SOIL BASED VEGETATION PRODUCTIVITY MODELS FOR RECLAIMING NORTHERN MICHIGAN LANDSCAPES: A MONOGRAPH[1]

Dustin L. Corr[2], Jon Bryan Burley, Bert Cregg, and Robert Schutzki

Abstract. Scholars, governmental agencies, and concerned citizens are interested in developing empirical predictive models to quantitatively assess the vegetative productivity potentials of reconstructed soils (neo- sols). This research presents equations for a northern Michigan mining region in the Upper Peninsula of Michigan, based on data derived from the National Resources Conservation Service. We employed principal component analysis to develop models to predict the vegetative productivity of corn, corn silage, oats, alfalfa/hay, Irish potatoes, red maple (*Acer rubrum* L.), white spruce (*Picea glauca* [Moench] Voss), red pine (*Pinus resinosa* Aniton), eastern white pine (*Pinus strobus* L.), jack pine (*Pinus banksiana* Lamb.), and lilac (*Syringa vulgaris* L.). Soil attributes that were examined in this research include: available water holding capacity, moist bulk density, % clay, % rock fragments, hydraulic conductivity, % organic matter, soil reactivity, % slope, and topographic position. Four predictive equations based on landscape topography have been developed and are described as an all-mesic woody plant and crop equation, a xeric equation, an equation specific to jack pine, and a wet environment equation. The models were highly significant ($p<0.0001$) and explained 87.93%, 74.52%, 65.33%, and 87.68% of the variation in site productivity of the respective landscape setting. These equations are intended to assist in efforts to assess the vegetative productivity potentials of reconstructed soils on post-mined landscapes and other disturbed landscapes.

Additional Key Words: environmental design, forestry, soil science, landscape architecture, agronomy, horticulture.

---

[1] Manuscript was submitted for consideration for publication in JASMR R.I. Barnhisel (Ed.) Published by ASRS, 1305 Weathervane, Champaign, IL 61821

[2] Dustin Corr is a landscape architect in the firm of Nederveld, Grand Rapids, Michigan 49594; Dr. Jon Bryan Burley is an Associate Professor, Landscape Architecture, School of Planning Design and Construction, Michigan State University, E. Lansing, Michigan 48824; Dr. Bert Cregg is a Professor of Horticulture, Michigan State University, E. Lansing, Michigan 48824; Dr. Robert Schutzki is an Associate Professor of Horticulture, Michigan State University, E. Lansing, Michigan 48824.

DOI: http://dx.doi.org/10.21000/JASMR20040001

Introduction and Associated Literature

The proliferation of mined landscapes and concern for the environmental impacts associated with these lands have led to an increased interest in developing empirical predictive models to quantitatively assess the vegetative productivity potentials of reconstructed soils (neo-sols). Accurate modeling can be used to evaluate the conditions that are most influential to plant growth in a given region and can aid in the creation of an optimum post-mine land use plan. Landscape applications of this approach include agriculture uses as well as forested lands for silviculture, habitat creation, visual quality, carbon sequestration, and watershed management. These equations provide an inexpensive alternative to many of the currently utilized methods used to assess the potential of disturbed lands to reach productivity levels greater than or equal to pre-mined conditions. This article examines the current knowledge base associated with reclamation productivity equations, as well as investigates practical topics that can lead to better understanding of the application of these equations. The research examines the application of a methodology published by Burley (1996) and Burley and Thomsen (1987) and for a multicounty mining region in Michigan's Upper Peninsula.

Reclamation specialists are concerned with creating models to predict vegetative productivity. Essentially, four general ecological model types have been developed that can be applied to predict post-mining soil productivity to assess vegetation growth of agricultural crops, rangeland plants, and woody plants (Le Cleac'h et al., 2004; Burley, 2001). Although some states' laws explicitly express the method to compare the productivity level of pre-mined productivity levels compared to post-mined levels, each of these models has been used in past reclamation efforts throughout the United States (Burley, 1994). Recognition and understanding of these model types gives reclamationists a broader understanding of past and present reclamation practices and inherent advantage and disadvantages of each described.

The first type of model is a heuristic method, known as the "reconstructing nature" approach. Federal and many state laws mandate that A, B, and C soil horizons be stripped and stockpiled separately so that these horizons may be reapplied in the correct order during reclamation. Although supposedly an important and beneficial process, it is extremely variable with limited ability to predict vegetative performance and has not been validated by adequate research. Dancer and Jansen (1981) as well as McSweeney et al. (1981) discovered that replacement or alteration of claypan subsoils commonly found in southern Illinois increased the chemical and physical properties of mined land. Here, mixtures of B and C horizons showed greater vegetative growth compared to B horizon materials alone. Stripping and reapplication of A horizon material is extremely important and a heavily used method in the reconstruction of prime farmland. However, mandates of topsoil depths to be respread are dependent on the characteristics of the soil material and the crops to be grown (Friedlander, 2001). Mandated depths vary among state due to differences in edaphic concerns including soil depth to bedrock or depth to toxic materials.

Post-mined soils are often vastly different from their pre-mining conditions (refer to section entitled Conditions of Post-mined Soils for a description of the potential differences and causes for these differences among post-mined and pre-mined soils). Recreating a soil system with similar productivity levels based on attempted recreation of pre-mined conditions is therefore difficult. The first model, although requiring minimal planning, has proven to be a poor predictor of precise vegetative performance.

The second model is a statistical comparison method known as the "reference site" approach. In this approach soils from an undisturbed site are compared with the same, or a similar, nearby mined site. If no statistical difference exists between undisturbed soils properties and those of post-mined soils, the reclamation effort is deemed acceptable. Zipper et al. (2011) investigated the reforestation potentials of 25 sites in the Appalachian region of the eastern United States and found that post-mined landscapes were comparable to nearby undisturbed lands. The results of the study indicated that post-mined soils have the capacity to support productive forest vegetation and identify conditions that affect growth. However, such studies do not give a quantified prediction of vegetative productivity potential and are associated with extensive and costly data collection (Burley, 2001). Doll and Wollenhaupt (1985) described the reference site approach as "an unreliable and expensive means of evaluating reclamation success." Although this model is appropriate, and widely used to *assess* post-mined growth potentials, it does little to *predict* post-mined vegetative productivity.

The reference site approach often determines successful restoration based on a comparison of post-mining crop yields to those of similar, undisturbed reference areas. Once adequate or comparable yields have been achieved, the land is considered reclaimed, thus satisfying the obligations of the mining operation. Upon satisfaction of reclamation obligations, the bond held by the governing body is released, withdrawing all financial connection to further reclamation. Such post-reclamation evaluation methods to determine neo-sol productivities are often conducted once the opportunities to cost-effectively amend the soils are lost (Burley and Thomsen, 1987). It is therefore, important to investigate methods that are capable of accurately predicting vegetative productivity of post-mined soils so as to give reclamation planners opportunities to address identified soil factors that inhibit optimal growth prior to the establishment of a post-mined land use.

The third model, the "sufficiency" approach, employs a series of expert derived tables and charts. Here the soil is evaluated based on defined criteria and either accepted as sufficient or rejected. This approach has been used to evaluate vegetative productivity potentials by assigning point values to particular soil attributes, and is commonly used by foresters to predict biomass production rates of various tree species. Foresters often investigate volume measurements, plant indicators, and height growth indexes to evaluate sites. Baker and Broadfoot (1978, 1979) used the sufficiency approach to develop methods to predict potential tree heights based on soil data published by the Natural Resource Conservation Service (NRCS). The methodology, as defined by Baker and Broadfoot (1978, 1979), assigns point values representing conditions that are good, fair, and poor for vegetative growth. These values were weighed depending on importance to plant growth and totaled to determine the predicted growth rates of a given tree species. Neill (1979) used a similar index methodology. Neill's work led to the identification of most of the soil factors useful for the regression analysis approach. Doll and Wollenhaupt (1985) later refined Neill's index approaches and applied the method to post-mined soils. However, the equation derived by Doll and Wollenhaupt is heuristic and hypothetical (not statistically validated) and could therefore not be mathematically applied to actual situations. More recent studies have employed the index model with research conducted in the Mississippi River Valley (Belli et al., 1998; Groninger et al., 2000), in China (Peng et al., 2002), and in Iowa (Burras et al., 2015). Similar to other heuristic index models, these studies lack statistical reliability yet established fundamental precedents leading to the creation of more accurate statistical models. However, Potter et al. (1988) argue that this model is beneficial in cost-effectively assessing the amendment and treatment needs of post-mined soils based on pre-mined soil conditions.

According to Burley and Thomsen (1987), index productivity models do not address at least six major points. 1) Soil attribute interactions are not accounted for. Soil attributes can interact independently with crop production, grouped with other soil attributes interacting collectively but independent from other soil attributes, or completely interdependent. For instance, research shows that electric conductivity (EC), is a soil attribute that correlates with many soil properties that exist in most agriculturally supportive lands such as clay content, organic matter, and bulk density, but is traditionally used to quantify soluble salt contents (Corwin and Lesch, 2005). However, the degree in which these attributes interact together to affect plant growth is unknown. These attributes may be further complicated by secondary interactions with additional attributes as well. In many existing index models, soil attributes are all multiplied as though it were one interaction model despite a lack of statistical basis to do so. 2) Soil attributes may also have quadratic forms such as squared terms, which are not represented in index models. Squared terms represent soil attributes that increase or decrease productivity to a certain point and then reverse its trend. These attributes are extremely important when explaining instances such as when moderate amounts of available water content aids in a plants ability to grow, yet when a point is reached in which soils are overly saturated plant growth is hindered. 3) Constants, also known as beta coefficients, are absent from index models, yet it may be appropriate to consider slope constants and intercepts. 4) Interactions of crop types are not reflected in index models. Soil attributes may affect various crop types differently and therefore warrant separate equations to describe the predicted productivities. This is discovered in statistical models by investigating what crop types covary together. If two or more crop types covary they can be described by the same equation. Therefore, multiple equations may be needed to describe the productivity of various crop types within a region. 5) Regionality may be a consideration when selecting soil attributes to investigate. Some attributes may not be significant to include in certain regions while important to other models. Electric conductivity, as an indicator of problematic soluble salt content is mostly associated with arid regions, such as those found in the American southwest (Power et al., 1978). Electric conductivity may not be beneficial to investigate if in a region that soil salinity is not as prominent such as the American northeast. Researchers must consider regional differences that significantly affect edaphic conditions when determining characteristics to investigate. 6) Finally, the significance of the attributes is not considered. Soil attributes may vary in significance or may not be included at all in the equation. For example, crop yields of specific plant groups may be reduced if available water levels are too high or too low. Although available water is known to effect plant growth, when investigated with other attributes such as bulk density, percent organic matter, and available water may not contribute to the accuracy of the model and therefore be omitted from the final equation. In addition to these six points, Burley (1995a, 1995b) also describes his concern for restrictions of variable exploration. Firstly, soils explored in this approach are often restricted to a limited number of soil types. Secondly, vegetation variables are often restricted to one type that describes all crop types. Other approaches may be further investigated for a broader range of soils and a more focused group of plant types.

The fourth and final model described here is the statistical "regression analysis" approach, in which empirical evidence is used to develop equations that predict vegetation performance. Similar to the reference site approach, the regression analysis approach is associated with extensive data collection, which can take years to collect. Development of a reliable statistical productivity equation requires a data set derived from growth of various species across all soil types averaged over a ten-year period (Burley, 2001). For this reason, many researchers have pursued sufficiency models in lieu of investigating regression models. The Natural Resources Conservation Service (NRCS), however, has compiled substantial county-based data that may be applied to alleviate the costs associated with the data collection process necessary for the develop of an accurate model employing the regression analysis approach. Similar studies have employed NRCS data to reduce the costs associated with data collection needed for statistical analysis of vegetative productivity potentials (Wen and Burley, 2020a; Bai et al., 2016; Burley et al., 2016; Chang et al., 2015; Le Cleac'h et al., 2004; Burley and Gray, 2001; Burley et al., 2001; Groninger et al., 2000; Burley, 1999; Burley et al., 1996; Burley, 1995a, b; Barnhisel and Hower, 1994; Burger et al., 1994; Burley and Bauer, 1993; Barnhisel et al., 1992; Burley, 1991; Gale et al., 1991; Burley, 1990; Burley and Thomsen, 1990; Burley et al., 1989). Studies by Groninger et al. (2000) used the regression approach to predict tree growth in southern Illinois. These studies used regression of a combination of collected soils data and expected derived indexes. Although their methods are considered scientifically accurate, the methodology described by Burley and Thomsen (1987) limit the amount of theoretical information (derived indexes) by limiting the amount of qualitative assumptions about variables explored. Interest in developing predictive methods concerning soil productivity continue as illustrated by Humphries et al. (2019).

