, two sets of variables are re-

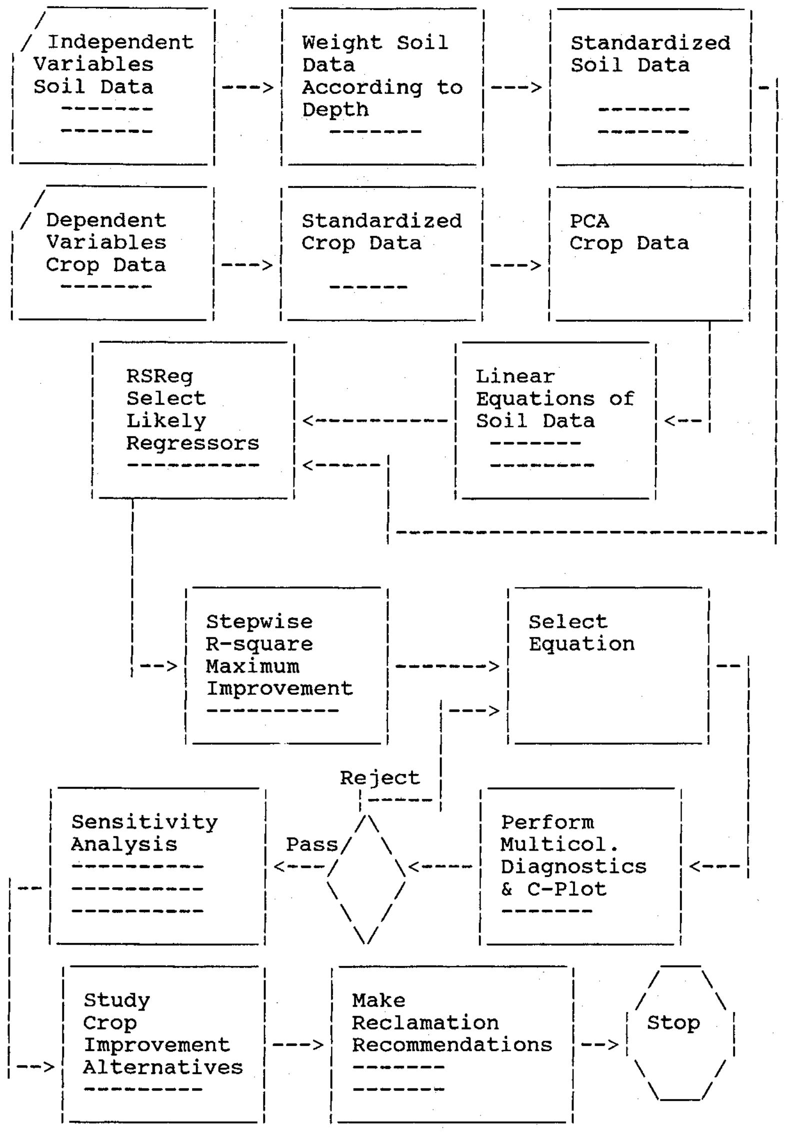

Figure 1. Flowchart of equation building and reclamation recommendation process.

quired. One set is the dependent variable list (response variables); the other set is the independent variable list (factor variables). The independent variables will be used to predict the outcomes of the dependent variables. The independent variables are physical and chemical soil properties. The dependent variables are crop yields. The physical and chemical soil properties will be used to develop an equation to predict crop yields.

The lists of potential variables are found in the United States Soil Conservation Service County Soils Surveys. In those surveys, the independent variables are described in the physical and chemical soil characteristics table(s). The dependent variables are described in the crop yield tables.

There were seven crop variables (dependent variables) selected for the study. These variables were spring wheat, barley, oats, sunflowers, soybeans, sugar beets, and grasses/legumes yields. The data set consisted of actual US Soil Conservation Service crop yields from the years 1975 to 1979 (Jacobson 1982, personal communication 1986). During those years a severe drought was experienced in 1977 and a severe flood experienced in 1975. The data were expressed as an average yield that included normal growing seasons, drought years, and flooding conditions.

