NEO-SOL VEGETATION PRODUCTIVITY EQUATIONS FOR RECLAIMING DISTURBED LANDSCAPES: A CENTRAL FLORIDA EXAMPLE[1]

by
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Abstract. This investigation examined the potential to build neo-sol vegetation productivity equations in Polk County, Florida for the reclamation of phosphate mining sites and to restore native vegetation associations impacted by landscape disturbance. The vegetation types examined in the study include: Watermelon (*Citrullus lanatus*), Cucumber (*Cucumis sativus*), Sweet Orange (*Citrus sinensis*), Grapefruit (*Citrus x paradisi*), Bahia Grass (*Paspalum notatum*), Grass-Clover, Longleaf Pine (*Pinus palustris*), Slash Pine (*Pinus elliottii* var. *elliottii*), South Florida Slash Pine (*Pinus elliottii* var. *densa*), Live Oak (*Quercus virginiana*), Turkey Oak (*Quercus laevis*), Sand Post Oak (*Quercus margaretta*), Cabbage Palm (*Sabal palmetto*), Bald Cypress (*Taxodium distichum*), Pond Cypress (*Taxodium distichum* var. *nutans*), Blackgum (*Nyssa sylvatica*), Red Maple (*Acer rubrum*), Sweetbay (*Magnolia virginiana*), and Wetland Range/Grassland. The vegetation types ordinated into two plant associations: an upland group and a lowland group. Therefore two equations were developed, an upland vegetation equation and a lowland vegetation equation. The upland vegetation equation suggested that non-alkaline soils with low hydraulic conductivity rates and high clay content were preferred ($p < 0.0001$ for overall regression, maximum p-value = 0.048 for regressors, and adjusted multiple R-squared = 0.595). The upland equation contains hydraulic conductivity, percent clay, available water holding capacity, topographic position, percent organic matter, bulk density, and pH as soil parameters. The lowland vegetation equation suggested that higher topographic positions were preferred providing the soils were not dense and did not have a high clay content ($p < 0.0001$ for the overall regression, maximum p-value = 0.029 for regressors, and adjusted multiple R-squared = 0.646). The lowland equation contains topographic position, bulk density, percent organic matter, and percent clay as soil parameters. These equations are cursory and represent an initial investigation to apply vegetation productivity modeling techniques to a Florida environment.

Key Words: Plant Ecology, Natural Resources, Wetland Restoration, Landscape Architecture, Agricultural Reclamation, Prime Farmland

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INTRODUCTION

Reclamation research has led to the formative development of empirical prediction models to forecast the suitability of reconstructed soils (neo-sols) in reclaimed surface mine landscapes and other post-disturbance landscape conditions, for native vegetation types and non-native vegetation situations. This article describes the current body of knowledge associated with neo-sol vegetation productivity models and reports the results of a study to develop an equation for the phosphate mining region in Polk County, Florida. While numerous investigators have contributed important research findings leading towards the development of neo-sol prediction equations, Burley and Thomsen (1987) reported on a methodology suitable for generating a neo-sol predictive model. Their paper is essential and strongly recommended reading in understanding the statistical and conceptual procedures for creating a neo-sol predictive equation. Based upon this methodology, Burley, Thomsen, and Kenkel (1989) reported the first application of these modeling procedures to create a neo-sol predictive equation for reclamation applications. Soil factors examined in their 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. Presently, three equations have been developed and published for one study site, Clay County, Minnesota, an Upper Midwest study area. The equations include a crop model (equation 1) (Burley, Thomsen, and Kenkel 1989), an all vegetation model (equation 2) (Burley 1991), and a sugar beet model (equation 3) (Burley 1990), each containing highly specific regressors and moderate multiple coefficient of determinations (0.63 to 0.79). The equations predict soil suitability for the vegetation associated with the model. The crops included in the crop model and the vegetation model are wheat, oats, barley, soybeans, sugar beets, sunflowers and grasses/legumes. The trees and shrubs included in the vegetation model are Siberian Peashrub (*Caragana arborescens*), Common Hackberry (*Celtis occidentalis*), Red-twig Dogwood (*Cornus sericea*), Green Ash (*Fraxinus pennsylvanica*), Eastern Red Cedar (*Juniperus virginiana*), Black Hills Spruce (*Picea glauca densata*), Colorado Spruce (*Picea pungens*), Ponderosa Pine (*Pinus ponderosa scopulorum*), Eastern Cottonwood (*Populus deltoides*), American Plum (*Prunus americana*), Common Chokecherry (*Prunus virginiana*), Weeping White Willow (*Salix alba tristis*), Common Lilac (*Syringa vulgaris*), and Siberian Elm (*Ulmus pumila*). The sugar beet model is pertinent for the crop, sugar beets, only. Currently, no other investigators have reported a neo-sol model for any other region disturbed by surface mining.