Burley and Thomsen (1987) describes the methodology for establishing empirically derived equations for predicting vegetative productivity. The first equation to use this methodology was developed by Burley et al. (1989) and is used in this research to investigate vegetative productivity on an area in Michigan's Upper Peninsula. The aim of the research is to explore the potential to derive predictive productivity equations for a study area in the Upper Peninsula of Michigan

Study Area and Methodology

The area of study is located in the western Upper Peninsula of Michigan (Fig. 1). The geology of the region is largely composed of sedimentary and igneous rock that is covered by glacial drift. Both of these types of rock are important to human activity. Sedimentary rock is often associated with extractable commodities such as petroleum, natural gas, salt, gypsum, and limestone. Igneous rock in the region is associated with extractable minerals, most notably, iron ore and copper. The mining of iron ore and copper accounts for the majority of mined surface area in the region, most of which occurs in Marquette County, Michigan. Koski (2005) describes some reclamation issues in the area and the use of paper mill residuals for soil modification. Lehmann et al. (2013) and Fleurant et al. (2009) studied fractal patterns of tree species, hills, and lakes in the region, assisting in the configuration of reclaimed surface mined lands (Fig. 2).

Study Area

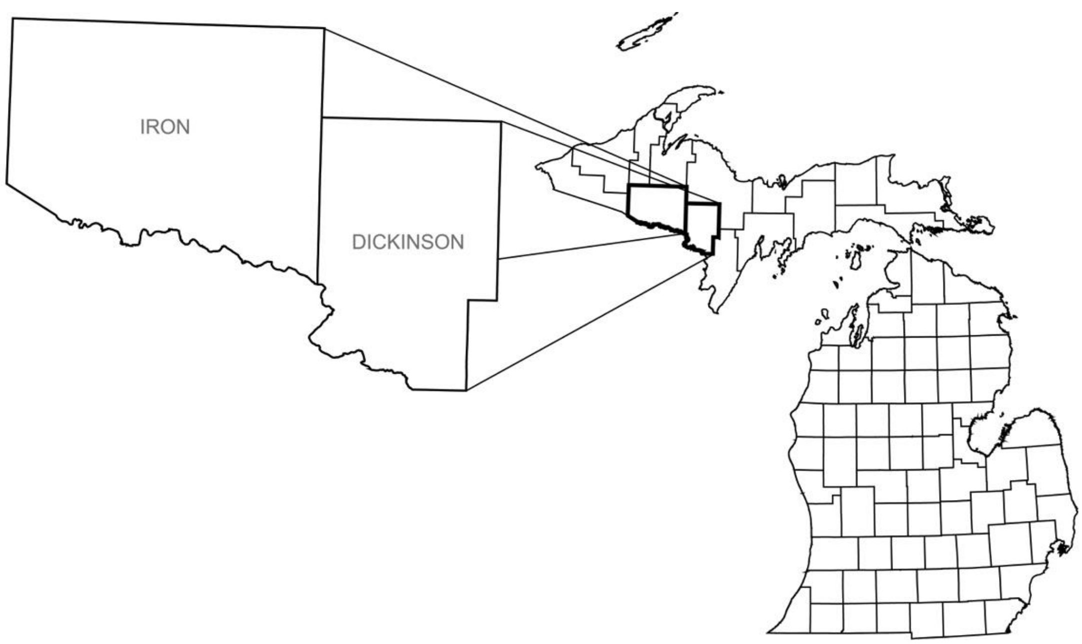

Figure 1. Location of study area in Michigan.

Figure 2. An image of Wade Lehmann on his study plot in the Upper Peninsula of Michigan recording the GPS location of individual trees on a rocky knoll, Dickinson County, Michigan. In northern Michigan, trees can grow in a primarily rocky/boulder substrate, (copyright © 2008 Jon Bryan Burley, all rights reserved, used by permission).

Marquette County is of particular interest to reclamationists as it currently hosts a large-scale iron ore mining operation and has recently opened a copper mine. However, the NRCS has not released the appropriate crop and woody species data necessary for the methodology employed in this study. Burley (1995a) found that multicounty models could be developed that could be applied throughout a region. Therefore, two adjacent counties that provided the appropriate yield and growth rate information, Iron County and Dickinson County, were selected. All three counties mentioned are within the Menominee Iron Range with the Marquette range in Marquette County, the western range in Iron County and the eastern range in Dickinson County. The similar geologies of the three counties of interest lend themselves well to the creation of a regional model (Figs. 3 and 4).

Figure 3. An iron mine in the Upper Peninsula of Michigan. The mining may proceed below sea level and produce waste rock mountains that may become some of the highest points in Michigan. Wang et al. (2013) studied approaches to develop portions of the post-mining site for down-hill skiing (copyright © 2007 Jon Bryan Burley, all rights reserved, used by permission).

Figure 4. Some of Dr. Burley's colleagues (all co-authors at various times) visiting an iron mine in the Upper Peninsula of Michigan.—from left to right Dr. Wang Hui from Nanjing, P.R. of China; Jin Xiaowen, Nanjing, P.R. of China; Dr. Burley, Michigan State University; Dr. Luis Loures, Portugal; Wade Lehmann, Michigan State University; and Jessica McHugh, Michigan State University (copyright © 2007 Jon Bryan Burley, all rights reserved, used by permission).

Historically, all three counties have been mined. Michigan is divided into four major metallic mining ranges, the Copper Mining District of Keweenaw, Houghton and Ontonagon counties; the Marquette Iron Range of Marquette and Baraga counties; the Menominee Iron Range of Dickinson and Iron Counties; and the Gogebic Iron Range of Gogebic county. Although not within the same range, the similarities in mining histories and extraction methods of ores makes the counties in which data was derived from, Iron and Dickinson counties, and other mined counties within the region, most notably Marquette County, comparable.

Iron County. Iron County has a long history of mining that began when surveyors reported abnormal compass readings in 1846. Soon after, iron ore exploration led thousands to the area to prospect the land, of what is now known as the western Menominee range. Lumbering also grew rapidly as an economic activity. Extensive iron formations were discovered near the Iron River and Crystal Falls. When the Chicago and Northwestern Railways reached the eastern range in 1882, miners had reportedly extracted 74,000 tons of ore. Mining steadily grew over the next forty years when it finally reached peak production in the 1920s (Linsemier, 1997). According to Linsemier (1997), the Sherwood was the last active mine in Iron County. Currently, approximately 90 percent of Iron County is forest, which is largely dominated by sugar maple (Linsemier, 1997).

Iron County is located in the high plateau region with land formations resulting from continental glaciation. Major bedrock types include the Michigamme slate and associated formations including greywacke, greenstone, and quartzite deposits. Although outcrops are common throughout the county, most of the area is covered by glacial drift. The landscape is characterized by rolling ground moraines, end moraines, steep ice-compact features, and outwash plains. Soils are predominately Spodisols, characterized as fine sands to sandy loams in texture (Albert, 1995). Linsemier (1997) described the taxonomic classification of each soil type examined in this study. Reynolds (2006) described early attempts to develop agriculture in the area. Kraft et al. (2004) present a study examining understory vegetation and white-tailed deer (*Odocoileus virginianus* Zimmerman) browsing.

Dickinson County. Similar to Iron County, the early history of Dickinson County is largely shaped by its lumber and mining activities. The contemporary economic activities within the county are heavily dependent upon the tree growth for lumber, pulpwood, and fuel (Linsemier, 1989). The physiology of the county is the result of continental glaciation, dominated by moraines, till plains, and outwash plains. More than 90 percent of Dickinson County is forested, with a similar species composition as Iron County. Albert (1995) describes the soils of the county to be thin layers of sandy to loamy sand soils on bedrock. A description of taxonomic classifications for all soils investigated in this study are provided by Linsemier (1989). Snider and Snider (1986) report an investigation in the study area concerning forest insects and monitoring. Racevskis and Lupi (2005) studied human perceptions in the area concerning forest management.

Methodology

The general methodology has been published by Burley (1996) and Burley and Thomsen (1987), and recently by Wen and Burley (2020a). Independent variables are representative of physical and chemical characteristics of each soil investigated based on the work of Doll and Wollenhaupt (1985). Data for soils are available in published NRCS county soil surveys, which provide these characteristics for nearly all soils included in the surveys. Other soil characteristics may be investigated if data is available. Wen and Bin (2020a) describe new NRCS county updates and potential new variables to consider. It has been 35 years since the late Eugene Doll (1921-2010) and Wollenhaupt suggested the ten soil characteristics to consider. The reclamation community may wish to consider a revised or updated list. Soil productivity has been linked to soil depth. According to research conducted by Doll et al. (1984), soil depths affect vegetative productivity in different proportions. The research describes a soil weighing method in which soil characteristics are assessed based on depth. This method contributes 40% of the total crop yield to the first 12 inches of the soil profile. Inch 13 to inch 24 contribute 30% of the crop yield, while inches 25 through 36 account for 20% of the yield. Finally, inches 37 through 48 contribute 10% of the crop yield value. This research suggests that 100% of the crop yield value can be attributed to the first 48 inches of the soil profile. Wick et al. (2005, 2011) have suggested that after initial establishment, soil depth may not be as critical.

Dependent variables in the vegetative productivity models are typically crop harvest data and woody plant growth rates. Crop yield data should be collected over several growing seasons including years of differing amounts of precipitation and temperature ranges, such as data provided by the NRCS. Gaining data that has been collected over several seasons, gives a more accurate understanding of crop yields in a typical year. It is important to note that crop yields must be actual measured quantities and not derived from another index. Modeling of values derived from other indexes will result in similar equations to the existing index, and thus result in no further understanding of the data. Crop harvest data may be expressed in terms of various units, most commonly bushels per acre, tons per acre, or pounds per acre, United States Department of Agriculture (USDA, 1992). The NRCS presents woody plant growth data in terms of feet of growth per year, although other growth rates or plant volumes could potentially be used. Dissimilar units of measurement among vegetative types do not necessarily pose a problem.

Once the data is standardized and organized it is ready to be further analyzed in SAS (2003). At this point it is possible to work towards the creation of regression equations for each crop type. However, creating separate equations may not be necessary. It may be possible to combine multiple crop types into one equation. By investigating the multivariate relationship among crop types using Principal Component Analysis (PCA), it is possible to identify crop types that covary and can therefore be combined into one equation. PCA is used to determine the number of dimensions needed to explain the variance across all crop types. Simply put, PCA is a dimension reduction tool. In this method each dimension explains a set of crop types that covary together. Ideally, all crop types will covary and investigators will be able to derive one equation that will explain all crops from one dimension. If all crops do not covary the investigator may have to develop additional equations to explain one or multiple significant dimensions. For instance, if PCA shows that soybean and corn silage covary together, while white pine (*Pinus strobus L.*) and red maple (*Acer rubrum L.*) covary together, these four crop types can be described within two different dimensions. Therefore, two separate equations will need to be developed to explain all four crops. In this way PCA is extremely helpful to simplify large arrays of vegetation variables. The solution to aggregating linear combinations of plant growth variables was first proposed by Kendall (1939). However, the calculations had to be accomplished by hand arithmetic methods and could not go beyond three dimensions. With the advent of the computer and approximation methods, PCA results could be extended beyond three dimensions. PCA has been employed widely in agriculture, geography, medicine, and genetics. Burley has published widely using PCA in his landscape studies (Wen and Burley, 2020b; Burley et al., 2020; [Xu et al., 2017a; 2017b; 2016;] Qi et al., 2012; Burley et al., 2009; Burley and Brown, 1995; Rauhe et al., 1994).