There were ten soil characteristics (independent variables) selected for the study. These variables included topographic position, percent slope, percent rock fragments >3 in., percent clay, bulk density, available water-holding capacity, hydraulic conductivity, pH, electrical conductivity, and percent organic

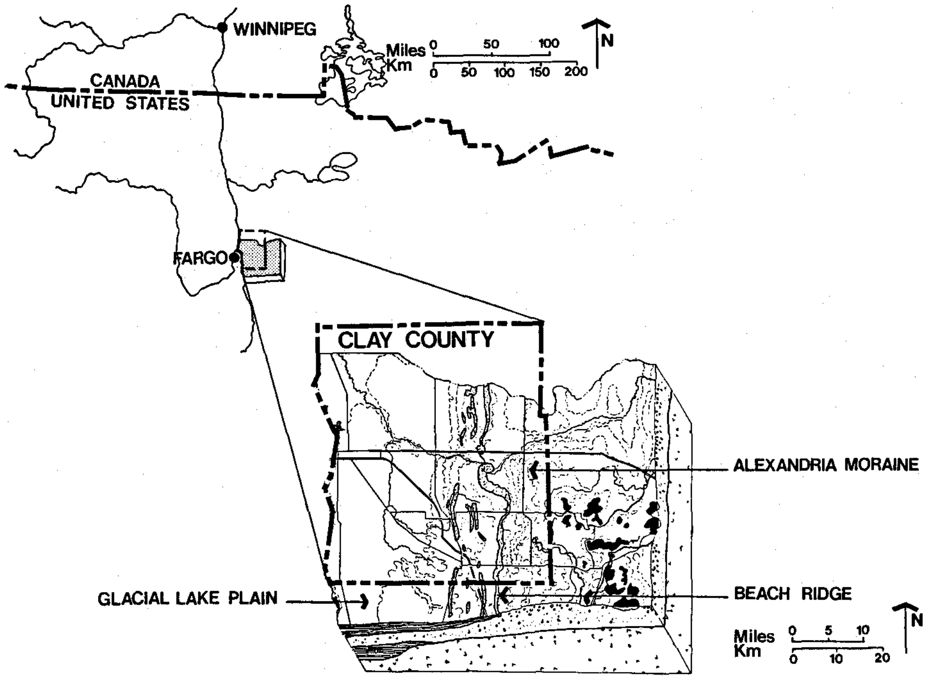

Figure 2. Map of Clay County and region.

matter. Burley and Thomsen (1987) provide details concerning the selection of the independent variables.

The soil data consisted of soil profile measurements at 1-in. increments to a depth of 60 in. Eighty soil types (mapping units) were represented in the study.

Data Analysis

The statistical procedures employed in this study are described and explained by Burley and Thomsen (1987). Essentially, the statistical procedures are lengthy and intricate, requiring an article devoted solely to mathematical methodology; the one by Burley and Thomsen (1987) gives a detailed, step-by-step description of instructions to create a reclamation productivity equation.

Results

The eigenvalues for the standardized crop data resulting from principal component analysis (PCA) of the covariance matrix indicated that only the first principal component (a number greater than 1) should be used for further model development. In the first principal component column, the set of eigenvectors all contain positive values. The values place almost equal weighting upon spring wheat, barley, oats, sunflowers, and soybeans. Sugar beets and grasses/legumes have smaller positive values. As suggested by Kendall (1980), the eigenvector elements associated with the first principal component are used to develop a linear equation to predict the sum of crop productivity (equation 2):

$$\begin{aligned}\text{PLANT} = {} & (0.4355 * SWZ) + (0.4364 * BAZ) \\ & + (0.4329 * OTZ) + (0.4042 * SFZ) \\ & + (0.2600 * SBZ) + (0.4239 * SNZ) \\ & + (0.1474 * GEZ) \end{aligned} \qquad (2)$$

where PLANT = weighted total plant productivity, *SWZ* = spring wheat *Z* score, *BAZ* = barley *Z* score, *OTZ* = oat *Z* score, *SFZ* = sunflower *Z* score, *SBZ* = sugar beet *Z* score, *SNZ* = soybean *Z* score, and *GEZ* = grasses/legumes *Z* score.