$$\begin{aligned}\mathrm{PLANTS}=.6206 &+(-1.1805\ast((\mathrm{HC}-3.9296)/4.0030))\\ &+(-0.3575\ast(((\mathrm{SL}-3.0000)/4.6810)\ast\ast 2))\\ &+(-1.9375\ast((\mathrm{BD}-1.3584)/0.2644)((\mathrm{FR}-0.9075/3.4929))\\ &+(-2.3420\ast((\mathrm{EC}-2.526)/1.0947)((\mathrm{FR}-0.9075)/3.4929))\\ &+(1.2424\ast((\mathrm{OM}-3.9512)/0.6638)((\mathrm{EC}-2.5269)/1.0947))\end{aligned}\qquad \text{Eq 1}$$

Where

PLANTS	=	Predicted Productivity Score
HC	=	Hydraulic Conductivity (inches/hour, 1 inch=2.54 cm)
SL	=	% Slope
BD	=	Moist Bulk Density (g/cm cubed)
FR	=	% Rock Fragments (percentage weight of particles > 7.62 cm)
EC	=	Electrical Conductivity (Mmhos/cm)
OM	=	% Organic Matter (percentage weight)

ALLPLANTS=.8916+(-1.4366*((HC-3.9296)/4.0030)) Eq 2
+(-1.1419*((SL-3.0000)/4.6810)((TP-2.575/0.9682)
+ (-2.3041*((EC-2.526)/1.0947)((FR-0.9075)/3.4929))
+ (-0.5887*((EC-2.526)/1.0947)((CL-22.843/14.3063))
+ (-1.9375*((EC-2.526)/1.0947)((BD-1.3584)/0.2644))
+ (1.2424*((OM-3.9512)/0.6638)((FR-0.9075)/3.4929))

Where

ALLPLANTS	=	Predicted Productivity Score
HC	=	Hydraulic Conductivity
SL	=	% Slope
TP	=	Topographic Position
BD	=	Moist Bulk Density
FR	=	% Rock Fragments
EC	=	Electrical Conductivity
CL	=	% Clay
OM	=	% Organic Matter

SBP=-0.342+(0.339*(CL-22.84)/14.3) Eq 3
+(0.425*(pH-7.50)/0.43)
+ (0.182*((CL-22.84*(CL-22.84)/14.31)
+ (-0.816*((AW-0.259)/0.69)*((CL-22.84)/14.31))
+ (0.363*((pH-7.50)/0.43)*((EC-2.53/1.09)))

Where

SBP	=	Sugar Beet Productivity (unitless)
CL	=	Percent Clay, by weight
PH	=	pH
AW	=	Available Water Holding Capacity, cm cm^{-1}
EC	=	Electrical Conductivity, Mmhos cm^{-1}

While these equations may prove to be useful in the reconstruction of post-mining and other post-disturbance applications for agroecosystems and reconstructed naturalized landscapes, Burley (1992) has suggested that the empirical equations may currently lack a theoretical basis. However, Barnhisel et al (1992) describe the development of a soil productivity index where they present a crop yield conceptual model first presented by Kirniry et al (1983). This model suggests that the soil environment supports root growth, thereby substantially affecting crop yield. Nevertheless, no investigator has attached an explanative theory to accompany this conceptual model. In addition to the lack of theory, Burley (1992) notes the equations may have coefficient instability (the Beta coefficients developed in the regression equations may fluctuate wildly with changes in selected soils representing the data set). To strengthen the reliability of these equations, investigators may wish to conduct Jackknife coefficient estimates, Bootstrap coefficient estimates, and sub-sampling coefficient estimates for the equations.[1] The equations could be further strengthened by incorporating post-mining (or post-disturbance) soil cases into the data set or corroborating the equations with independent data sets. Investigators may wish to include additional variables into the equation building process such as a "time" variable through a calculus integration equation, or other parameters such as vegetation toxicity factors, possibly improving the general applicability of predictive equations.