Results

Independent variables employed in this study included nine soil parameters. The soil parameters investigated in this study were available water holding capacity, moist bulk density, percent clay, percent rock fragments, hydraulic conductivity, percent organic matter, soil reaction, percent slope, and topographic position. Units and abbreviations of these variables as they are shown in the following results are included in Table 1.

A total of 95 soils were investigated between Dickinson and Iron Counties, with 45 applicable soils from Iron County and 50 applicable soils from Dickinson County. Soils that did not have crop or woody plant data were not included. These soils were most often lowland mucks that did not provide adequate soil characteristic information. Additionally, soil complexes were not included in the data because the proportions of the soils that comprised the complexes that the crop and woody plants were grown on are unknown. Most soils that comprise these soil complexes were included in the data set as singular soil types.

Table 1. Independent variable soil parameter units and abbreviations as they appear in the regression models and final developed equations.

Abbreviation	Factor	Unit of Measurement
AW	Available Water Holding Capacity	2.54 cm/2.54 cm (inches/inch)
BD	Moist Bulk Density	g/cc
CL	% Clay	Proportion by weight
FR	% Rock Fragments	Proportion by weight of particles > 7.62 cm
HC	Hydraulic Conductivity	2.54 cm/hour (inches/hour)
OM	% Organic Matter	Proportion by weight
PH	Soil Reaction	pH
SL	% Slope	(Rise/Run)*100
TP	Topographic Position	Scale 1 to 5 where: 1 = Lowlands (Bottomlands) 2.5 = Mid-slopes 5 = Highlands (Ridge lines)

Dependent variables consisted of five crop types and six woody plant species. Crops investigated in this study include corn, corn silage, oats, alfalfa/hay, and Irish potatoes. Woody plant species investigated were red maple (*Acer rubrum* L.), white spruce (*Picea glauca* [Moench] Voss), red pine (*Pinus resinosa* Aniton), eastern white pine (*Pinus strobus* L.), jack pine (*Pinus banksiana* Lamb.), and lilac (*Syringa vulgaris* L.). A list of dependent variables and their associated units and abbreviations as they are shown in the eigenvector analyses are included in Tables 2 and 3. These specific plants were selected for investigation due to the availability of information of these plants in both counties.

Table 2. Dependent variable crop units and abbreviations as they appear in the eigenvector analyses.

Abbreviation	Crop Type	Measured Average Yield
CO	Corn	Bushels/acre (0.1470 hectoliters per hectare)
CS	Corn Silage	Tons/acre (368.2 kg per hectare)
OA	Oats	Bushels/acre (0.1470 hectoliters per hectare
IP	Irish Potatoes	Hundredweights/acre, 100lbs/acre (18.49 kg per hectare)
AH	Alfalfa Hay	Tons/acre (368.2 kg per hectare))

Table 3. Dependent variable woody plant units and abbreviations as they appear in the eigenvector analyses.

Abbreviation	Crop Type	Botanical Name	Measured Average Yield
RM	Red Maple	*Acer rubrum* L.	Feet/20 years (30.48 cm/ 20 years)
WS	White Spruce	*Picea glauca* [Moench] Voss	Feet/20 years (30.48 cm/ 20 years)
RP	Red Pine	*Pinus resinosa* Aniton	Feet/20 years (30.48 cm/ 20 years)
EP	Eastern White Pine	*Pinus strobus* L.	Feet/20 years (30.48 cm/ 20 years)
JP	Jack Pine	*Pinus banksiana* Lamb.	Feet/20 years (30.48 cm/ 20 years)
LI	Lilac	*Syringa vulgaris* L.	Feet/20 years (30.48 cm/ 20 years)

Table 4 illustrates the eigenvalues of the combined Iron County and Dickinson County crop and woody plant data set. There were four principal component axes with eigenvalues greater than 1.0. The eigenvalue for the first principal component axis contains 28.80 percent of the variance in the crop and woody plant variables. The first axis contains the largest proportion of the variance in the data set and is therefore the primary candidate for further investigation. The eigenvalue for the second, third and fourth principal component axes contained 23.32 %, 16.15 %, and 10.94 % of the variance, respectively. The first four principal components together comprised 79.21 percent of the variance in the data set.

As illustrated in Table 5, all the eigenvector coefficients for the first principal component were positive suggesting that all crop and woody plant types investigated covary together. Dependent variable values ranged from 0.447 to 0.193. The first principal component could be described as an all crop and woody plant response axis. Values >0.4 or <-0.4 are considered to have strong association with their principal components and are the most descriptive terms of the variables investigated. There are two such variables in the first principal component: corn and corn silage. These two terms represent the two most significant variable of the equation. In this way, the equation could also be described as a corn-corn silage axis.

Table 4. Principal component analysis eigenvalues of the covariance matrix for Iron County and Dickinson County, Michigan.

	Eigenvalue	Difference	Proportion	Cumulative
Prin1	3.16822981	0.60353241	0.2880	0.2880
Prin2	2.56469741	0.78771328	0.2332	0.5212
Prin3	1.77698412	0.57343332	0.1615	0.6827
Prin4	1.20355081	0.63213620	0.1094	0.7921
Prin5	0.57141461	0.07981335	0.0519	0.8441
Prin6	0.49160125	0.09542970	0.0447	0.8888
Prin7	0.39617155	0.08579710	0.0360	0.9248
Prin8	0.31037446	0.03691405	0.0282	0.9530
Prin9	0.27346041	0.14526776	0.0249	0.9779
Prin10	0.12819264	0.01286972	0.0117	0.9895
Prin11	0.11532292	0.11532292	0.0105	1.0000

Table 5. Principal component analysis eigenvectors for Iron County and Dickinson County, Michigan dependent variables. See Tables 2 and 3 for explanations of variable abbreviations. The number 1 attached to each variable indicates that that variable has been standardized to a mean of zero and a standard deviation of 1.

	Prin1	Prin2	Prin3	Prin4
CO1	0.403014	-.129644	-.165482	-.453338
CS1	0.446947	-.197810	-.119725	-.313282
OA1	0.388777	-.286682	-.041966	-.030582
IP1	0.334832	-.083064	-.298629	0.387424
AH1	0.333357	-.108640	-.177557	0.455676
RM1	0.192615	-.113110	0.591965	-.137687
WS1	0.255142	-.003187	0.464371	0.436319
RP1	0.175800	0.515927	-.080397	0.093462
EP1	0.280114	0.454817	0.229088	0.092214
JP1	0.075413	0.436752	-.410653	-.039082
LI1	0.214888	0.408141	0.205355	-.331010

In the Appendix, Fig. A1 illustrates the best suitable model (from SAS, 2003) output, developed for the first principal component. The model was found to explain 87.93 % of the variance. The model is not over specific, having 21 terms in the equation and C(p)=21.54. C(p) values that are close to the number of terms in the equation are considered to "fit" well (Agresti and Franklin, 2012. Therefore, further validating the strength of this model.

Table 5 illustrates the eigenvector coefficients for the second principal component. The coefficients in the second eigenvector can be organized in three separate groups: positively associated (positive values), negatively associated (negative values), and weakly associated (values near zero). Positive coefficients include red pine, eastern white pine, jack pine, and lilac. All of these species also had values that were considered to be strongly associated ($x>0.4$, $x<-0.4$). White Spruce was the only plant type to have a value near 0, indicating that it is not described well by this model. Plant types with negative values were not as strongly associated as those plant types with positive values. Negative values ranged from -0.083 to -0.287.

Table 5 also illustrates the eigenvector coefficients associated with the third principal component. This eigenvector can be divided into two main groups. Out of all plant species investigated there were only two tree species that had positive values, red maple and white spruce. Both red maple and white spruce showed values that were considered strongly associated ($x>0.4$, $x<-0.4$), with values of .592 and .464, respectively. All other crop and woody plant types had negative values. This suggests that this model can be best described as a red maple-white spruce dimension.

Figure A3 (see Appendix) illustrates the first equation derived for the third principal component, in which all p values were less than 0.04. The equation was found to explain 91.79 % of the variance, which was the highest of all the best-fit models developed in this study. There were 38 terms in this model and had a C(p) value of 33.95. Although some researchers consider models with C(p) values less than the number of terms to be over specific (Burley and Thomsen, 1987), others suggest that the relativity of the values is what should be considered (Agresti and Franklin, 2012). Depending on the interpretation of these terms, the model could be considered reliable. Because of possible discrepancies of interpretations, a second, more conservative model was developed.

Figure A4 illustrates a second model for the third principal component. This equation was found to explain 87.68 % of the variance, which is comparable to the r-square value of the first principal component. In contrast to the model shown in Figure A3, the number of terms in this model shown in Fig. A4 (32 terms) is less than the C(p) value (48.00). This equation would not be considered over specific according to criteria described by Burley (1988), and is therefore a more conservative model than that shown in Fig. A3.

Although the eigenvalue for the fourth principal component, as shown in Table 5 was larger than 1.0 (1.2), the best model from the stepwise regression analysis was not significant enough to be considered a relevant model (Fig. A5). The best model found had a R-squared value of 0.3133. Because the model explained such a small portion (31.33 %) of the variation in the crop and woody plant axis, it was not considered for further analysis. No equation was produced for this model.

Discussion and Conclusion

A total of three equations were developed for the three principal components investigated with suitable results. The equations were developed for all significant principal components identified from the data of Iron and Dickinson Counties. All equations developed are highly specific with p-values less than 0.0001, and are considered statistically significant. As previously discussed, the significant eigenvector values indicate plant species that each equation best describes and can be used to further investigate similarities among dependent variables to categorize the equations.

Revegetation efforts in reclamation projects often involve an attempt to recreate a biological community that previously existed on the site or to blend the reclaimed landscape into adjacent lands. Therefore, it is beneficial to investigate possible ways to categorize developed equations to better describe the communities in which they are intended to predict. Similar studies have categorized equations based on the plant species the derived equations best describe. In a study of a three-county North Dakotan coal mining region, Burley (1995a) investigated the potential to find a predictive equation to describe the lowlands and the transitional zones that composed the study area. By referring equations directly to a landscape type or post-land use, reclamation specialists can more effectively use such equations to aid in reclamation projects. Furthermore, categorization is dependent upon the variable analyzed. For instance, Burley (1995a) investigated biophysical variables to describe vegetative productivity across a spatial region and found that the equations developed in the study could be categorized as a geomorphology equation, a climatology equation, and a biological equation. Based on the variables investigated in this study, the most appropriate method of categorization would be to describe equations as community types.

John T. Curtis, a plant ecologist and botanist from the University of Wisconsin conducted an in-depth inventory of the Wisconsin's northern floristic zone (Curtis, 1959). This series of studies gives a comprehensive analysis of a neighboring region that shows similar geological and climatic characteristics (Linsemier, 1989, 1997). Both the study area of the Curtis studies and the study area of this investigation have been classified by the International Union for Conservation and Nature and Natural Resources (IUCN) (Udvardy, 1975) as being in the Great Lakes biogeographical province and by the United States Department of Agriculture, Forest Service (McNab et al., 2005) as being within the Laurentian Mixed Forest Province. Due to the strong, established similarities between these study areas the data reported by Curtis is considered comparable and applicable to the area of this study.