To illustrate the application of the linear equation, the total plant productivity score for soil S33B is calculated in equation 3. Soil S33B (33B in Jacobson 1982) is a Barnes loam, 1–3% slope. It is a neutral to calcareous soil found on upland areas in Clay County. The soil is heavily cultivated, supporting crops of small grains, sunflowers, corn, soybeans, and hay.

$$\begin{aligned}\text{PLANT} = {} & (0.4355 * 1.0372) + (0.4364 * 0.8069) \\ & + (0.4329 * 0.9136) + (0.4042 * 0.7021) \\ & + [0.2600 * (-0.6874)] + (0.4239 * 1.2145) \\ & + (0.1474 * 0.0388) \qquad (3) \\ = {} & 1.8288 \end{aligned}$$

where PLANT = total weighted (first principal component), plant productivity for soil S33B, 1.0372 = spring wheat *Z* score for soil S33B, 0.8069 = barley *Z* score for soil S33B, 0.9136 = oat Z score for soil S33B, 0.7021 = sunflower Z score for soil S33B, −0.6874 = sugar beet Z score for soil S33B, 1.2145 = soybean Z score for soil S33B, and 0.0388 = grasses/legumes Z score for soil S33B.

Equation 4 is the projected best productivity equation developed in the regression analysis. Table 1 lists the results of the optimum regression equation ($p <$ .0001 for each variable).

$$\begin{aligned}\text{PLANTS} = {} & 0.6206 + (-1.1805 * HCZ) \\ & + (-0.3575 * SLZ * SLZ) \\ & + (-1.9376 * BDZ * FRZ) \\ & + (-2.3420 * ECZ * FRZ) \\ & + (1.2424 * OMZ * ECZ) \qquad (4)\end{aligned}$$

where PLANTS = regression model predicted productivity score, HCZ = hydraulic conductivity Z score, SLZ = percent slope Z score, BDZ = bulk density Z score, FRZ = percent rock fragments Z score, ECZ = electrical conductivity Z score, and OMZ = percent organic matter.

Productivity Prediction

The equation selected for this study contains an intercept, one main effects term, one squared term, and three interaction terms (Table 1). In addition, the coefficient of multiple determination in the equation is 0.740. In other words, the regressors explain 74% of the variation in the regression model.

To predict the agricultural productivity of a particular soil, the best equation can be modified slightly. Instead of having to calculate the Z score for each regressor before calculating the predicted plant productivity score, equation 4 can be rewritten, as illustrated by equation 5, to allow direct soil readings to be entered into the equation.

$$\begin{aligned}& \text{PLANTS} = \\ & \quad 0.6206 + (-1.1805 * [(HC - 3.9296)/4.0030] \\ & \quad + (-0.3575 * \{[(SL - 3.0000)/4.6810] ** 2\}) \\ & \quad + \{-1.9375 * [(BD - 1.3584)/0.2644] \\ & \quad [(FR - 0.9075)/3.4929]\} \\ & \quad + \{-2.3420 * [(EC - 2.526)/1.0947] \\ & \quad [(FR - 0.9075)/3.4929]\} \\ & \quad + \{1.2424 * [(OM - 3.9512)/0.6638] \\ & \quad [(EC - 2.5269)/1.0947]\} \qquad (5)\end{aligned}$$

where PLANTS = predicted productivity score, HC = hydraulic conductivity, SL = percent slope, BD = bulk density, FR = percent rock fragments, EC = electrical conductivity, OM = percent organic matter.