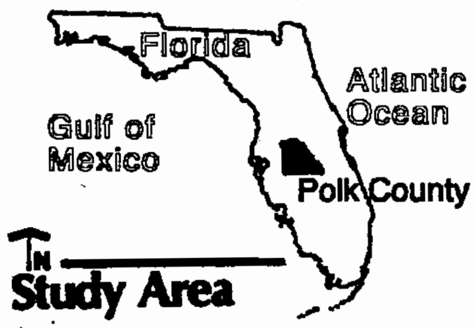

Figure 1. This drawing illustrates the location of Polk County, Florida.

Figure 2. This photograph depicts the condition of a Polk County phosphate mining site in 1989. The light colored overburden soil material is sand. Once mining is complete, the overburden is graded to form surfaces suitable for cropland, rangeland, woodlots, and wetlands.

Investigators are now exploring the implications and applications of these new models. Burley (1988), and Burley and Thomsen (1990) have described an approach, employing a soil productivity equation for reclaiming surface mines in Clay County, Minnesota. Currently, Burley is conducting related research upon the North Dakota Coal Fields. Concurrently, the investigator examined the potential to develop an equation for the phosphate region in Central Florida.[2] A study of the region outside the Upper Midwest afforded the opportunity to test the applicability of techniques first reported by Burley and Thomsen (1987) to other areas where soil landscape disturbance is present and where there is a concern to reconstruct the landscape.

STUDY AREA AND METHOD

Polk County, Florida (Figure 1) is located in a region where extensive phosphate mining occurs. Often the surficial material is sandy and the water table is near the surface (Ford *et al* 1990). Figure 2 depicts the condition of the landscape during the phosphate mining process. Before mining, surficial topography is gentle and relatively flat, comprised of Entisols and Spodosols (Myers and Ewel 1990). Pine forests, watermelon fields, and citrus groves reside upon the well drained Entisols. Flatwoods, wet and dry prairies, ponds, cypress domes, pastures and citrus groves reside .upon the Spodosol dominated land-scape. When phosphate bearing materials

Figure 3. This photograph (1989) presents a post-mining wetland created in Polk County, Florida.

are removed during the mining process from a flat low lying Spodosol landscape, the post-mining landscape can be transformed into a wetland condition not suitable for upland vegetation and affording opportunities to create a variety of wetland types (Figure 3). The placement and landscape configuration of overburden material is an important form-giving feature driving the post-mining establishment of vegetation.

Based upon the data supplied by Ford *et al* (1990), the vegetation types applicable for study and development of neo-sol equations included Watermelon (*Citrullus lanatus*), Cucumber (*Cucumis sativus*), Sweet Orange (*Citrus sinensis*), Grapefruit (*Citrus x paradisi*), Bahia Grass (*Paspalum notatum*), Grass-Clover, Longleaf Pine (*Pinus palustris*), Slash Pine (*Pinus elliottii*), Southern Slash Pine (*Pinus elliottii* var. *densa*), Live Oak (*Quercus virginiana*), Turkey Oak (*Quercus laevis*), Post Oak (*Quercus margaretta*), Cabbage Palm (*Sabal palmetto*), Bald Cypress (*Taxodium distichum*), Pond Cypress (*Taxodium distichum* var. *nutans*), Blackgum (*Nyssa sylvatica*), Red Maple (*Acer rubrum*), Sweetbay (*Magnolia virginiana*), and Wetland Range Grassland.

Vegetation productivity values across soil types were gathered by Ford *et al* (1990). These values were measured in units such as tons per acre, bushels per acre, or feet per unit of time.