<u>Principal Component 1: Mesic Model</u>

Equation 1 presents the equation developed from the stepwise maximum r-squared improvement for the first principal component (see Table 1 for the terms in the equation). All plant species investigated in the first principal component were found to covary together indicating that the model can be described as an all crop and woody plant model. An analysis of eigenvector values implied that the model could also be described as a corn-corn silage model. However, it may be more beneficial to describe this equation according to its community type so as to connect the model to a post-mined community rather than a particular set of plants. The plants selected for this study are all adapted to growth in moderate soils that are typical in this region. Moderate soils in the northern Upper Peninsula are often sandy to loamy, well-drained soils that are slightly alkaline to slightly acidic. These soils are well suited to support a broad range of plant types and are typical of northern mesic forests. It is important to note the distinction of these soils abilities to support growth and the actual plant growth patterns that occur in natural conditions.

$$
\begin{aligned}
\text{Plant} = -0.872 &+ [((TP-3.121)*1.267^{-1})*(0.505)] \\
&+ [((SL-8.00)*7.765^{-1})*(-2.073)] \\
&+ [((CL-8.915)*4.138^{-1})*(0.803)] \\
&+ [((HC-5.227)*4.302^{-1})*(-0.966)] \\
&+ [((AW-0.122)*0.040^{-1})*(-2.374)] \\
&+ [((PH-5.971)*0.671^{-1})*(0.406)] \\
&+ [((SL-8.00)*7.765^{-1})* ((SL-8.00)*7.765^{-1})*(0.398)] \\
&+ [((FR-4.571)*6.760^{-1})* ((FR-4.571)*6.760^{-1})*(-0.263)] \\
&+ [((AW-0.122)*0.040^{-1})* ((AW-0.122)*0.040^{-1})*(0.882)] \\
&+ [((TP-3.121)*1.267^{-1})* ((CL-8.915)*4.138^{-1})*(0.370)] \\
&+ [((TP-3.121)*1.267^{-1})* ((BD-1.506)*0.084^{-1})*(-0.595)] \\
&+ [((TP-3.121)*1.267^{-1})*((HC-5.227)*4.302^{-1})*(-0.488)] \\
&+ [((TP-3.121)*1.267^{-1})*((OM-1.995)*1.201^{-1})*(2.067)] \\
&+ [((SL-8.00)*7.765^{-1})* ((OM-1.995)*1.201^{-1})*(-1.454)] \\
&+ [((FR-4.571)*6.760^{-1})*((BD-1.506)*0.084^{-1})*(-0.768)] \\
&+ [((CL-8.915)*4.138^{-1})* ((HC-5.227)*4.302^{-1})*(-0.747)] \\
&+ [((CL-8.915)*4.138^{-1})* ((PH-5.971)*0.671^{-1})*(-0.429)]
\end{aligned}
\qquad \textbf{(1)}
$$

$$+ [((BD-1.506)*0.084^{-1})*((OM-1.995)*1.201^{-1})*(-0.674)]$$
$$+ [((HC-5.227)*4.302^{-1})* ((PH-5.971)*0.671^{-1})*(-0.761)]$$
$$+ [((AW-0.122)*0.040^{-1})*((PH-5.971)*0.671^{-1})*(-1.201)]$$

<u>Principal Component 2 Equation: Northern Dry Forest Model</u>

Equation 2 presents the equation developed from the stepwise maximum r-squared improvement for the second principal component (see Table 1 for the terms in the equation). The eigenvector analysis of this principal component found that four woody species were found to be strongly associated with this axis, jack pine, red pine, eastern white pine, and lilac. Curtis identifies five dominate species for the northern dry forest, the three most dominant of which, in order of importance, are jack pine (*Pinus banksiana* Lamb.), red pine (*Pinus resinosa* Aniton), and white pine (*Pinus strobus* L.). Additionally, Curtis identified red pine as one of two "species which attain optimum importance" in this community (Curtis, 1959: 537). This finding coincides with the findings of the second eigenvector values, which shows that red pine is the most strongly associated coefficient of the axis with a value of 0.516.

It is important to recognize that although jack pine was considered the most important tree identified by Curtis, red pine was identified as reaching its maximum growth potential in this community. This is most likely accounted for by the influence of interspecies competition, as previously discussed. Due to the strong connection between the findings of Curtis and the eigenvector results of this study, the second principal component equation would best be described as a northern dry forest equation.

$$PLANT = -0.420 + [((SL-8.000)*7.765^{-1})*(0.488)] \quad \mathbf{(2)}$$
$$+ [((FR-4.571)*6.760^{-1})*(0.875)]$$
$$+ [((AW-0.122)*0.040^{-1})*(-1.979)]$$
$$+ [((AW-0.122)*0.040^{-1})* ((AW-0.122)*0.040^{-1})*(0.773)]$$
$$+ [((TP-3.121)*1.267^{-1})*((FR-4.571)*6.760^{-1})*(0.686)]$$
$$+ [((TP-3.121)*1.267^{-1})*((CL-8.915)*4.138^{-1})*(0.632)]$$
$$+ [((TP-3.121)*1.267^{-1})*((BD-1.506)*0.084^{-1})*(-0.338)]$$
$$+ [((FR-4.571)*6.760^{-1})*((HC-5.227)*4.302^{-1})*(1.925)]$$
$$+ [((FR-4.571)*6.760^{-1})*((PH-5.971)*0.671^{-1})*(-0.482)]$$
$$+ [((FR-4.571)*6.760^{-1})*((OM-1.995)*1.201^{-1})*(1.299)]$$
$$+ [((CL-8.915)*4.138^{-1})*((HC-5.227)*4.302^{-1})*(-0.831)]$$
$$+ [((BD-1.506)*0.084^{-1})*((HC-5.227)*4.302^{-1})*(0.622)]$$

Principal Component 3 Equation: Wet Mesic Model

Equation 3 shows the equation developed for the third principal component. The equation explains 87.68% of the variance.

The eigenvector coefficients that were strongly associated with the third principal component were red maple and white spruce (refer to Table 5). Both of these species are considered to be well suited for growth in more lowland conditions or transitional zones between wet lowlands and uplands. Curtis identified black spruce (*Picea mariana* [Mill.] Britton, Sterns and Poggenb.) as the most dominant species in northern lowland forests. The study showed that although white spruce (*Picea glauca* [Moench] Voss) was found in some stands, numbers of observed trees were limited. Both species prefer comparable soils and have similar North American distributions that cover portions of the northern United States and much of Canada. While these two species commonly occur together in more northern limits of their distributions, white spruce is often "out competed" by black spruce in southern range limits (Rook, 2002), which could account for the low occurrence of the species in the areas surveyed. Although black spruce growth rates were not included in the available data provided by the NRCS, due to the commonalities between white spruce and black spruce, these species have been considered comparable species for analytical purposes of this model.

White spruce is known to grow poorly in soils with high water tables yet is not considered a true wet lowland plant but rather is most commonly found in transitional zones between swampy lowlands and uplands or in alluvial zones. Similarly, red maple (*Acer rubrum* L.) is commonly associated with a wide variety of wet sites and transitional zones. The strong associations of these species to the third principal component would suggest that this axis could be best described as a wet mesic model or an alluvial zone model.

$$
\begin{aligned}
PLANT = -0.648 &+ [((TP-3.121)*1.267^{-1})*(-0.566)] \\
&+ [((SL-8.000)*7.765^{-1})*(0.854)] \\
&+ [((FR-4.571)*6.760^{-1})*(-1.422)] \\
&+ [((AW-0.122)*0.040^{-1})*(-0.538)] \\
&+ [((TP-3.121)*1.267^{-1})*((TP-3.121)*1.267^{-1})*(0.671)] \\
&+ [((SL-8.000)*7.765^{-1})*((SL-8.000)*7.765^{-1})*(-0.243)] \\
&+ [((CL-8.915)*4.138^{-1})*((CL-8.915)*4.138^{-1})*(-1.518)] \\
&+ [((BD-1.506)*0.084^{-1})*((BD-1.506)*0.084^{-1})*(0.664)] \\
&+ [((HC-5.227)*4.302^{-1})*((HC-5.227)*4.302^{-1})*(-1.334)] \\
&+ [((AW-0.122)*0.040^{-1})*((AW-0.122)*0.040^{-1})*(0.577)] \\
&+ [((PH-5.971)*0.671^{-1})*((PH-5.971)*0.671^{-1})*(-0.240)]
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
&+ [((TP-3.121)*1.267^{-1})*((FR-4.571)*6.760^{-1})*(-1.906)] \\
&+ [((TP-3.121)*1.267^{-1})*((BD-1.506)*0.084^{-1})*(-1.634)] \\
&+ [((TP-3.121)*1.267^{-1})*((HC-5.227)*4.302^{-1})*(-2.135)] \\
&+ [((TP-3.121)*1.267^{-1})*((AW-0.122)*0.040^{-1})*(-1.530)] \\
&+ [((TP-3.121)*1.267^{-1})*((PH-5.971)*0.671^{-1})*(-0.803)] \\
&+ [((SL-8.000)*7.765^{-1})*((FR-4.571)*6.760^{-1})*(0.538)] \\
&+ [((SL-8.000)*7.765^{-1})*((BD-1.506)*0.084^{-1})*(0.471)] \\
&+ [((SL-8.000)*7.765^{-1})*((HC-5.227)*4.302^{-1})*(0.548)] \\
&+ [((SL-8.000)*7.765^{-1})*((AW-0.122)*0.040^{-1})*(0.612)] \\
&+ [((SL-8.000)*7.765^{-1})*((PH-5.971)*0.671^{-1})*(0.280)] \\
&+ [((FR-4.571)*6.760^{-1})*((CL-8.915)*4.138^{-1})*(-8.013)] \\
&+ [((FR-4.571)*6.760^{-1})*((HC-5.227)*4.302^{-1})*(-1.469)] \\
&+ [((FR-4.571)*6.760^{-1})*((AW-0.122)*0.040^{-1})*(2.057)] \\
&+ [((FR-4.571)*6.760^{-1})*((PH-5.971)*0.671^{-1})*(1.270)] \\
&+ [((FR-4.571)*6.760^{-1})*((OM-1.995)*1.201^{-1})*(0.631)] \\
&+ [((CL-8.915)*4.138^{-1})*((HC-5.227)*4.302^{-1})*(-5.909)] \\
&+ [((CL-8.915)*4.138^{-1})*((AW-0.122)*0.040^{-1})*(-1.469)] \\
&+ [((BD-1.506)*0.084^{-1})*((OM-1.995)*1.201^{-1})*(-1.134)] \\
&+ [((HC-5.227)*4.302^{-1})*((AW-0.122)*0.040^{-1})*(1.504)] \\
&+ [((HC-5.227)*4.302^{-1})*((PH-5.971)*0.671^{-1})*(1.082)]
\end{aligned}
$$

One concern with naming the third principal component model the wet mesic model is that Curtis found jack pine (*Pinus banksiana* Lamb.) to show a spike in occurrence in the wet mesic range as illustrated in Fig. 5. However, the eigenvalues of this axis indicate that jack pine was strongly negatively associated with the model with a value of -0.411 (refer to Table 5). This strong negative association could cause some explanatory concern for this model. However, because jack pine results showed a strong positive association with the second principal component and a strong negative association with the third principal component, neither axis is considered to be truly descriptive of the species. It is therefore necessary to develop an additional model that combines these two axes to best predict the productivity potential of jack pine.

<u>Jack Pine Model</u>

An equation was developed specifically for jack pine due to the findings of the principal component analysis. As illustrated in Table 5, the eigenvector values for jack pine in both the second and the third principal components were either greater than 0.4 or less than -0.4 showing that this species is strongly associated with both axes. Because there are two models that could be used to predict the vegetative productivity of jack pine, neither model alone is best suited as a predictive model for this species. Therefore, it is necessary to develop an additional model that is most reliable to predict the vegetative productivity of jack pine.