The computation of the plant productivity score for a specific soil profile such as soil S33B is illustrated in equation 6.

$$\begin{aligned}& \text{PLANTS} = \\ & \quad 0.6206 + \{-1.1805 * [(1.3 - 3.9296)/4.0030]\} \\ & \quad + (-0.3575 * \{[(2.0 - 3.0000)/4.6810] ** 2\}) \\ & \quad + \{-1.9375 * [(1.52 - 1.3584)/0.2644] \\ & \quad [(2.5 - 0.9075)/3.4929]\} \\ & \quad +\{-2.3420 * [(2.9 - 2.526)/1.0947] \\ & \quad [(2.5 - 0.9075)/3.4929]\} \\ & \quad + \{1.2424 * [(1.05 - 3.9512)/0.6638] \\ & \quad [(2.9 - 2.5269)/1.0947]\} \qquad (6) \\ & \text{PLANTS} = 0.3343\end{aligned}$$

Discussion

Equation Interpretation

In the selected equation, there were five regressors that were significant ($P <$ .0001). Each regressor can be interpreted and assessed for its importance and meaning in the construction of neo-sols.

Ideal soil. These five terms (one main effect, one squared term, three interaction terms) plus the beta-intercept are the only significant factors necessary for productivity prediction. All other factors do not add to the model's ability to predict crop productivity. While pH reaction, available water-holding capacity, topographic position, and other factors may be important alone, these factors as a group are not important.

Following the model, the ideal soil will contain the following features: (1) hydraulic conductivities ranging from 3.3 mm/h (0.13 in./h) to 10.16 cm/h (4.0 in./h), (2) the soil will be placed on slopes approaching three percent, (3) bulk densities ranging from 1.36 g/cm^3 to 1.6 g/cm^3 with no rock fragments, and (4) electrical conductivity ranging from 2.5 to 6.8 Mmho/cm with 4%–10% organic matter.

An example of a soil with characteristics close to the ideal soil is Bearden silty clay loam (S93). This soil has the highest soil productivity level of the soils examined in the thesis. Sites consisting of Bearden silty clay loam have a hydraulic conductivity of 0.8072 in./h, an average slope of 0.5%, a bulk density of 1.39 g/cm^3, an electrical conductivity of 6.4 Mmho/cm, 0% rock fragments, but only 2% organic matter. In contrast, Sioux bouldery loamy coarse sand with slope type E is a soil with a low predicted productivity value. Its characteristics include a hydraulic conductivity of 24.44 cm/h (9.625 in./h), an average slope of 21%, bulk density of 1.52 g/cm^3, an electrical conductivity of 2 Mmho/cm, 30% rock fragments, and 0.2% organic matter.

Limitations of model. The regressors in the equation have limits concerning the applicability of the soil productivity model. First, the hydraulic conductivity levels examined in the study range from 3.3 cm/h to 33 cm/h, the bulk density levels examined in the study

Table 1. Best equation from stepwise R-square improvement procedure.[a]

Maximum R-square improvement for dependent variable plant
R square = 0.73987201 $C(P)$ = 21.83218626

	DF	Sum of squares	Mean square	*F*	Prob > *F*
Regression	5	293.89333360	58.77866672	42.10	0.0001
Error	74	103.32852364	1.39633140		
Total	79	397.22185724			
	B value	Standard error	Type II SS	*F*	Prob > *F*
Intercept	0.62056451				
HCZ	−1.18051872	0.13668694	104.15502747	74.59	0.0001
SLZSLZ	−0.35746843	0.05254259	64.63100583	46.29	0.0001
BDZFRZ	−1.93755091	0.30923954	54.81566745	39.26	0.0001
ECZFRZ	−2.34196309	0.30371693	83.02532676	59.46	0.0001
OMZECZ	1.24238777	0.27557903	28.37987725	20.32	0.0001

[a] See equation 4 for definition of regressors.

range from 0.175 g/cm^3 to 1.6 g/cm^3, the electrical conductivity levels examined in the study range from less than 2 Mmho to 6.8 Mmho, and the organic matter levels examined in the study range from 0.2% to 53.7%. This means the effects on plant growth above and below these ranges are beyond the predictive bounds of the equation. Second, the lower limit for both percent slope and percent rock fragments were encountered in the study. The lower limit has a bound of zero. Therefore, soils reaching the lower limit of these two regressors are still applicable. However, average slopes greater than 24% and rock fragments greater than 30% are also beyond the bounds of the equation.