Ford *et al* (1990) describe the methods employed to gather soil profile data and plant growth data. These methods follow the U. S. Soil Conservation Service (SCS) approach for developing county soil survey information. Plant growth data are typically a compilation of field trials, past yield records, and heuristic estimates by seasoned agriculturists (see Burley 1987). SCS plant growth data sorted by soil profile type are considered suitable in some states for reference area comparisons. Each SCS soil survey is an extensive, professionally acquired data source with potential for incorporation into ecological modeling investigations such as developing agricultural productivity equations.

The procedures employed to develop the equation(s) were similar to those techniques described by Burley and Thomsen (1987) with the following exception: the statistical software employed in this study was SYSTAT (Wilkinson 1990); while the statistical software used by Burley and colleagues was SAS (SAS Institute Inc. 1982). Therefore, this change precluded the opportunity to use the RSREG search procedures (SAS Institute Inc. 1982:91-

100). Instead, each main effect, squared term and first interaction term were assessed individually, one variable at a time, searching for the top 20 most likely regressors suitable for further analysis. Since SYSTAT has fewer regression analysis options, Maximum R-squared improvement Stepwise analysis (SAS Institute Inc. 1982:102-103) was not possible and Forward Stepwise analysis (Wilkinson 1990:153), a less desirable analysis procedure, was employed.

In the study, those eigenvalues greater then 1.0 are considered likely candidates to project a linear combination important in predicting meaningful environmental relationships between the dependent crop/woody vegetation variables. The eigenvectors associated with each eigenvalue present a numerical linear combination of weightings assigned to crop/woody plant variables and then employed in the regression analysis (see Burley and Thomsen 1987). In past studies, only the sugar beet model (Burley 1990) generated significant results beyond the linear combination associated with the first eigenvalue.

The procedures to complete the modeling process are complex and lengthy. Burley and Thomsen (1987) provide a detailed description of the modeling procedures. Investigators are en-couraged to examine their document.

Table 1. Eigenvalues for vegetation variables.

Component	Eigenvalue	% of Variance
1	8.448	44.465
2	2.278	13.042
3	2.077	10.932
4	1.167	6.145
5	0.933	4.908
6	0.873	4.592
7	0.675	3.552
8	0.549	2.891
9	0.511	2.689
10	0.349	1.838
11	0.294	1.548
12	0.238	1.250
13	0.129	0.667
14	0.105	0.550
15	0.073	0.386
16	0.051	0.270
17	0.024	0.125
18	0.020	0.107
19	0.006	0.033

RESULTS

In an examination of the statistical results, the Principal Component Analysis (PCA) illu-strates the latent structure of the vegetation (dependent variables). Table 1 presents the eigen- values for the 19 axis PCA. Each eigenvalue represents a portion of the variance in multi- dimensional space that is orthogonal (thus inde-pendent) to all other component axis. Axis with large eigenvalues represent alignments where the variables express large variance along some continuum. In plant ecology, these continuums often pertain to temperature, light, nutrient, or water availability dimensions (see Curtis 1959 for classic examples of PCA/Factor Analysis ordination). In this study, the first four eigenvalues are greater then 1.0 with the first component containing 44% of the variance and the second component containing 13% of the variance. Table 2 presents the eigenvectors for the first four components.

Interpreting these eigenvectors can be a difficult task because there is really no specific procedure to assess the eigenvectors. Notice that in the first component there is a group of plants positively associated with the component and another group negatively associated with the component. The positive group consists of upland plants and the negative group represents wetland vegetation. When the two groups are separated and analyzed with PCA,. the upland group contains all positive numbers for the first component and the lowland group has all positive numbers for the first component (see Table 3).

Table 2. Eigenvectors for first four components.

