SOIL BASED VEGETATION PRODUCTIVITY MODELING FOR A NORTHERN MICHIGAN SURFACE MINING REGION

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ABSTRACT

SOIL BASED VEGETATION PRODUCTIVITY MODELING FOR A NORTHERN MICHIGAN SURFACE MINING REGION

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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). This research presents equations for a northern Michigan mining region 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. Five predictive equations based on land use have been developed and are described as an all woody and crop equation, a xeric equation, an equation specific to jack pine, and two semi-wet equations of varying conservativeness. The models were highly significant ($p<0.0001$) and explained 87.93%, 74.52%, 65.33%, 91.79% and 87.68% of the variation in site productivity of the respective land uses. These equations are intended to be used in efforts to assess the vegetative productivity potentials of reconstructed soils on post-mined landscapes.

DEDICATION

This thesis is dedicated to Steven L. and Donna K. Corr

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I would also like to thank my parents, Steven and Donna Corr, for their constant support throughout my entire life. There personal sacrifices that made my education possible have not gone unnoticed. I appreciate everything you both have done for me with all of my heart.

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INTRODUCTION

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 agricultural uses as well as forested lands for timber production, 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 thesis 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 and Thomsen (1987) in a multicounty mining region in Michigan's Upper Peninsula.

1.1 UNDERSTANDING RECLAMATION TERMINOLOGY

There are several terms that are used interchangeably throughout the collective body of land reclamation literature. It is therefore important to address the nomenclature associated with the renewal of disturbed land resources. *Reclamation* is most accurately used to describe instances in which the post-mine land use is planned to be different from its pre-mine land use. *Rehabilitation* and *restoration* are most often used to describe returning land to a previously realized use. The term *renewal* has been used most often in instances in which there are some type of built development associated with the project, or in cases in which a defined land use has yet been established. Throughout this thesis *reclamation* will be used as an all-inclusive term describing all activities that repair, redefine, or otherwise enhance disturbed lands, although discuss will heavily focus on the establishment or reestablishment of vegetation on mined lands.

1.2 CONDITIONS OF RECONSTRUCTION SOILS

Numerous mining laws mandate that soil profiles be separately stripped and stockpiled and subsequently reapplied during the reclamation process. There is inevitably some degree of mixing of the soil profiles throughout this process, thus creating new soil textures, profiles and patterns. These neo-soils are often vastly different from their pre-mining conditions and are associated with unsuitable pH levels, increased bulk densities, greater percentage of rock fragments, decreased water-holding capacity, lack of organic content and lack of microbial activity (Bradshaw and Chadwick, 1980; Evanylo et al., 2005).

The pH of mined soils can change as newly exposed rock is weathered and dissolves. Pyritic minerals oxidize to form sulfuric acid, which can rapidly lower the pH of a soil. For the majority of plants, when soil pH is reduced below 5.5, plant growth is hindered due to metal toxicities such as manganese or aluminum, phosphorus fixation, and reduced populations of N-fixing bacteria (Sheoran, 2010). Minerals containing carbonate, which is found in much of the bedrock within Michigan's Upper Peninsula, increases pH as they are weathered. Most plants grow in pH levels ranging from slightly acidic to slightly alkaline, so breakdown of newly exposed bedrock has the potential to greatly influence plant productivity.

Soil fertility is of major concern to post-mined soils. As previously mentioned, many state laws mandate that soil horizons be stripped and reapplied in a specific order. Once these horizons have been removed they are stockpiled until the land is reclaimed. While stockpiled, nutrients may be leached from the soil, topsoil is eroded, and nutrient cycles are disrupted. Reclamation specialists often plant cover crops on soil stockpiles to slow these processes, but there is inevitably some degree of degradation when soils are disrupted. Macronutrients such as N, P and K are commonly found to be deficient in reconstructed soils (Coppin and Bradshaw, 1982; Sheoran et al., 2008). In many cases, such nutrients are reintroduced through the application of fertilizers to establish plant cover and initiate nutrient cycling.