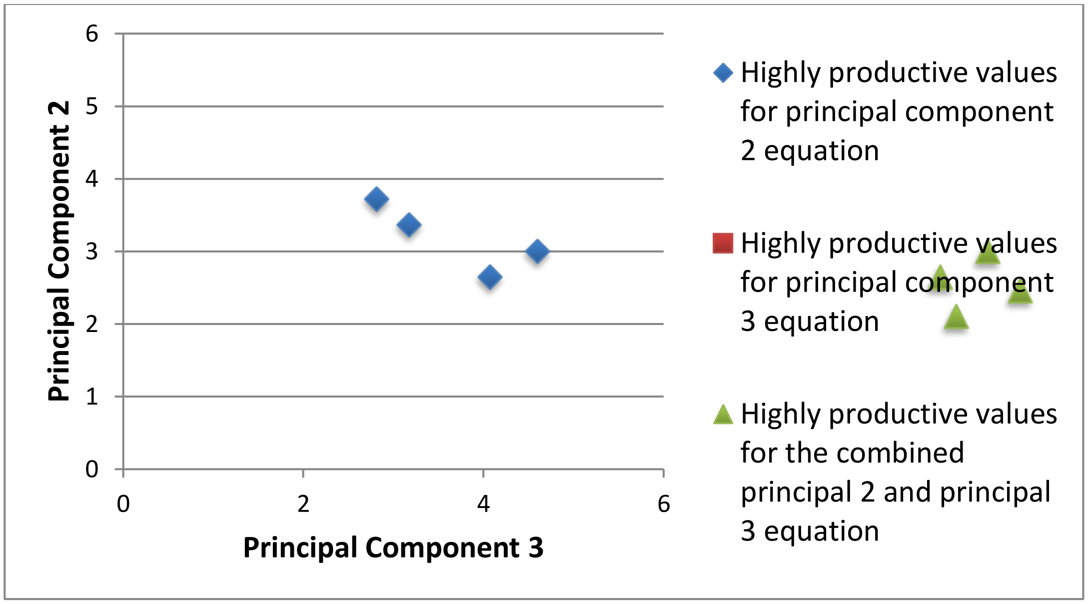

Figure 5. Plot of hypothetical values to illustrate potential findings of principal component 2 and principal component 3 as separate axes and a combined axis that shows the most reliable jack pine axis.

Figure 5 illustrates a plotting of hypothetical findings of equations that could be derived from the second and the third principal components. The values plotted are not derived from any developed equation, but rather are used to illustrate that combining the principal component 2 axis with the principal component 3 axis will result in a new axis that will most accurately describe the productivity of jack pine. By using only one model, the reliability of the results is not as strong, as shown by plot points near the x or y axes. By combining the two equations the predictability of the model is not split between two axes, but rather combined into one that specifically describes one plant, jack pine. Results from such a model would show trends more similar to those of the combined principal 2 and principal 3 equations' plot points. As this illustration suggests, the most accurate equation to predict the productivity potential of jack pine would be derived by combining the equations developed from principal component 2 and principal component 3.

Equation 4 shows the best equation that describes jack pine. The equation is considered to be highly specific and explains 65.33% of the variance. This model was developed by multiplying the equation from each dimension that was strongly associated with jack pine. It should be noted that the second equation, that of principal component 3, was multiplied by a factor of -1 to reverse the association with this species. This equation should be used to most accurately predict the vegetative productivity of jack pine.

$$
\begin{aligned}
\mathrm{PLANT} = \{&-0.420 + [((SL-8.000)*7.765^{-1})*(0.488)] \\
&+ [((FR-4.571)*6.760^{-1})*(0.875)] \\
&+ [((AW-0.122)*0.040^{-1})*(-1.979)] \\
&+ [((AW-0.122)*0.040^{-1})*((AW-0.122)*0.040^{-1})*(0.773)] \\
&+ [((TP-3.121)*1.267^{-1})*((FR-4.571)*6.760^{-1})*(0.686)] \\
&+ [((TP-3.121)*1.267^{-1})*((CL-8.915)*4.138^{-1})*(0.632)] \\
&+ [((TP-3.121)*1.267^{-1})*((BD-1.506)*0.084^{-1})*(-0.338)] \\
&+ [((FR-4.571)*6.760^{-1})*((HC-5.227)*4.302^{-1})*(1.925)] \\
&+ [((FR-4.571)*6.760^{-1})*((PH-5.971)*0.671^{-1})*(-0.482)] \\
&+ [((FR-4.571)*6.760^{-1})*((OM-1.995)*1.201^{-1})*(1.299)] \\
&+ [((CL-8.915)*4.138^{-1})*((HC-5.227)*4.302^{-1})*(-0.831)] \\
&+ [((BD-1.506)*0.084^{-1})*((HC-5.227)*4.302^{-1})*(0.622)]\} \\
&\qquad * \\
&\{[-0.648 + [((TP-3.121)*1.267^{-1})*(-0.566)] \\
&+ [((SL-8.000)*7.765^{-1})*(0.854)] \\
&+ [((FR-4.571)*6.760^{-1})*(-1.422)] \\
&+ [((AW-0.122)*0.040^{-1})*(0.538)] \\
&+ [((TP-3.121)*1.267^{-1})*((TP-3.121)*1.267^{-1})*(0.671)] \\
&+ [((SL-8.000)*7.765^{-1})*((SL-8.000)*7.765^{-1})*(-0.243)] \\
&+ [((CL-8.915)*4.138^{-1})*((CL-8.915)*4.138^{-1})*(-1.518)] \\
&+ [((BD-1.506)*0.084^{-1})*((BD-1.506)*0.084^{-1})*(0.664)] \\
&+ [((HC-5.227)*4.302^{-1})*((HC-5.227)*4.302^{-1})*(-1.334)] \\
&+ [((AW-0.122)*0.040^{-1})*((AW-0.122)*0.040^{-1})*(0.577)] \\
&+ [((PH-5.971)*0.671^{-1})*((PH-5.971)*0.671^{-1})*(-0.240)] \\
&+ [((TP-3.121)*1.267^{-1})*((FR-4.571)*6.760^{-1})*(-1.906)] \\
&+ [((TP-3.121)*1.267^{-1})*((BD-1.506)*0.084^{-1})*(-1.634)] \\
&+ [((TP-3.121)*1.267^{-1})*((HC-5.227)*4.302^{-1})*(-2.135)] \\
&+ [((TP-3.121)*1.267^{-1})*((AW-0.122)*0.040^{-1})*(-1.530)] \\
&+ [((TP-3.121)*1.267^{-1})*((PH-5.971)*0.671^{-1})*(-0.803)] \\
&+ [((SL-8.000)*7.765^{-1})*((FR-4.571)*6.760^{-1})*(0.538)] \\
&+ [((SL-8.000)*7.765^{-1})*((BD-1.506)*0.084^{-1})*(0.471)] \\
&+ [((SL-8.000)*7.765^{-1})*((HC-5.227)*4.302^{-1})*(0.548)] \\
&+ [((SL-8.000)*7.765^{-1})*((AW-0.122)*0.040^{-1})*(0.612)] \\
&+ [((SL-8.000)*7.765^{-1})*((PH-5.971)*0.671^{-1})*(0.280)] \\
&+ [((FR-4.571)*6.760^{-1})*((CL-8.915)*4.138^{-1})*(-8.013)] \\
&+ [((FR-4.571)*6.760^{-1})*((HC-5.227)*4.302^{-1})*(-1.469)] \\
&+ [((FR-4.571)*6.760^{-1})*((AW-0.122)*0.040^{-1})*(2.057)] \\
&+ [((FR-4.571)*6.760^{-1})*((PH-5.971)*0.671^{-1})*(1.270)] \\
&+ [((FR-4.571)*6.760^{-1})*((OM-1.995)*1.201^{-1})*(0.631)] \\
&+ [((CL-8.915)*4.138^{-1})*((HC-5.227)*4.302^{-1})*(-5.909)] \\
&+ [((CL-8.915)*4.138^{-1})*((AW-0.122)*0.040^{-1})*(-1.469)] \\
&+ [((BD-1.506)*0.084^{-1})*((OM-1.995)*1.201^{-1})*(-1.134)] \\
&+ [((HC-5.227)*4.302^{-1})*((AW-0.122)*0.040^{-1})*(1.504)] \\
&+ [((HC-5.227)*4.302^{-1})*((PH-5.971)*0.671^{-1})*(1.082)]] \quad * -1\}
\end{aligned}
\qquad \textbf{(4)}
$$

Limitations of the Study

Although the models investigated in this study all explained significant amounts of variance, there are some factors that were not considered that could have strengthened the study. Firstly, there is a general lack of consideration for post-mined nutrient conditions. Nutrients are often leached from spoil piles greatly limiting the abilities of soils to support the growth of a wide variety of vascular species, including the crop and woody plant species investigated in this study. The loss of soil nutrients from disturbed soils makes it difficult to compare soils measured in soil surveys that have an established A horizon and functioning nutrient cycles.

Reestablishment of nutrient contents throughout soil profiles that are similar to concentrations found in undisturbed soils is often a lengthy process. Research by Ottenhof et al. (2007) suggests that soil organic matter as it relates to N, P, S, K, Ca, Na, and Mg concentrations, is largely dependent upon the species grown. In this study, the reestablishment of soil organic content in post-mined soils to pre-mined conditions ranged from estimates of 30 to 120 years. Acton et. al. (2011) identified the soil organic carbon content as an indicator of soil health; however, carbon concentrations were found to be greatly limited to the first 10 cm of soil on mined soils of up to 14 years since reclamation. Berg (1975) identified nitrogen as the most limiting factor on mine tailings in Colorado. Often disturbed soils are planted with plants associated with nitrogen fixation such as member of the legume family, including clover, soybean, or alfalfa (Berg, 1975) to initiate the nitrogen cycle in deficient soils. However, establishment of a sustainable nitrogen system can take years. Although bringing soil nutrient levels equal to or greater than pre-mined conditions throughout soil profiles may take a considerable amount of time, bringing these concentrations to adequate levels to foster vegetative growth may take much less time.

Microorganism populations in post-mined soils are often much smaller when compared to undisturbed soils and restoration of populations takes time. Jeanne et al. (2019), Harris (2009, 2003), Jasper (2007), Růžek et al. (2012), as well as Whitford and Elkins (1986) emphasized the importance of soil microorganisms to ecosystems and recommended proper soil management during restoration to ensure biological health of the system. There is no variable that has been explored in this study that addresses the microfauna of soils directly. Wen and Burley (2020a) discuss the possibilities of using such variables in the future.

The variables presented in this study are not a fully comprehensive set of soil quality indicators, but rather a set of variables which experts that developed county soil surveys have identified as significant soil parameters. Further exploration of possible variables should be conducted to strengthen variance explanations. Furthermore, it is important to recognize that these equations are regional and land-use based. Regional factors may be included as the importance of soil attributes that affect plant productivity are identified within various regions of study. For instance, electric conductivity, as an indicator of soluble salts in the soil, was not included in this study because salt content is not commonly considered a major limiting factor for plants in the Upper Peninsula of Michigan. Instead, electric conductivity would more likely be used to assess soil quality in arid regions such as the southwestern United States (Scholl, 1986).

Some regional factors that have not been explicitly included in this study are still represented in the data set. For instance, there are many regions throughout the study that are characterized by shallow soils and outcrops that would be expected to limit growth of larger species, however, depth to bedrock was not one of the independent variables investigated in this study. Although not represented with their own independent variable, bedrock depths were measured to be within the first 48 inches of certain soil profiles. The observed properties of the impermeable rock did influence the soil attribute values associated with that soil type. For instance, the bulk density of bedrock is considerably greater for all soil types in this region and would therefore produce relatively high values for these soils. Similarly, the values of hydraulic conductivity, percent clay content, organic matter content, and percent rock fragments would all be heavily influenced by the presence of bedrock within the first 48 inches of earth.

Frost heave was identified by Linsemier (1989) as being a significant regional factor that affects plant growth. Frost heave is generally associated with soil texture, depth of soil, and depth of water table. As soils holding high amounts of water freeze and therefore expand and shift, root systems are damaged and trees can be uprooted. The harsh winters and shallow soils throughout the region make frost heave an issue of major concern to the productivity of plants. Although soil texture and depth to water table are attributes not directly expressed in the equation as independent variables, the measured properties used to create the data set for accounting for the influence of them were considered adequate. The texture of the soil is partially accounted for by the parameters, percent clay and percent rock fragments, although could be strengthened by including other texture variables such as percent sand content. As previously mentioned, depth to bedrock is represented in the equations as the values of bedrock with the first 48 inches of soil affect attribute values. Depth to water table is largely unrepresented in this investigation. The soil surveys used to derive soil data showed no crop or woody plant growth values for soils with high water tables, commonly classified as mucks. It may therefore be beneficial to investigate other variables that account for the influence of high-water tables.

The equations derived from this methodology are also land-use based. The concept of land use includes uses before, during, and the intended land use after mining. Land use prior to mining as it relates to soil conditions is usually not a major concern for most reclamation projects. However, rare instances in which industrial use could have contaminated soils prior to mining could affect the reapplied A horizon of the post-mined soil. Soil contamination is most likely to occur during the mining operations themselves. Soil contaminates can greatly influence the soil quality and therefore the productivity potential of soils. Soil toxicity was not considered a major variable to be considered in the development of the models due to the type of mineral extraction that is currently being conducted in this region.