Variable	Component 1	Component 2	Component 3	Component 4
Orange	0.815	-0.003	0.313	-0.171
Grapefruit	0.823	0.025	0.309	-0.133
Watermelon	0.462	-0.445	0.434	0.133
Cucumber	0.204	0.446	-0.131	0.601
Bahia Grass	0.902	0.222	0.117	0.058
Grass-Clover	0.444	0.670	-0.152	0.226
Rangeland Grass	-0.433	0.548	0.578	0.123
Slash Pine	0.827	0.299	0.075	-0.075
Long Leaf Pine	0.713	0.162	0.124	0.253
Turkey Oak	0.318	-0.627	0.400	0.272
Post Oak	0.339	-0.487	0.513	0.258
Live Oak	0.557	0.063	0.288	-0.596
Cabbage Palmetto	-0.445	0.469	0.188	-0.243
Pond Cypress	-0.824	0.195	0.478	0.019
Bald Cypress	-0.439	-0.280	-0.371	-0.049
Blackgum	-0.873	0.110	0.371	0.020
Red Maple	-0.901	-0.002	0.138	-0.034
Sweetbay	-0.849	0.176	0.461	0.028
Southern Slash Pine	0.756	0.389	0.094	-0.154

Table 3. Separated vegetation types with eigenvalues and eigenvectors.

Upland Group	Component 1	Component 2	Lowland Group	Component 1	Component 2
Eigenvalue	5.530	2.241	Eigenvalue	4.515	1.303
% Variance Explained	44.081	18.679	% Variance Explained	64.497	18.612
Orange	0.874	-0.132	Cabbage Palmetto	0.729	0.477
Grapefruit	0.885	-0.104	Pond Cypress	0.588	0.123
Watermelon	0.503	-0.584	Bald Cypress	0.953	0.171
Cucumber	0.233	0.464	Blackgum	0.263	-0.928
Babia Grass	0.921	0.160	Red Maple	0.959	-0.079
Grass-Clover	0.472	0.667	Sweetbay	0.891	-0.393
Southern Slash Pine	0.815	0.223	Rangeland Grass	0.973	0.089
Slash Pine	0.849	0.101			
Long Leaf Pine	0.753	-0.752			
Turkey Oak	0.317	-0.679			
Post Oak	0.398	-0.108			
Live Oak	0.628	0.297			

Therefore, the vegetation types were divided into two groups for further modeling analysis. The eigenvectors of the first component for the upland group formed the linear combination to generate an upland vegetation dependent variable for regression study. The eigenvectors of the first component for the lowland group formed the linear combination to generate a lowland veg-etation dependent variable for regression study.

Equation 4 and Table 4 represent the results of the upland regression study, illustrating the model suited to predict soil characteristics pertinent to predict upland vegetation growth. Consequently Equation 5 and Table 5 represent the results of the lowland regression study, illustrating the model deemed to be the best model to predict soil characteristics pertinent to predict lowland vegetation growth.

$$
\begin{aligned}
UPLAND = 6381 &+ (-0.006*HC*HC) \\
&+ (0.012*CL*CL) \\
&+ (220.671*AW*AW) \\
&+ (-5.550*HC*AW) \\
&+ (24.056*TP*AW) \\
&+ (-0.751*OM*BD) \\
&+ (-0.141*PH*CL) \\
&+ (0.038*CL*HC)
\end{aligned} \tag{Eq 4}
$$

Where

UPLAND	=	Predicted Productivity Score
HC	=	Hydraulic Conductivity
AW	=	Available Water Holding Capacity
PH	=	pH
TP	=	Topographic Position
BD	=	Moist Bulk Density
CL	=	% Clay
OM	=	% Organic Matter

Table 4. Regression statistics for selected upland model.

	N: 54	Multiple r:0.810		Squared Multiple R: 0.656		
	Adjusted Squared Multiple R: 0.595			Standard Error of Estimate 3.521		
Variable	Coefficient	Std Error	Std Coef	Tol	T	P(2 Tail)
Constant	6.381	1.533	0.000	.	4.161	0.000
HC*HC	-0.006	0.002	-0.276	0.612	-2.472	0.017
CL*CL	0.012	0.003	1.608	0.037	3.524	0.001
AW*AW	220.671	62.033	1.091	0.081	3.557	0.001
HC*AW	-5.550	1.661	-0.927	0.099	-3.342	0.002
TP*AW	24.056	5.998	0.510	0.474	4.011	0.000
OM*BD	-0.751	0.259	-0.661	0.147	-2.895	0.006
PH*CL	-0.141	0.032	-2.221	0.030	-4.401	0.000
CL*HC	0.038	0.019	0.302	0.346	2.030	0.048