One of the most influential edaphic factors that reclamation specialists must address during reclamation efforts is the effect of increased bulk density of soils. Bulk densities are in many cases drastically increased as heavy machinery involved in earth moving practices compact soils. Compaction reduces the amount of pore space within the soil, thus limiting the amount of water the soil is able to hold and make available to plants. Potter and others (1988) found that reconstructed soils have greatly reduced hydraulic conductivity, largely due to increased macropore space with increased bulk density. This reduction in pore space also reduces soil aeration. Rooting of plants is also hindered by soils with high bulk densities. Many plants will not penetrate soil profiles that are severely compacted. Sheoran (2010) suggests that three to four feet of non-compacted media are needed to maintain available water contents adequate to support plant growth through periods of drought. Darmody and others (2002) suggest that in instances in which compaction caused by machinery cannot be avoided, that tillage of the first 120 cm can assuage the negative effects of highly compacted soils.

Microbial activity in reconstructed soils is greatly reduced in comparison to undisturbed soils. Microbial activity has been found to decrease with depth and as the time soils are stockpiled increase (Harris et al., 1989). Microbe populations are associated with maintaining soil structure, decomposition of organic matter, as well as facilitating uptake of nitrogen and phosphorus. Reduced pore space of compacted soils decrease the amount of spaces in which these organisms survive (Edgerton et al., 1995). Nutrient content of soils is closely linked to soil microbial activity. For instance, N-fixing microorganisms are needed to fix nitrogen in the soil into nitrate (NO_3^-). Without sufficient populations of these microorganisms soils will be deficient of nutrients necessary to support vegetative growth.

Comparing the productivities of reconstructed soils to those of undisturbed soils is often difficult due to the inherent differences between these soil conditions. Reconstructed soils are often associated with soil attributes that are vastly different from pre-mined conditions making it difficult for reclamation specialists to accurately predict the abilities of these soils to support plant growth and to what degree. Potter and others (1989) suggest that it is possible to predict post-mine productivity based on assessing soil attributes, however this practice is still being refined.

1.3 MINE RECLAMATION LEGISLATION

Federal involvement in surface mine reclamation began with proposed legislation in the 1940s, which eventually led to the passage of Surface Mining Control and Reclamation Act of 1977 (SMCRA). Prior to the passage of the SMCRA there was no national regulatory system for mine reclamation in the U.S. Many mined lands were abandoned after mining operations ceased with no plans for reclamation of the disturbed landscapes.

Early mining law in the United States focused heavily on land ownership and mineral rights and did little to address the reclamation of disturbed lands. As the federal government became increasingly involved in leasing public lands to mining operators, the environmental impacts and regulation of these lands became increasingly apparent to the scientific community. In the early 1900s, ecologists, planners, and landscape architects throughout the United States, and elsewhere, became increasing concerned with the unproductive and hazardous nature of these lands and began raising public concern for ways to assuage the environmental impacts associated with mined landscapes. However, the development of legislation in response to this movement toward land reclamation was slow and prior to the SMCRA, made little effort was made to make mine operators responsible for the reclamation of disturbed lands. In 1914, Congress passed an Act that made one of the first moves toward making the mining prospector, the responsible party for damages, to the disturbed lands. The Act focused on the disturbance of productive agricultural land, mandating a separate disposal of the surface of the land to the original agricultural landowner prior to the removal of any minerals. Furthermore, the Act provided that the mining operation was responsible for compensation to the agricultural landowner for any damages to the production of the land (Colby, 1945). Although primary intent of this legislation was not to mitigate the environmental impacts of disturbances associated with the mining practice in particular, it is used as an example to mark an important period in mining law in which the scientific and political communities began to actively seek change in the environmental policy of mined lands.