In addition to bounds placed upon the model by the regressors in the equation, the model is limited to location of applicability and origination of parent material. All soils studied were from Clay County, Minnesota. Therefore the model is effective for soil types found in Clay County only; it is not applicable for any other region. Furthermore, the model should be applied in situations where the site soils originate from parent material examined in the study. Soils derived from other parent materials or site conditions are beyond the predictive applicability of the equation.

Conclusion

An equation was developed from a data set consisting of 80 soils in Clay County, Minnesota. Each soil had measurements for ten properties (independent soil factors) at each 2.54-cm interval in a 152.4-cm profile. Crop harvest data were available for seven vegetative crops (dependent variables). The crop harvest data were collected over a period of approximately ten years. Using principal components analysis, a single crop production value for each soil was obtained. This single value was used to regress soil factors against crop production. An equation was made which had regressors at $P < .0001$, satisfied C-plot requirements, and multicollinearity requirements. This equation can predict soil productivity values and compare means between predicted soil productivity values with 95% confidence levels.

Unless one is intending to reclaim sites in Clay County, Minnesota, the equation is of only modest immediate and practical significance; however, this equation is the first to be developed. As the first, it is highly significant. Many other reclamation researchers may wish to develop their own regional model and many postmining land-use designers may apply a productivity model to reclamation efforts. Therefore, the researcher and designer should consider the points discussed below.

Neo-sol Productivity Equations for Broad Reclamation Applications

While it is possible to develop a productivity equation, the equation has very tight limitations in its applicability. The equation described in this article is not applicable to areas outside Clay County, Minnesota. Even within Clay County, the equation is not applicable to situations where chemical and physical soil properties are above or below the properties encountered in this study.

For those professionals working outside the Clay County region, this article is useful to illustrate that it is possible to create a highly predictive productivity equation. It also illustrates the specific composition and construction of one equation.

Neo-sol Equations as a Landscape Form-Giver

The equation can be applied to guide the development of Clay County surface mine reclamation plans.

The model can determine landform and suggest appropriate soil amendments. However, as with most mathematical simplifications of the real world, caution should be exercised in the application of the equation. The equation is only as good as the original data set. Future data sets may generate revised editions of this equation. Verbyla (1986) illustrates further complications and cautions associated with multiple regression analysis.

Productivity Equations and Long-Term Landscape Neo-sol Development

The long-term stability of neo-sol profiles has not been ascertained. Therefore, it is theoretically possible that a carefully planned prescription for composing a productive neo-sol profile could lead to an unproductive, degenerating soil. Future projects may address the long-term stability of agricultural productivity prescriptions.

Productivity Models as an Immediate Landscape Technology

For those professionals seeking to immediately develop a productivity model, there are limitations concerning how quickly and what type of models can be developed. If there are no existing data, the soonest a good model can be developed is about five to ten years. All desired crops must be tested on all soil profiles. Ideally there should be very wet years and very dry years in the collected data. Thus the ability to develop a model may not be immediately possible.

Productivity Models Challenging Current Concepts of Landscape Soil Amendments

As more productivity models are developed, these models may begin to challenge current soil reconstruction practices. The productivity equation indicates those soil variables that best contribute to plant growth. Variables not in the equation are redundant and do not add to the improved predictability of the equation.

In the past, landscape architects, planners, soil scientists, and reclamation specialists may have applied soil improvement recommendations using a broad, generalized approach. Some of the recommendations for a particular soil in a particular region could have been actually contrary to good plant growth, resulting in the opposite effects from the desired goal. The productivity equation can give insight into which factors actually contribute to improving plant growth.

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