Analysis of Variance

Source	Sum-of-Squares	DF	Mean-Square	F-Ratio	P
Regression	1062.959	8	132.870	10.716	0.000
Residual	557.961	45	12.399		

$$
\begin{aligned}
LOWLAND = 6.077 &+ (1.505*TP*TP) \\
&+ (-2.685*TP*BD) \\
&+ (0.570*TP*OM) \\
&+ (-0.814*TP*CL)
\end{aligned}
\qquad \text{Eq 5}
$$

Where

LOWLAND	=	Predicted Productivity Score
TP	=	Topographic Position
BD	=	Moist Bulk Density
PH	=	% Clay
OM	=	% Organic Matter

Table 5. Regression statistics for selected lowland model.

N: 54 Multiple R:0.820 Squared Multiple R: 0.672
Adjusted Squared Multiple R: 0.646 Standard Error of Estimate 2.687

Variable	Coefficient	Std Error	Std Coef	Tol	T	P(2 Tail)
Constant	6.077	0.736	0.000	.	8.260	0.000
TP*TP	1.505	0:255	1.607	0.090	5.892	0.000
TP*BD	-2.685	1.145	-1.115	0.030	-2.345	0.023
TP*OM	0.570	0.253	0.227	0.658	2.255	0.029
TP*PH	-0.814	0.310	-1.186	0.033	-2.621	0.012

Analysis of Variance

Source	Sum-of-Squares	DF	Mean-Square	F-Ratio	P
Regression	726.520	4	181.630	25.154	.000
Residual	353.819	49	7.221		

DISCUSSION AND CONCLUSION

Equation Interpretation

Interpreting the equations is a difficult task. Often the interpretations are rather naive. It may take decades to fully explore the implications of these empirical models. Critics of the models may claim that the equations provide no new information; conversely, other critics claim that the models suggest spurious relationships that are not grounded or supported by a substantial body of knowledge.

The results obtained in the study suggest that there are two ordinated groups of vegetation with a different set of neo-sol environmental preferences. In the upland group, there appears to a definite preference for higher topographic positions that have a higher available water holding capacity and a slow hydraulic conductivity rate. The equation suggests that for upland vegetation, the addition of clay particles may be an important soil amendment. In phosphate surface mining operations an abundance of clay can be found in water filtration/recycling ponds. Clay particles that have settled into these ponds may be an important post-mining soil asset. However, as indicated in the model, clay particles that are associated with a high pH or in soils with a high bulk density may not be beneficial.

In the lowland vegetation equation, topographic position is a major constituent of the model. As the topographic position in elevation increases, the equation suggests that the lowland vegetation will prefer less dense soils,soils with abundant organic matter and a

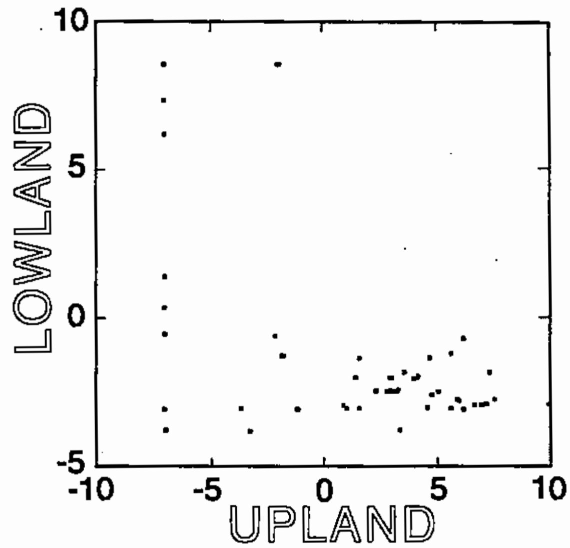

Figure 4. This plot compares the vegetation productivity scores from the two PCA dimensions.

low abundance of clay particles. The preference for less clay is in contrast to the upland model. This study indicates that lowland plants may not prefer wetland conditions and may actually prefer higher topographic positions. In other words, the wetland landscape may be in a topographic position where hydric tolerant vegetation can survive, but the vegetation may not actually prefer the wetland conditions. For example, it is widely known in the landscape/horticulture industry that in a controlled competition situation where humans manage the landscape, Bald Cypress can be found thriving in upland urban savannas, even in parking lots, growing at yearly rates greater than growth rates found in the suppressing environmental conditions of a lowland.