Legislation that directly addressed the reclamation of mined lands first occurred at the state level. The oldest of such state laws, was passed by the state of Indiana in 1941. Several additional states enacted similar laws in the years to follow. These early reclamation laws focused primarily on establishing vegetative cover, without any major concern for slope management of spoil piles. Dissatisfaction with the resulting topography from these early reclamation efforts led to amendments in various state laws in the early 1950s, which required lands to be returned to particular ranges of slope (LaFevers, 1977). Over the next two decades, numerous states passed and amended regulatory legislation concerning post-mined lands. However, inconsistencies among these state laws suggested need for national legislation to establish minimal criteria for reclamation.

With growing political concern for environment protection in the 1960s, the federal government began proposing legislation that would create a federal law to regulate mining operations and reclamation of post-mined lands. The House of Representatives' Bill 25, which proposed such legislation, was voted in by congress but subsequently vetoed by President Ford in May of 1975. However, the idea for federal surface mining regulation was reintroduced as H.R. 2 to President Carter soon after taking office. The bill was quickly signed into law thereafter on August 3, 1977 (Simpson, 1985).

In accordance with the National Environmental Policy Act of 1969, the federal Office of Surface Mining (OSM) released an Environmental Impact Statement (EIS). The EIS released by the OSM in 1979 outlined the purposes of the Act as to: "1) establish a national program to protect society from the adverse impacts of coal mining; 2) where reclamation as required by the Act is not feasible, to prohibit mining; 3) to require contemporaneous reclamation (no lag allowed); 4) to balance coal production with the preservation of agricultural lands; 5) to assist states in developing, administering, and enforcing a regulatory program; 6) to reclaim abandoned mine lands; 7) to insure public participation in the development of regulations, standards and programs within the SMCRA" (Burley, 2001 pg. 77). A full list of objectives is listed in the official congressional Statement of Purpose of the SMRCA of 1977. The implicit intent of the bill was not to prevent the surface mining of coal, but rather to set boundaries for these operations that expressed the societal inclination that reclamation must be an integral component of mining operations (Munshower and Judy, 1988).

Although the SMCRA developed a national regulatory system for mine reclamation, the act imparted the primary responsibility of surface mining regulation and reclamation standards to state governments. Congress authorized state governing bodies to administer surface mine regulations as each deem fit so as to address the unique natures of their states' various terrains, climates, biological factors, geochemical factors, among other conditions that affect coal mining areas (Workman, 1987). State regulations, therefore, vary considerably causing much debate over the effectiveness of the SMCRA. Some critics argue that the SMCRA of 1977 and many state mine reclamation laws overly emphasize water quality and erosion control, often compromising site productivity, reforestation, carbon sequestration, and seeking alternative productive land uses (Rodrigue and Burger, 2004). Other criticisms focus on the confusion the duality of regulation that state and federal mandates can impose on mine operators (Lucas, 1987). Despite perceived flaws, the SMCRA of 1977 currently sets minimal standards for surface coal mining operations and reclamation efforts in the U.S. All other additional mandates are the responsibilities of the states to administer.

Although the SMCRA of 1977 requires mined lands to be reclaimed, the language that is used leaves a significant amount of interpretation to be had in regards to what is considered reclaimed. Section 515 of the SMCRA of 1977 requires mining operations to "restore the land affected to a condition capable of supporting the uses which it was capable of supporting before any mining, or higher or better use". The inexplicit condition "higher or better use" can be interpreted in many ways. When considering an alternative uses for post-mined lands there are a variety of issues reclamationists explore to determine if the use is indeed "better". Smith (2001) presents a Canadian case study in which describes productivity calculations that assess the productivity of a pre-mined land use of a forested landscape when compared to its post-mined land use as a cattle ranch. However, comparisons among less comparable factors such as environmental benefits (wildlife habitat, stormwater management, carbon sequestration, etc.), economic benefits (crop and fiber production, tourism, job creation, etc.), and social benefits (recreation, aesthetics, education, etc.) may all be considered when evaluating the appropriateness of an alternative post-mined land use. Actually quantifying these factors is difficult in many cases. Moreover, accurately predicting the probability that these land uses can be brought to fruition can be particularly challenging and costly. Due to the intentionally vague language of the SMCRA, states have formed their own laws that address the distinctive concerns regarding mine reclamation.