According to the United States Department of the Interior, U.S. Geological Survey, there are currently no active mining operations in Iron County or Dickinson County (USGS, 2012), the equations are to be applied on a regional basis to be applied directly to a mine reclamation effort. The Tilden and Empire Mines are located in the adjacent, Marquette County. Both mines are open pit iron mines. Iron mining is associated with relatively low occurrence of toxic materials that persist in the soil when compared to the mining of many other materials, such as gold, silver, nickel, or copper sulfide. The presented equations can only be applied to mining of relatively inert substances such as sand, gravel, coal, and iron when compared to mineral extraction processes that result in more hazardous chemicals. However, the recent opening of a copper and nickel mine in Marquette County may warrant the addition of further variable investigation if being applied to this site. In September of 2011, the Kennecott Eagle Minerals Company began underground copper and nickel mining operation. Bech et al. (1997) reported the presence of Cu, Zn, Pb, Co, Ni, Cd, and As in soils surrounding copper mines. Although the types of metal contaminates that are associated with copper mining depends on the ore being mined, it is possible that some or all of these contaminants are present in post-mined soils from this operation. Bech et al. (1997) linked the availability of these elements to uptake by vegetation to soil parameters suggesting that the exploration of such variables is beneficial. It may be beneficial to investigate additional variables and redevelop the models if this study intends to be accurately applied to mines that result in toxic materials.

The selection of crop and woody plant types in this study is also a limiting factor to its use. Plant types were selected based on the NRCS data that was available. Although the methodology presented in this study can be applied to any available data set, species are limited in this case due to the data set being derived from a secondary source. Species are therefore limited to those published in soil surveys. Increasing the number of species could have varying effects on resulting equations. Firstly, it may give a more accurate indication on the community type that the eigenvector describes. Investigating a broader array of plant types could also develop equations for plant or community types that were not investigated in this study. However, as previously stated, data collection for use in such equations is both time consuming and costly. The methodology employed in this study presents a cost-effective process for the development of empirical models to predict vegetative productivity potentials of post-mined soils.

Conclusions

Since the efforts of instigators such as Vories (1985) and Doll and Wallenhaupt (1985), the development and generation of vegetation soil productivity equations have slowly evolved for reclaiming disturbed landscapes. This article presents several equations for a mining region in the Upper Peninsula of Michigan, in mesic, xeric, and somewhat wet-mesic settings. The equations are highly specific and explain a fair amount of the variance across soil profiles. These equations may eventually contribute to the development of a set of equations predicting soil productivity for the eastern United States

Literature Cited

Acton, P., J.F. Fox, J.E. Campbell, A.L. Jones, H. Rowe, D. Martin, and S. Bryson. 2011. Role of soil health in maintaining environmental sustainability of surface coal mining. Environmental Science and Technology 45(23): 10265-10272. https://doi.org/10.1021/es202764q

Albert, D.A. 1995. Regional Landscape Ecosystems Of Michigan, Minnesota And Wisconsin: A Working Map And Classification. General Technical Report NC-178. U.S. Department of Agriculture, Forest Service, North Central Forest Experiment Station: St. Paul, MN:

Agresti, A., and C. Franklin. 2012. Statistics: The Art and Science Of Learning From Data. Pearson College Division: London, United Kingdom, 3rd edition.

Bai, Y., Q. Chang, C. Guo, J.B. Burley, and S. Partin. 2016. Neo-sol productivity models for disturbed lands in Wisconsin and Georgia, USA. International Journal of Energy and Environment, 10: 52-60.

Baker, J.B., and W.M. Broadfoot. 1978. A new technique of site selection for hardwoods. Southern Journal of Applied Forestry, 2:42-43. https://doi.org/10.1093/sjaf/2.2.42

Baker, J.B., and W.M. Broadfoot. 1979. A Practical Field Method Of Site Evaluation For Commercially Important Southern Hardwoods. U.S. Department of Agriculture, Forest Service, Southern Forest Experiment Station (General Technical Report SO-26). U.S. Department of Agriculture, Forest Service, Southern Forest Experiment Station: Asheville, North Carolina.

Barnhisel, R.I., and J.M. Hower. 1994. The use of productivity index to predict corn yields of restored prime farmland. *In*: International Land Reclamation and Mine Drainage Conference and the Third International Conference on the Abatement of Acidic Drainage: Volume 3 of 4: Vegetation and Reclamation; Bureau of Mines Special Publication SP 06D-94. United States Department of the Interior: Pittsburgh, PA, USA: 20–27. https://doi.org/10.21000/JASMR94030020

Barnhisel, R.I., J.M. Hower, and L.D. Beard. 1992. Development of a soil productivity model for use in prime farmland reclamation. *In* Dunker R.E., R.I. Barnhisel, and R.G. Darmody (eds.): Prime Farmland Reclamation National Symposium, (St. Louis, Missouri). Department of Agronomy, University of Illinois: Champaign, Illinois: 205-211.

Bech, J., C. Poschenrieder, M. Llugany, J. Barcelo, P. Tume, F.J. Tobias, and J.L. Barranzuela. 1997. Arsenic and heavy metal contamination of soil vegetation around a copper min in Northern Peru. The Science of the Total Environment, 203(1): 83-91. https://doi.org/10.1016/S0048-9697(97)00136-8

Belli, K.L., J.D. Hodges, and C.G. Jeffery. 1998. Site productivity assessment for cherrybark oak on minor stream bottoms in Mississippi: a comparison on methods. Southern Journal of Applied Forestry, 22(1): 7-10. https://doi.org/10.1093/sjaf/22.1.7

Berg, W.A. 1975. Revegetation of land disturbed by surface mining in Colorado. *In* M. Wali (ed.): Practices and Problems of Land Reclamation in Western North America. The University of North Dakota Press: Grand Forks, ND: 79-89.

Burger, J.A., J.E. Johnson, J.A. Andrews, and J.L. Torbert. 1994. Measuring mine soil productivity for forests. *In*: International Land Reclamation and Mine Drainage Conference and Third International Conference on the Abatement of Acid Drainage, volume 3: Reclamation and Revegetation. United States Department of the Interior, Bureau of Mines Special Publication SP 06-94: 48-56 https://doi.org/10.21000/JASMR94030048

Burley, J.B. 1984. Landscaping after the elms are gone. The Minnesota Horticulturist, 112:100-103,107,108.

Burley, J.B. 1986. Gardens among evergreens. The Minnesota Horticulturist, 114(1):4-5,10-11, 22.

Burley, J.B., and C.J. Burley. 1989. River scaping. The Minnesota Horticulturist 117(6):6-8.

Burley, J. B. 1990. Sugar beet productivity model for Clay County, Minnesota. Journal of Sugar Beet Research, *27*(3&4): 50-57. https://doi.org/10.5274/jsbr.27.3.50

Burley, J.B. 1994. Vegetation productivity equation compatibility with selected state environmental reclamation laws and regulations. *In*: International Land Reclamation and Mine Drainage Conference and the Third International Conference on the Abatement of Acidic Drainage: Volume 4 or 4: Abandoned Mined Lands and Topical Issues. United States Department of the Interior, Bureau of Mines Special Publication SP 06D-94: 294-303. https://doi.org/10.21000/JASMR94040294

Burley, J.B. 1995a. Vegetation Productivity Soil Reclamation Equations For The North Dakota Coal Fields. Doctoral dissertation (Landscape Architecture), University of Michigan: Ann Arbor, Michigan.

Burley, J.B. 1995b. A multi-county vegetation productivity equation for soil reclamation. *In* Hynes, T.P. and Blanchette, M.C. (eds.): Proceedings of Sudbury '95-Mining and the Environment. CANMET: Ottawa, Ontario, (3): 1113-1112.

Burley, J.B. 1996. Methodology for building soil-based vegetation productivity equations: a statistical approach. *In* Daniels, W.L., J. Burger, C.E. Zipper (eds.): Proceedings Thirteenth

Annual Meeting American Society for Surface Mining and Reclamation: Successes and Failures: Applying Research Results to Insure Reclamation Success (May 18-23, 1996, Knoxville, Tennessee). Virginia Tech Research Division, Powell River Project, Blacksburg, Virginia: 789-798. https://doi.org/10.21000/JASMR96010789

Burley, J.B. 1999. A spatial application of a vegetation productivity equation for neo-sol reconstruction. *In*: 1999 Proceedings Mining and Reclamation for the Next Millennium. August 13-19, 1999 American Society for Surface Mining and Reclamation 16th Annual National Meeting in conjunction with Western Region Ash Group 2nd Annual Forum, American Society for Surface Mining and Reclamation: Scottsdale, Arizona: 708-714. https://doi.org/10.21000/JASMR99010708

Burley, J.B. (ed.). 2001. Environmental Design for Reclaiming Surface Mines. Edwin Mellen Press: Lewiston, New York.

Burley, J.B., and A. Bauer. 1993. Neo-soil vegetation productivity equations for reclaiming disturbed landscapes: a central Florida example. *In* B. A. Zamora and R. E. Conally (eds.): The Challenges of Integrating Diverse Perspectives in Reclamation: Proceedings of the 10th Annual National Meeting of the American Society for Surface Mining and Reclamation. American Society for Surface Mining and Reclamation, Spokane, Washington: 334-347. https://doi.org/10.21000/JASMR93010334

Burley, J.B., and T.J. Brown. 1995. Constructing interpretable environments from multidimensional data: GIS suitability overlays and principal component analysis. Journal of Environmental Planning and Management, 38(4): 537-550. https://doi.org/10.1080/09640569512805

Burley, J.B., G.W. Fowler, K. Polakowski, and T.J. Brown. 2001. Soil based vegetation productivity model for the North Dakota coal mining region. International Journal of Surface Mining, Reclamation, and Environment, 15(4): 213-234. https://doi.org/10.1076/ijsm.15.4.213.7415

Burley, J.B., and D. Gray. 2001. Soil ordination: implications for post-mining disturbance land-uses. *In* Vincent, R., J.A. Burger, G.G. Marino, G.A. Olyphant, S.C. Wessman, R.G. Darmody, T.C. Richmond, S.A. Bengson, and J.R. Nawrot (eds.): Land Reclamation -- A Different

Approach. June 3-7, American Society for Surface Mining and Reclamation, Albuquerque, New Mexico: 241-245. https://doi.org/10.21000/JASMR01010241

Burley, J.B., N. Li, J. Ying, H. Tian, and S. Troost. 2016. Chapter 3: Metrics in master planning low impact development for Grand Rapids, Michigan. *In* Egren, M. (ed.): Sustainable Urbanization. Intech: Rijeka, Croatia: 61- 86. https://doi.org/10.5772/63708

Burley, J.B., V.B.P. Singhal, C.J. Burley, D. Fasser, C. Churchward, D. Hellekson, and I. Raharizafy. 2009. Citation analysis of transportation research literature: a multi-dimensional map of the roadside universe. Landscape Research, 34(4): 481-495. https://doi.org/10.1080/01426390903009297

Burley, J.B., and C. Thomsen. 1987. Multivariate techniques to develop vegetation productivity models for neo-sols. *In* D.H. Graves (ed.): Proceedings, 1987 Symposium on Surface Mining, Hydrology, Sedimentology and Reclamation (Lexington, Kentucky). Office of Scientific and Technical Information, United States Department of Energy: Washington, D.C.: 153-161.

Burley, J.B., and C.H. Thomsen. 1990. Application of an agricultural soil productivity equation for reclaiming surface mines: Clay County, Minnesota. International Journal of Surface Mining and Reclamation, *4*, 139-144. https://doi.org/10.1080/09208119008944181

Burley, J.B., C.H. Thomsen, and N. Kenkel. 1989. Development of an agricultural soil productivity equation for reclaiming surface mines in Clay County, Minnesota. Environmental Management, *13*(5), 631-638. https://doi.org/10.1007/BF01874969

Burley, J.B., Z. Wu, S. He, and X. Li. 2020. Soil-based vegetation productivity models for disturbed lands along the northern and central, western Great Plains, USA. Journal of Advanced Agricultural Technologies, 7 (1): 1-7. https://doi.org/10.18178/joaat.7.1.1-7

Burras, C.L., G.A. Miller, T.E. Fenton, and A.M. Sassman. 2015. Corn Suitability Rating 2 (CSR2) Equation and Component Values. Iowa State University: Ames, Iowa.