As suggested, both models indicate that the vegetation studied in this investigation will actually tolerate or prefer higher topographic positions but that the components of the upland soil may be different. A plot of the two predicted productivity scores (Figure 4) indicates that the two preferences are indeed different; when the soil condition is ideal for one vegetation type, the other vegetation type will not prefer the soil. Notice the plot in Figure 4 places the soils in relative proximity to the two axis and not in the center or upper left corner of the plot, locations that would indicate overlap in preference. Despite the evidence supplied by statistical results, there may be a methodological flaw in the collection of the data as applied to this investigation. The procedures described by Burley and colleagues were intended for studying the prediction of plant growth on soils from data collected where each vegetation type was grown on each soil type with competition strictly controlled. In the case of Polk County, Florida, not all vegetation types may have been grown on all soils types in a controlled competition environment. Instead the growth of some vegetation types may have been recorded under plant competition conditions. The investigator suspects that the lowland vegetation equation may have been partially influenced by the soil preference of lowland plants under competition stress from upland vegetation and that the equation does not represent the actual preference of lowland vegetation when competition is controlled. Despite the limitations of the study, the equations may be helpful to the recla-mation/restoration specialist. For example, when reconstructing wetlands in a post-mining landscape, an equation derived from wetland tolerant vegetation under competition forces may actually be advantageous for wetland environments. In addition, restraining upland vegetation invasions may be beneficial in limiting the need for extensive vegetation management measures to control upland vegetation invasions.

Comparison To Past Work

In the past, the work of Burley and associates suggests that the soil reconstruction requirements for both noospheric and biospheric upland vegetation types in the Upper Midwest and the Northern Great Plains may be similar. In other words, 'What is preferred by native vegetation types is also preferred by introduced and cultivated vegetation, posing a dilemma for reclamation specialists.' This 'Pan-Preference' may not be as distinct in the Florida study. While plant ecologists have indicated that under competition, stress, and disturbance regimes, vegetation types may ordinate themselves into occupying different survival zones governed by such factors as fire, severe drought, high pH, and extreme cold; it seems that all of the plant types (both native and non-native) previously studied by Burley have nearly identical soil preference, the 'Co-preference Theory,' as predicted by previous reclamation equations. This means that in the establishment of native vegetation types on lands being reclaimed, reconstructed soils suitable for native plants can be developed by employing the productivity equations to predict native plant development but that these productive reconstructed soils may also be suitable for non-native colonization. In contrast, the study reported in this paper indicates that although a reclamation specialist might employ the equations presented in this investigation to create neo-sols that generate a greater yearly plant biomass level than pre-disturbance soils (a goal often employed by post-mining reclamation specialists), one should not necessarily build these highly productive soils when creating post-mining landscapes for native lowland vegetation. For the Florida case study, reconstructing productive soils may be encouraging non-native vegetation at the expense of native vegetation. This premise is not new, but this study presents quantitative evidence to support the construct. Conversely, a reclamation/ restoration specialist who does not develop productive post-disturbance soils, may be risking development of native vegetation stands which are unhealthy or slow to develop (traditionally slow growing vegetation has been a sign of poor reclamation success and is not favored in current reclamation regulations where quick post-mining plant growth is preferred). Should the reclamation/restoration specialist develop neo-sols that are highly productive but may lead to the exclusion of some vegetation types? or should the reclamation/restoration specialist create less productive soils that may accommodate a variety of vegetation types?