1.4 MICHIGAN RECLAMATION LEGISLATION

Currently mining in the state of Michigan is regulated and enforced by the Michigan Department of Environmental Quality (MDEQ). Regulation of mining operations and reclamation is mandated under Parts 615, 625, 631, 632, 635, and 637 of Public Act 451, the Natural Resources and Environmental Protection Act (NREPA). These parts regulate the mining of oil and gas, mineral wells (mineral exploration), general mine reclamation rules, nonferrous metallic mining, coal mining, and sand dune mining respectively. Although regulations of mining types vary to some degree, due to the means of extraction and geological conditions associated with the location of the mined material, all types require the submittal and acceptance of proper permits including a reclamation plan before extraction begins.

MDEQ require mining companies to submit reclamation plans as part of the permit application process. Part 632 section 324.63527 [2.b] of the NREPA requires submission of a reclamation plan that will effectively “restore the land affected to a condition capable of supporting the uses that it was capable of supporting prior to any mining, or higher or better uses”. The vague language “higher or better use” is echoed from the 1977 SMCRA. Although this undefined language gives reclamationists flexibility when determining post-mine land uses, it lacks identification of proper means of quantifying productivity. Additionally the law requires that A and B soil horizons be stripped, stored, and reapplied separately, unless information can provided that an available alternative would be more supportive to vegetative growth. The flexibility in this section gives reclamationists the opportunity to explore different substrates to be applied as growth media. A considerable amount of research has investigated the applications of various alternative substrates as growth media or soil amendments (Zornoza et al., 2012; Watts et al., 2012;

this method, describing it as unreliable and costly. Despite the perceived flaws of the methods used, P.A. 451 Rule 9 of section 425 empowers "the supervisor of reclamation" to evaluate the reclamation plan to determine if it adheres to the mandates of the act. It is the authority of this person to assess the productivity of the land prior to mining, yet not acceptable evaluation method is specified. It is therefore beneficial to explore accurate methods of quantifiably predict vegetative productivity of post-mine soils based on observed crop yields within the mining region.

Burley (2001) compares several state reclamation laws. In this Burley acknowledges the applicability of a regression approach to many state mandates that require comparative productivity level studies of pre-mined and post-mined lands. Although vegetative productivity models, such as the one explored in this research, are not yet required by any state, these models show great potential to accurately predict state mandated vegetative success rates.

1.5 RECLAMATION EVALUATION APPROACHES

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 et al., 2001). Although some states' laws explicitly express the method to compare the productivity level of pre-mined and post-mined soil productivity levels, each of these models has been used in past reclamation efforts throughout the United States. 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 model is a heuristic method, known as the “reconstructing nature” approach. Federal and many state laws mandate that mine operators strip and stockpile A, B and C separately so that these horizons may be reapplied in the correct order during reclamation. Although stratified stockpiling is supposedly an important and beneficial process, results are extremely variable with limited ability to predict vegetative performance and have not been validated by adequate research. Dancer and Jansen (1981) as well as McSweeney and others (1981) discovered that replacement or alteration of claypan subsoils commonly found in southern Illinois improved 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 as a post-mined land use. However, mandates of topsoil depths to be respreads are dependent on the characteristics of the soil material and the crops to be grown (Friendland, 2001). Mandated depths vary depending among state due to differences in edaphic parameters 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-mine and pre-mine soils). Recreating soil system with similar productivity levels based on attempted recreation of pre-mine conditions is therefore, difficult. The first model, although requiring minimal planning, has proven to be a poor predictor of 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 and others (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-mine 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-mine growth potentials, it does little to *predict* post-mine 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, 1987). It is therefore, important to investigate methods to 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 soils 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 (Woolery et al., 2002). 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 specie. 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-mine 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 been employed the index model with research conducted in the Mississippi River Valley (Belli, 1998; Groninger, 2000). Similar to other heuristic index models, these studies lack statistical reliability yet established fundamental precedents leading to creation of more accurate statistical models. However, Potter and others (1988) argue that this model is beneficial in cost-effectively assessing the amendment and treatment needs of post-mine 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 exhibit non-linear responses 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. 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 (Powers 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 not 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 and percent organic matter, 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 (1995) 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 describe 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 need for statistical analysis of vegetative productivity potentials (Le Cleac'h et al., 2004; Woolery et al., 2002; Burley, 2001; Groninger et al., 2000, 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 Woolery and others (2002) and Groninger and other (2000) used the regression approach to predict tree growth in southern Illinois. These studies used regression of a combination of collected soils data and expect 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.