Casault, J., and J.B. Burley. 2010. Restored Versailles: A French Garden with a message. The Michigan Landscape, November/December: 37-42.

Chang, Q., Y. Bai, J.B. Burley, and S. Partin. 2015. Soil-based vegetation productivity model for mined lands in Chippewa County, Wisconsin. *In* Bulucea, A. (ed.): Recent Advances in Environment, ecosystems and Development. Proceedings of the 13th International Conference on Environment, Ecosystems and Development (EED'15), (Kuala Lumpur, Malaysia, April 23-25). WSEAS, Energy, Environmental and Structural Engineering Series, 35: 15-22.

Corwin, D.L., and S.M. Lesch. 2005. Apparent soil electric conductivity measurements in agriculture. Computers and Electronics in Agriculture, 46(1-3), 11-43. https://doi.org/10.1016/j.compag.2004.10.005

Curtis, J.T. 1959. The Vegetation Of Wisconsin: An Ordination Of Plant Communities. Wisconsin Press: Madison, Wisconsin.

Dancer, W.S., and I.J. Jansen. 1981. Greenhouse evaluation of solum and substratum materials in the southern Illinois coal field. Journal of Environmental Quality, *10*, 396-400. https://doi.org/10.2134/jeq1981.00472425001000030031x

Doll, E. C., S.D. Merril, and G.A. Halvorson. 1984. Soil replacement for reclamation of strip mined lands in North Dakota. Bulletin of the North Dakota Agricultural Experiment Station, 514.

Doll, E.C., and N.C. Wollenhaupt. 1985. Use of soil parameters in the evaluation of reclamation success in North Dakota. ASSMR Second Annual Meeting. American Society for Surface Mining and Reclamation: Denver, Colorado: 91-94. https://doi.org/10.21000/JASMR85010094

Friedlander, J. 2001. Design principles for reclamation of agricultural lands. *In* J. B. Burley (ed.): Environmental Design For Reclaiming Surface Mines. Edwin Mellen Press: Lewiston, New York: 155-183.

Fleurant, C., J.B. Burley, L. Loures, W. Lehmann, and J. McHugh. 2009. Inverse box-counting method and application: a fractal-based procedure to reclaim a Michigan surface mine. WSEAS Transactions on Environment and Development, 5(1): 76-89.

Gale, M. R., D.F. Grigal, and R.B. Harding. 1991. Soil productivity index: prediction of site quality for white spruce plantations. Soil Science Society of America Journal, *55*: 1701-1708. https://doi.org/10.2136/sssaj1991.03615995005500060033x

Groninger, J.W., W.W. Aust, M. Miwa, and J.A. Stanturf. 2000. Growth predictions for tree species planted on marginal soybean lands in the Lower Mississippi Valley. Journal of Soil and Water Conservation, 55(1): 91-95.

Harris, J.A. 2003. Measurements of the soil microbial community for estimating the success of restoration. European Journal of Soil Science, 54: 801–808. https://doi.org/10.1046/j.1351-0754.2003.0559.x

Harris, J.A. 2009. Soil microbial communities and restoration ecology: Facilitators or followers? Science, 325: 573–574. https://doi.org/10.1126/science.1172975

Humphries, R.N., R.J.K. Thompson, and M.D. Heames. 2019. Case study: Appraisal of four soil-based metrics in the establishment of sustainable upland grassland at a mine site in south Wales, United Kingdom. Journal of the American. Society for. Mining and. Reclamation*:* 1–21, https://doi.org/10.21000/JASMR19030001

Jasper, D.A. 2007. Beneficial soil microorganisms of the Jarrah forest and their recovery in bauxite Southwestern Australia. Restoration Ecology, 15: S74–S84. https://doi.org/10.1111/j.1526-100X.2007.00295.x

Kendall, M.G. 1939. The geographical distribution of crop productivity in England. Journal of the Royal Statistical Society, *102*: 21–48, https://doi.org/10.2307/2980138.

Koski, A.E. 2005. Reclamation of waste rock stockpiles utilizing paper mill residuals at Cliffs Michigan Mining Company. *In* Barnhisel, R.I. (ed.): 2005 National Meeting of the American Society of Mining and Reclamation, (June 19-23, 2005, Breckenridge, Colorado). American Society of Surface Mining and Reclamation: Lexington, Kentucky: 627-644. https://doi.org/10.21000/JASMR05010627

Lehmann, W.J., J.B. Burley, C. Fleurant, L. Loures, and A. MacDowell. 2013. Replicating species-based fractal patterns for reclaiming northern Michigan waste rock piles. Journal of the American Society of Mining and Reclamation, 2(2):175-194. https://doi.org/10.21000/JASMR13010114

Kraft, L.S., T.R. Crow, D.S. Buckley, E.A. Nauertz, and J.C. Zasadae. 2004. Effects of harvesting and deer browsing on attributes of understory plants in northern hardwood forests, Upper Michigan, USA. Forest Ecology and Management, 199(2-3): 219-230. https://doi.org/10.1016/j.foreco.2004.05.044

Le Cleac'h, G., M. Salles, and J.B. Burley. 2004. Vegetation productivity model for Grand Traverse County, Michigan. *In* Barnhisel, R.I. (ed.): 21st National Meeting of the American

Society of Mining and Reclamation and The 25th West Virginia Surface Mine Drainage Task Force (Morgantown, West Virginia, April 18-24, 2004). American Society of Mining and Reclamation: Lexington, Kentucky: 1176-1191. https://doi.org/10.21000/JASMR04011176

Linsemier, L.H. 1989. Soil survey of Dickinson County, Michigan. Natural Resources Conservation Service: Washington, D.C.

Linsemier, L.H. 1997. Soil survey of Iron County, Michigan. Natural Resources Conservation Service: Washington, D.C..

McNab, W.H., D.T. Cleland, J.A. Freeouf, J.E. Keys Jr., G.J. Nowacki, and C.A. Carpenter. 2005. Description Of Ecoregional Subregions: Sections Of The Conterminous United States. U.S. Department of Agriculture, Forest Service: Washington, DC. (5-8).

McSweeney, K., I.J. Jansen, and W.S. Dancer. 1981. Subsurface horizon blending: An alternative strategy to B horizon replacement for the construction of post-mine soils. Soil Science Society of America Journal, *45*: 795-799. https://doi.org/10.2136/sssaj1981.03615995004500040024x

Neill, L.L. 1979. An Evaluation of Soil Productivity Based on Root Growth and Water Depletion. M.S. Thesis, Univ. of Missouri: Columbia Missouri.

Ottenhof, C.J.M., A. Faz Cano, J.M. Arocena, K.G.J. Nierop, J.M. Verstraten, and J.M. van Mourik, 2007. Soil organic matter from pioneer species and its implications to phytostabilization of mined sites in the Sierra de Cartagena (Spain). Chemosphere, 69(9): 1341-1350. https://doi.org/10.1016/j.chemosphere.2007.05.032

Peng, L., L. Zhanbin, and Z. Zhang. 2002. An index system and method for soil productivity evaluation on the hillsides on the Loess Plateau. *In*: *12th ISCO Conference*. Tsinghua University Press: Beijing China.

Potter, K.N., F.S. Carter, and E.C. Doll. 1988. Physical properties of constructed and undisturbed soils. Soil Science Society of America Journal: 1435-1438. https://doi.org/10.2136/sssaj1988.03615995005200050043x

Power, J.F., F.M. Sandoval, and R.E. Ries. 1978. Restoration of productivity to disturbed land in the northern Great Plains. *In* R.A. Wright (ed.): *Reclamation of Disturbed Arid Lands*. University of New Mexico Press: Albuquerque, New Mexico: 33-49.

Qi, J., S. Wang, J.B. Burley, and T. Machemer. (translated by Sihui Wang). 2012. Defining ecological regions in Michigan based on native tree distributions. Landscape Architecture, 2012(6):138-145.

Rauhe, W., D. Conners, and J.B. Burley. 1994. Beaver Island: bridging geomorphology, ecological processes, and environmental planning and design. *In* Salling, M. (ed.): Integrating Information and Technology: IT Makes Sense: 1994 Annual Conference Proceedings. Urban and Regional Information Systems Association: Washington, D.C.: 634-645.

Reynolds, T.S. 2006. "Quite an experiment": a mining company's attempt to promote agriculture on Michigan's Upper Peninsula, 1895-1915. Agriculture history., 80(1): 64-98. https://doi.org/10.1525/ah.2006.80.1.64

Racevskis, L.A., and F. Lupi. 2005. Comparing rural and urban perceptions of and familiarity with the management of forest ecosystems. Society and Natural Resources, 19(6): 479-495. https://doi.org/10.1080/08941920600663862

Rook, E.J.S. 2002. Flora, fauna, Earth, and sky: The natural history of the north woods. In: *Rook.org*. Retrieved November 2, 2012, from http://www.rook.org/earl/bwca/nature/trees/index.html

Růžek L., M. Růžková, K. Voříšek, J. Vráblíková, and P. Vráblík. 2012. Slit seeded grass-legume mixture improves coal mine reclamation. Plant, Soil and Environ*ment*, *58*(2): 68-75. https://doi.org/10.17221/397/2011-PSE

SAS. 2003 *SAS 9.1*. SAS Institute Inc.: Cary, North Carolina.

Scholl, D.G. 1986. The study of soil water in mine reclamation. *In* C. C. Reith & L. D. Potter (eds.): Principles and Methods of Reclamation Science. University of New Mexico Press: Albuquerque, New Mexico: 151-182.

Snider, R.M., and R.J. Snider. 1986. Evaluation of pit-trap transects with varied trap spacing in a northern Michigan forest. The Great Lakes Entomologist, 19(2): 11p. Available at: https://scholar.valpo.edu/tgle/vol19/iss2/1

Udvardy, M. 1975. A classification of the biogeographical provinces of the world. *In*: UNESCO's Man and the Biosphere Programme Project *No. 8.* (1-50). UNESCO: Morges, Switzerland.

USDA. 1992. Weights, measurements, and conversion factors for agricultural commodities and their products. In: Agriculture Handbook Number 697. U.S. Department of Agriculture: Washington, D.C.

USGS. 2012. Mineral Resources On-Line Spatial Data. In: *USGS.gov*. Retrieved November 1, 2012, from http://mrdata.usgs.gov/mineplant/find-mines.php

Vories, K.C. 1985. Proof of vegetative productivity: research needs. *In* D.H. Graves (ed.): Proceedings, 1985 Symposium on Surface Mining, Hydrology, Sedimentology and Reclamation (Lexington, Kentucky). Office of Scientific and Technical Information, United States Department of Energy: Washington, D.C.: 145-149.

Wang, Y., J.B. Burley, and S. Partin. 2013. Case study: post-mining and lands-use planning and design: an overview. Journal of Mining Reclamation, 2(1):114-135. https://doi.org/10.21000/JASMR13020175

Wen, B., and J.B. Burley. 2020a. Soil-based vegetation productivity model for Coryell County, Texas. Sustainability, 12(5240):1-14. https://doi.org/10.3390/su12135240

Wen, B., and J.B. Burley. 2020b. Expert Opinion Dimensions of Rural Landscape Quality in Xiangxi, Hunan, P.R. of China: Principal Component Analysis and Factor Analysis. Sustainability, 12(4):1316. https://doi.org/10.3390/su12041316

Wick, A.F., S.D. Merrill, T.J. Toy, J. Hendrickson, and M.A. Liebig. 2005. The effects of soil depth and other soil characteristic on plant community development in North Dakota. *In* Barnhisel, R.I. (ed.): 2005 National Meeting of the American Society of Mining and Reclamation, (June 19-23, 2005, Breckenridge, Colorado). American Society of Surface Mining and Reclamation: Lexington, Kentucky: :1233-1243. https://doi.org/10.21000/JASMR0501223

Wick, A.F., S.D. Merrill, T.J. Toy, and M.A. Liebig. 2011. Effect of soil depth and land structure on plant productivity and community development on 28-year old reclaimed mine lands. Journal of Soil and Water Conservation 66: 201-211 https://doi.org/10.2489/jswc.66.3.201

Whitford, W.G., and N.Z. Elkins. 1986. The importance of soil ecology and the ecosystem perspective in surface-mine reclamation. *In* C.C. Reith, and L.D. Potter (eds.): Principles &

Methods of Reclamation Science. University of New Mexico Press: Albuquerque, New Mexico: 151-182

Xu, H., J.B. Burley, P. Crawford, Y. Wang, Z. Yue, and R. Schutzki. 2017a. An ordination of western and Chinese burial sites. WSEAS Transactions on Environment and Development, 13: 452-469.