Conclusion

Before applying these equations for establishing native vegetation associations, investigators may wish to expand the work of Burley and colleagues to study vegetation productivity scores with various native vegetation types across a wide variety of landscape environments. In addition, restoration specialists may have to carefully control competition on highly productive neo-sols to prevent non-native plant invasions and allow native vegetation to become dominant. The work of Burley and colleagues may offer some empirical soil preference insight into why competition control is necessary and how to control competition.

The landscape restoration specialist should be cognizant of neo-sol vegetation productivity equations, their potential, the methodology employed to create the equations, and their limitations. Since the data base for creating the equations already exists for many regions of the United States of America and since there is an increased effort to restore landscapes with disturbed soils, many more neo-sol equations may be developed. This article has presented the current neo-sol equation literature, contemporary theoretical neo-sol equation issues, and latest equations developed by investigators.

ENDNOTES

1. During the fall of 1991 while working upon a Ph.D. course of study and enrolled in a course at the University of Michigan addressing "Agroecosystems" taught by Dr. J.H. Vandermeer (an agroecosystem ecologist), Burley wrote a paper describing the results of a small study in which he conducted a Jackknife estimate of Beta coefficients for Equation 2 and conducted a Bootstrap estimate of Beta coefficients for Equation 2. In the Jackknife study, he removed one observation case and then calculated the Beta coefficients for the regressors. He then replaced the observation case to the data set and selected another case for removal (n=12). The cases removed in the study were case numbers 1, 4, 5, 9, 10, 11, 13, 19, 24, 31, 44, and 54. Table 6 depicts the variation in the coefficients. The standard deviations of each coefficient were rather small ranging from 0.019 to 0.207.

In the Bootstrap study, he randomly selected 200 observation cases from an original set of 80 cases and computed the Beta coefficients. He then randomly selected another 200 observations to repeat the computations. This process was conducted five times (n=5). Table 7 depicts the variation in the coefficients. Again, the standard deviations of the coefficients were relatively small ranging from 0.028 to 0.118.

Table 6. This table presents the descriptive statistics for the Jackknife study conducted by Burley.

	Beta Coefficient						
	B0 Constant	B1 HC	B2 SLTP	B3 ECFR	B4 ECCL	B5 ECBD	B6 OMFR
Description							
N of Cases	12	12	12	12	12	12	12
Minimum	0.873	-1.484	-1.241	-2.387	-0.678	-1.325	2.632
Maximum	0.932	-1.307	-1.134	-2.057	-0.519	-1.042	3.422
Mean	0.896	-1.430	-1.155	-2.287	-0.591	-1.242	2.799
Standard Dev	0.019	0.042	0.029	0.079	0.035	0.097	0.207

Where

B0 = Beta Intercept Constant
Bn = Beta Slope Constant
HC = Hydraulic Conductivity
SL = % Slope
TP = Topographic Position
BD = Moist Bulk Density
FR = % Rock Fragments
EC = Electrical Conductivity
CL = % Clay
OM = % Organic Matter

Table 7. This table presents the descriptive statistics for the Bootstrap study conducted by Burley.

	Beta Coefficient						
	B0 Constant	B1 HC	B2 SLTP	B3 ECFR	B4 ECCL	B5 ECBD	B6 OMFR
Description							
N of Cases	5	5	5	5	5	5	5
Minimum	0.873	-1.552	-1.148	-2.337	-0.613	-1.397	2.641
Maximum	0.932	-1.361	-1.064	-2.270	-0.521	-1.283	2.925
Mean	0.896	-1.450	-1.110	-2.292	-0.574	-1.348	2.783
Standard Dev	0.019	0.073	0.040	0.028	0.041	0.045	0.118

Where

B0 = Beta Intercept Constant
Bn = Beta Slope Constant
HC = Hydraulic Conductivity
SL = % Slope
TP = Topographic Position
BD = Moist Bulk Density
FR = % Rock Fragments
EC = Electrical Conductivity
CL = % Clay
OM = % Organic Matter

2. The Central Florida study was initiated by A. Bauer as an exam question in a PhD candidacy written examination for Burley, conducted in January 1992. The Polk County results reported in this article were initially generated during this exam.

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