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.

METHODS

2.1 METHODOLOGY

Independent variables are representative of physical and chemical characteristics of each soil investigated. Soil factors included in similar studies include topographic position, percent slope, percent organic matter, bulk density, soil reactivity, percent clay, percent rock fragments greater than 3 inches in diameter, hydraulic conductivity, and available water content. These characteristics were selected based on the work of Neill (1979), and later refined by other researchers 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. Additionally, the values for the soil characteristics must be available for the first 48 inches of each soil type. In some cases, availability of soil characteristic values was limited by the depth of the soil type. This was often due to shallow soils over bedrock or high water tables. The values that were not included in the NRCS tables must therefore be interpolated based on other empirical evidence.

Soil productivity has been linked to soil depth. According to research conducted by Doll and other (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. Although it could be argued that this weighing method is flawed as being only an estimate of the relationship between soil depth and plant productivity, there has been no other method found that can provide a more accurate means of this affect. This methodology employs this soil characteristic weighing method to gain a more accurate assessment of soil-plant correlations.

To be statistically analyzed variables must be represented as a single value. Deriving single values NRCS soil surveys is complicated by the way in which the data provided is presented. Firstly, soil attributes are often given ranges of values as opposed a single value. Bulk density, for example may be given a range of 1.0 g/cc to 2.0 g/cc for a given depth. This range must be averaged so as to generate a single value, a value of 1.5 g/cc in this example. Secondly, the chemical and physical soil characteristics provided in NRCS soil surveys are often presented according to soil profile depths. For example, a characteristic such as pH may be given for depths of 0 to 8, 8 to 25, 25 to 32, and 32 to 80 inches. These values must be reorganized into appropriate depth ranges so they can be weighed according to the weighing method used in this methodology.

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. 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.

Units of measurement may vary among both independent variables and dependent variables. For example, discrepancies in soil characteristic (independent variable) units include g/cc for moist bulk density and percentages for characteristics such as for clay content and organic content. Similarly, crop data can be presented as tons per acre or bushels per acres. It is therefore necessary to standardize by a mean of zero and a variance of one all variable to accurately compare variables with different units of measurement. If variables are not standardized, variable with higher real number values will dominate the equation.

Furthermore, these larger real numbers may not even be greater quantities than their smaller counterparts. Crop yields, for instance, may be presented as 75 bushels per acre of oats and 13 tons per acre of corn silage for a given soil unit. In this example, 13 tons of corn silage is a much larger quantity than 75 bushels of oats, but this is not reflected in the real number values of the data. According to the United States Department of Agriculture (USDA, 1992), one ton of oats contains 68.8944 bushels. By converting bushels of oats to tons of oats per acre, a value of approximately 1.1 tons per acre of oats is found. The converted value of 1.1 is a much smaller real number than 75, and now oats has a much smaller relative value when compared to the 13 tons per acre value of the corn silage. Such conversions are time consuming and in some cases are not able to be made, such as converting units of g/cc to In/hr. Standardizing crop and soil data alleviates the complications associated with different units and makes it possible to analyze variables with different units. All variables must be standardized to be converted to z-scores of the crop yield or soil characteristic sets of observations.

Once the data is standardized and organized it is ready to be analyzed. At this point it is possible to create 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 a 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 dimension. 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 amounts of variable.