Xu, H., J.B. Burley, P. Crawford, and R. Schutzki. 2017b. Cross-cultural ordination of burial sites. International Journal of Cultural Heritage, 2: 92-104.

Xu, Y., J.B. Burley, P. Machemer, and A. Allen. 2016. A dimensional comparison between classical Chinese gardens and modern Chinese gardens. WSEAS Transactions on Environment and Development, 12(2016): 200-213.

Zipper, C.E., J.A. Burger, J.M. McGrath, J.A. Rodrigue, and G.I. Holtzman. 2011. Forest restoration potentials of coal-mined lands in the eastern United States. Journal of Environmental Quality, 40(5): 1567-1577. https://doi.org/10.2134/jeq2011.0040

Appendix A

Maximum R-Square Improvement: Step 41

R-Square = 0.8793 and C(p) = 21.5359

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	258.95863	12.94793	26.60	<.0001
Error	73	35.53447	0.48677		
Corrected Total	93	294.49310			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-0.87194	0.16672	13.31485	27.35	<.0001
TP	0.50466	0.14014	6.31249	12.97	0.0006
SL	-2.07312	0.17001	72.38096	148.70	<.0001
CL	0.80349	0.29730	3.55540	7.30	0.0086
HC	-0.96635	0.22510	8.97071	18.43	<.0001
AW	-2.37413	0.30757	29.00372	59.58	<.0001
PH	0.40641	0.12497	5.14788	10.58	0.0017
SL2	0.39799	0.07666	13.12078	26.95	<.0001
FR2	-0.26293	0.03837	22.85670	46.96	<.0001
AW2	0.88193	0.13862	19.70213	40.47	<.0001
TPCL	0.36989	0.11895	4.70698	9.67	0.0027
TPBD	-0.59481	0.10137	16.76003	34.43	<.0001
TPHC	-0.48820	0.12425	7.51535	15.44	0.0002
TPOM	2.06655	0.22987	39.34052	80.82	<.0001
SLOM	-1.45369	0.30566	11.01033	22.62	<.0001
FRBD	-0.76847	0.22587	5.63458	11.58	0.0011
CLHC	-0.74717	0.20693	6.34626	13.04	0.0006
CLPH	-0.42867	0.15428	3.75814	7.72	0.0069
BDOM	-0.67422	0.15699	8.97763	18.44	<.0001
HCPH	-0.76090	0.18229	8.48116	17.42	<.0001
AWPH	-1.20130	0.23201	13.05026	26.81	<.0001

Bounds on condition number: 22.894, 3308.2

Figure A1. SAS "print-out" Best model found for the Stepwise Maximum R-squared Improvement for Principal Component 1. Refer to Table 1 for an explanation of independent variable soil parameters.

Maximum R-Square Improvement: Step 24

R-Square = 0.7452 and C(p) = 36.7759

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	177.86957	14.82246	19.74	<.0001
Error	81	60.82255	0.75090		
Corrected Total	93	238.69212			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-0.42029	0.14323	6.46564	8.61	0.0043
SL	0.48772	0.09661	19.13846	25.49	<.0001
FR	0.87531	0.21882	12.01465	16.00	0.0001
AW	-1.96851	0.19208	78.86507	105.03	<.0001
AW2	0.77296	0.11849	31.95257	42.55	<.0001
TPFR	0.68607	0.19490	9.30484	12.39	0.0007
TPCL	0.63153	0.11230	23.74723	31.63	<.0001
TPBD	-0.33830	0.10738	7.45230	9.92	0.0023
FRHC	1.92499	0.27429	36.98520	49.25	<.0001
FRPH	-0.48216	0.19359	4.65801	6.20	0.0148
FROM	1.29944	0.19656	32.81805	43.71	<.0001
CLHC	-0.83076	0.16952	18.03317	24.02	<.0001
BDHC	0.62243	0.12067	19.97710	26.60	<.0001

Bounds on condition number: 8.1439, 462.11

Figure A2. A "print-out" from SAS (2003) illustrating the best model found for the Stepwise Maximum R-squared Improvement for Principal Component 2. Refer to Table 1 for an explanation of independent variable soil parameters. The equation was found to explain 74.52 percent of the variance. The model is not over specific, having 13 terms and a C(p) value of 36.78.

Maximum R-Square Improvement: Step 78
R-Square = 0.9179 and C(p) = 33.9479

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	37	151.70037	4.10001	16.93	<.0001
Error	56	13.56251	0.24219		
Corrected Total	93	165.26288			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-0.58174	0.15337	3.48424	14.39	0.0004
TP	-0.63534	0.16313	3.67348	15.17	0.0003
SL	0.94986	0.12365	14.29269	59.01	<.0001
FR	-1.98688	0.32976	8.79217	36.30	<.0001
AW	-0.47879	0.17128	1.89255	7.81	0.0071
PH	-0.31093	0.11289	1.83737	7.59	0.0079
OM	0.83128	0.21698	3.55463	14.68	0.0003
TP2	0.46565	0.14067	2.65374	10.96	0.0016
SL2	-0.23547	0.07126	2.64424	10.92	0.0017
FR2	-0.56152	0.08572	10.39341	42.91	<.0001
CL2	-1.66751	0.15338	28.62412	118.19	<.0001
BD2	0.84355	0.08690	22.82194	94.23	<.0001
HC2	-2.74580	0.32562	17.22179	71.11	<.0001
TPFR	-1.99879	0.26111	14.19194	58.60	<.0001
TPBD	-1.79813	0.19132	21.39216	88.33	<.0001
TPHC	-2.12934	0.34823	9.05563	37.39	<.0001
TPAW	-1.45257	0.29009	6.07261	25.07	<.0001
TPPH	-0.64835	0.13853	5.30537	21.91	<.0001
SLFR	0.59705	0.13604	4.66457	19.26	<.0001
SLBD	0.52308	0.09160	7.89863	32.61	<.0001
SLHC	0.55404	0.15350	3.15520	13.03	0.0007
SLAW	0.55188	0.16719	2.63872	10.90	0.0017
SLPH	0.21506	0.08479	1.55815	6.43	0.0140
FRCL	-7.30507	0.57101	39.63747	163.66	<.0001
FRBD	-0.47675	0.18432	1.62033	6.69	0.0123
FRHC	-4.55352	0.61478	13.28637	54.86	<.0001
FRPH	0.53054	0.17869	2.13505	8.82	0.0044
FROM	2.86700	0.53390	6.98382	28.84	<.0001
CLHC	-5.84236	0.58049	24.53200	101.29	<.0001
CLAW	-1.16284	0.38663	2.19076	9.05	0.0039
CLPH	0.72328	0.21485	2.74472	11.33	0.0014
BDPH	-0.52386	0.14214	3.28952	13.58	0.0005
BDOM	-0.66791	0.19598	2.81284	11.61	0.0012
HCPH	0.90940	0.19840	5.08856	21.01	<.0001
HCOM	1.58268	0.39057	3.97694	16.42	0.0002
AWPH	-0.48875	0.23002	1.09348	4.52	0.0380
AWOM	1.20690	0.32471	3.34585	13.82	0.0005
PHOM	-0.34027	0.10984	2.32418	9.60	0.0030

Bounds on condition number: 152.86, 44747

Figure A3. A "print-out" from SAS (2003) presenting the first model found for the Stepwise Maximum R-squared Improvement for Principal Component 3 with all P values below 0.04. The number of terms in this model (38 terms) was greater than the C(p) value (33.95) and may be considered over specific. Refer to Table 1 for an explanation of independent variable soil parameters.

Maximum R-Square Improvement: Step 60

Variable PH Removed: R-Square = 0.8768 and C(p) = 48.0039

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	31	144.89768	4.67412	14.23	<.0001
Error	62	20.36520	0.32847		
Corrected Total	93	165.26288			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-0.64768	0.15896	5.45334	16.60	0.0001
TP	-0.56620	0.16100	4.06219	12.37	0.0008
SL	0.85356	0.13144	13.85171	42.17	<.0001
FR	-1.42155	0.26872	9.19248	27.99	<.0001
AW	-0.53829	0.16094	3.67441	11.19	0.0014
TP2	0.67112	0.13881	7.67752	23.37	<.0001
SL2	-0.24282	0.08060	2.98123	9.08	0.0037
CL2	-1.51835	0.14372	36.66066	111.61	<.0001
BD2	0.66391	0.08253	21.25649	64.71	<.0001
HC2	-1.33439	0.32871	5.41298	16.48	0.0001
AW2	0.57716	0.21442	2.37983	7.25	0.0091
PH2	-0.23985	0.09895	1.93000	5.88	0.0183
TPFR	-1.90574	0.25036	19.03170	57.94	<.0001
TPBD	-1.63418	0.19261	23.64559	71.99	<.0001
TPHC	-2.13468	0.31306	15.27275	46.50	<.0001
TPAW	-1.53045	0.26143	11.25712	34.27	<.0001
TPPH	-0.80303	0.13070	12.39936	37.75	<.0001
SLFR	0.53827	0.14504	4.52414	13.77	0.0004
SLBD	0.47082	0.10204	6.99323	21.29	<.0001
SLHC	0.54800	0.16483	3.63047	11.05	0.0015
SLAW	0.61201	0.18416	3.62761	11.04	0.0015
SLPH	0.28039	0.09621	2.78965	8.49	0.0050
FRCL	-8.01308	0.71664	41.06728	125.03	<.0001
FRHC	-1.46864	0.37425	5.05827	15.40	0.0002
FRAW	2.05719	0.36236	10.58654	32.23	<.0001
FRPH	1.26966	0.17728	16.84806	51.29	<.0001
FROM	0.63147	0.22656	2.55187	7.77	0.0070
CLHC	-5.90892	0.58555	33.44890	101.83	<.0001
CLAW	-1.46907	0.38887	4.68798	14.27	0.0004
BDOM	-1.13415	0.19548	11.05651	33.66	<.0001
HCAW	1.50420	0.52412	2.70549	8.24	0.0056
HCPH	1.08156	0.12385	25.05197	76.27	<.0001

Bounds on condition number: 89.777, 18983

Figure A4. A “print-out” from SAS (2003) presenting the second model found for the Stepwise Maximum R-squared Improvement for Principal Component 3 with all P values below 0.04. The number of terms in this model (32 terms) was greater than the C(p) value (48.00) and is not considered over specific. Refer to Table 1 for an explanation of independent variable soil parameters.

Maximum R-Square Improvement: Step 4

R-Square = 0.3133 and C(p) = 105.8427

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	35.03746	8.75936	10.15	<.0001
Error	89	76.80084	0.86293		
Corrected Total	93	111.83830			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-0.42257	0.14536	7.29247	8.45	0.0046
TP	0.26187	0.09767	6.20256	7.19	0.0087
BD	-0.31102	0.10184	8.04777	9.33	0.0030
BD2	0.18310	0.07441	5.22483	6.05	0.0158
AW2	0.24152	0.08266	7.36694	8.54	0.0044

Bounds on condition number: 1.1179, 17.144

Figure A5. A “print-out” from SAS (2003) illustrating the best model found for the Stepwise Maximum R-squared Improvement for Principal Component 4. Refer to Table 1 for an explanation of independent variable soil parameters.