The PCA procedure begins with a selected set of dependent variable to be investigated being organized into a covariance matrix. PCA of the matrix will generate a set of eigenvalues that represent each dimension of the dataset. The maximum number of dimensions is equal to the number of crop types (dependent variables) in the dataset. This means that if a total of seven crop types are used, there can be no more than seven dimensions. The largest eigenvalue will be the first value of the PCA results and can be no greater than the number of variables investigated. Furthermore, the sum of all eigenvalues can equal no greater than the total number of variables. For example, if there are three vegetative types used and the first eigenvalue is 2.6, the sum of the remaining two eigenvalues must be equal to 0.4. The proportion of each eigenvalue of the total dimension illustrates how much of the variance is explained by that eigenvalue. These values can also be added to gain a perspective on how much a group of variables explains. For instance, if the first five of nine eigenvalues represent 90 percent (a combined value of 8.1) of the variance, the remaining four eigenvalues represent only 10 percent (a combined value of 0.9) of the variance. In this way researchers are able to interpret the significance of eigenvalues so as to more accurately make decisions on what is significant to the study.

Eigenvalues greater than 1.0 are considered to represent significant dimensions worthy of further investigation. In smaller data sets, those consisting of less than 100 soil types, eigenvalues greater than 0.8 should be selected. However, it is recommended that a data set consists of approximately 100 independent variables for accurate modeling. Table 1.1 gives an example of an eigenvalue table that examine 11 crop types. The results in Table 1.1, Table 1.2, as well as in Table 1.3 were taken from preliminary trials of data used in this study, but were not used in further investigations. These results are used strictly for illustrational purposes and do not reflect any actual results used to develop equations in this study. The first four eigenvalues, represented by Prin1, Prin2, Prin3, and Prin4, are significant enough to be considered for further modeling analysis (>1.0). Additionally, notice the results give the relative proportion of the data that each dimension explains. Collectively the first four eigenvalues explain more than 79% of the variance.

Table 1.1 Example eigenvalue table. These results are strictly to illustrate the methods of this study and do not reflect any actual values derived from this investigation.

Eigenvalues of the Covariance Matrix

	Eigenvalue	Difference	Proportion	Cumulative
Prin1	3.46188048	0.90373795	0.2978	0.2978
Prin2	2.55814253	0.69077766	0.2200	0.5178
Prin3	1.86736487	0.53020775	0.1606	0.6784
Prin4	1.33715712	0.64996588	0.1150	0.7934
Prin5	0.68719124	0.17634190	0.0591	0.8525
Prin6	0.51084934	0.15208652	0.0439	0.8965
Prin7	0.35876282	0.04780339	0.0309	0.9273
Prin8	0.31095943	0.03326234	0.0267	0.9541
Prin9	0.27769709	0.14698777	0.0239	0.9779
Prin10	0.13070932	0.00494302	0.0112	0.9892
Prin11	0.12576630	0.12576630	0.0108	1.0000

Significant dimensions are then investigated by examining the eigenvector coefficients. Table 1.2 investigates the four significant dimensions from Table 1.1. Eigenvector scores range from 1.0 to -1.0. These scores indicate the strength of the association with the corresponding principal component axis. Scores close to 1.0 or -1.0 are considered to be strongly associated, while scores closer to 0 are considered weaker. Positive scores indicate a positive association and negative scores indicate negative associations.

Table 1.2 Example eigenvalue chart. These results are strictly to illustrate the methods of this study and do not reflect any actual values derived from this investigation.

Eigenvectors

	Prin1	**Prin2**	**Prin3**	**Prin4**
Corn	0.383742	-.103134	-.032841	-.486517
Corn Silage	0.477603	-.186402	-.000236	-.390847
Oats	0.328985	-.223164	0.045024	-.072393
Irish Potato	0.457793	-.099761	-.372264	0.385713
Alfalfa Hay	0.363850	-.099289	-.162625	0.376985

Table 1.2 (cont'd)

Red Maple	0.144508	0.078080	0.608105	-.015604
White Spruce	0.220520	0.027231	0.435188	0.455841
Red Pine	0.152413	0.522985	-.101128	0.080511
Eastern White Pine	0.226707	0.482660	0.222298	0.108421
Jack Pine	0.073695	0.428711	-.394658	-.129633
Lilac	0.157724	0.433474	0.239349	-.267075

Interpretation of the eigenvector analysis allows researchers to understand the potential for each principal to be translated into a vegetative productivity equation and which of the dependent variable developed models will describe. It is important to understand how to interpret these results so as to create models that will be most helpful for specific intent. By understanding ways in which crop types covary, researchers are better able to derive equations that will predict vegetative growth for particular planning objectives such as agriculture lands, habitat creation, aesthetics, carbon sequestration, or growth for lumber production. It is suggested that interpretation of the eigenvectors be conducted in order, as this is the order of significance.

Eigenvector results are presented and can be interpreted in three main ways; all positive numbers, some positive and some negative numbers, and one positive number with all other numbers negative. All positive values, especially in the first principal component column reveals that all crop types covary in this dimension, suggesting that one model could be derived to explain all crop types. It is preferred that all crop types can be explained in one equation, as in the example of principal 1 of Table 1.2. Alone, however, this example principal only explains 29.78% of the total variance (refer to Table 1.1). Therefore, it may be useful to investigate additional models. Because the first four principals in Table 1.1 have eigenvalues greater than 1.0, further analysis of these principals is recommended.

Both positive and negative values within one eigenvector, indicates a predictive model that describes soil characteristics that support two contrasting sets of crop types. The second principal of Table 1.2, for instance, shows that the first six crops covary together, all having positive signs, while the last five crop types, all having negative signs, covary together. Notice that all crop types with a negative sign are agricultural field crops, and that all those with a positive sign are woody plants. Therefore principal 2 may be investigated further as a field crop versus woody plant model in which positive scores show favorable conditions for woody plants and negative score for conditions that favor field crop production.

Eigenvectors with one positive number and all the remaining values are negative, can be further investigated to derive equations for one crop type. In these types of vectors, the equation will be suitable for predicting the vegetative success of the crop type with the positive value. Burley (1990) derived a single crop equation for sugar beets in a similar study.

Once eigenvectors (dependent variables) have been identified and soil characteristic data has been weighed, the data set is ready for regression analysis. Regression analysis is used to examine the ability of soil attributes to predict the vegetative productivity of investigated crop types. This procedure identifies main affects (ex. % clay), squared terms (ex. % clay x % clay), and two variable interaction terms (ex. % Clay x pH) as they correspond to dependent variables. Important variables are then entered into a stepwise regression procedure. The maximum R-squared improvement technique is used to create a list of possible equations.

Selecting the strongest equation is determined by selecting an equation with the largest explanation of the data, represented as an R-squared score, for equations presented that consist of significant p-values. P-values less than or equal 0.05 are considered specific, while those less than 0.01 are considered highly specific (refer to Table 1.3). Burley and Thomsen (1987) recommend searching for two types of models when considering possible equations. The first type of model is one in which all p-values are less than 0.01 and an R-squared value greater than 0.7. If this does not exist, it is suggested that an equation in which all variables have p-values less than 0.05 and has an R-squared value greater than 0.7.

Table 1.3 Example Stepwise Maximum R^2 Improvement acceptable equation. These results are strictly to illustrate the methods of this study and do not reflect any actual values derived from this investigation.

Maximum R-Square Improvement: Step 26
Variable SLCL Entered: R-Square = 0.7563 and C(p) = 10.0819

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	45409	3784.04297	20.95	<.0001
Error	81	14632	180.64020		
Corrected Total	93	60040			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-52.67096	19.35937	1337.13197	7.40	0.0080
SL2	-0.20017	0.04212	4080.71941	22.59	<.0001
BD2	70.25217	13.36404	4991.81143	27.63	<.0001
AW2	2826.95353	895.83163	1798.86660	9.96	0.0022
TPSL	1.51899	0.27008	5713.91270	31.63	<.0001
TPFR	1.44884	0.34309	3221.41360	17.83	<.0001
TPPH	-1.80908	0.40871	3539.23420	19.59	<.0001
TPOM	-4.26685	1.06019	2925.92286	16.20	0.0001
SLCL	0.08558	0.04244	734.56634	4.07	0.0471
FRBD	-6.97459	1.31855	5054.26848	27.98	<.0001
FRHC	1.01052	0.14887	8323.08235	46.08	<.0001
FROM	1.35934	0.59059	956.97113	5.30	0.0239
BDAW	-636.30437	165.40282	2673.36574	14.80	0.0002

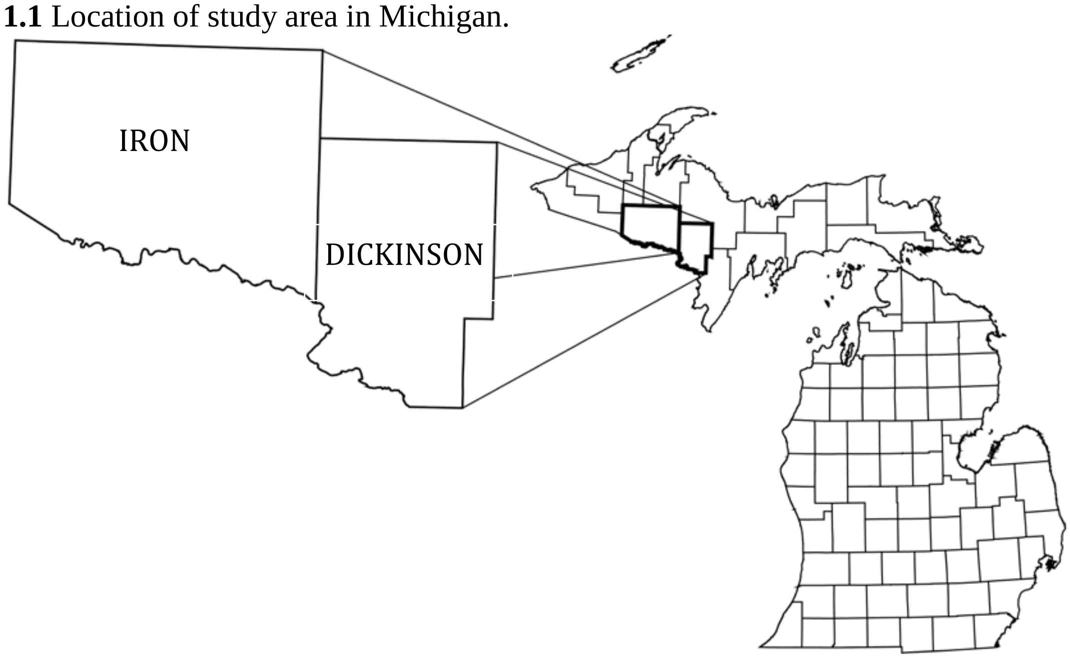
Bounds on condition number: 86.929, 4546.4

Table 1.3 illustrates an example of significant stepwise regression equation. From a list of potential equations, researchers are to select the equation with the least significant p-values that explain the most variance of the dataset. This example explains 75.63% of the variance (R-square = 0.7563). Additionally, all 12 of the variables are considered significant (<0.05) and all but two variables are considered highly significant (<0.0001). This equation would be considered acceptable to be developed into an accurate equation.

The resulting equations from the process described here employs soil parameters to predict a productivity index. The productivity index is a unitless value that indicates relative productivity of a given soil. Typically index scores have ranged from five to negative ten, with scores near five indicating highly productive soils and scores near negative ten being highly unproductive (Le Cleac'h, 2004). These scores should be used in conjunction with eigenvector values to indicate the appropriateness of a soil to plant species that are associated to varying degrees with the equation employed.

2.2 STUDY AREA

Figure 1.1 Location of study area in Michigan.

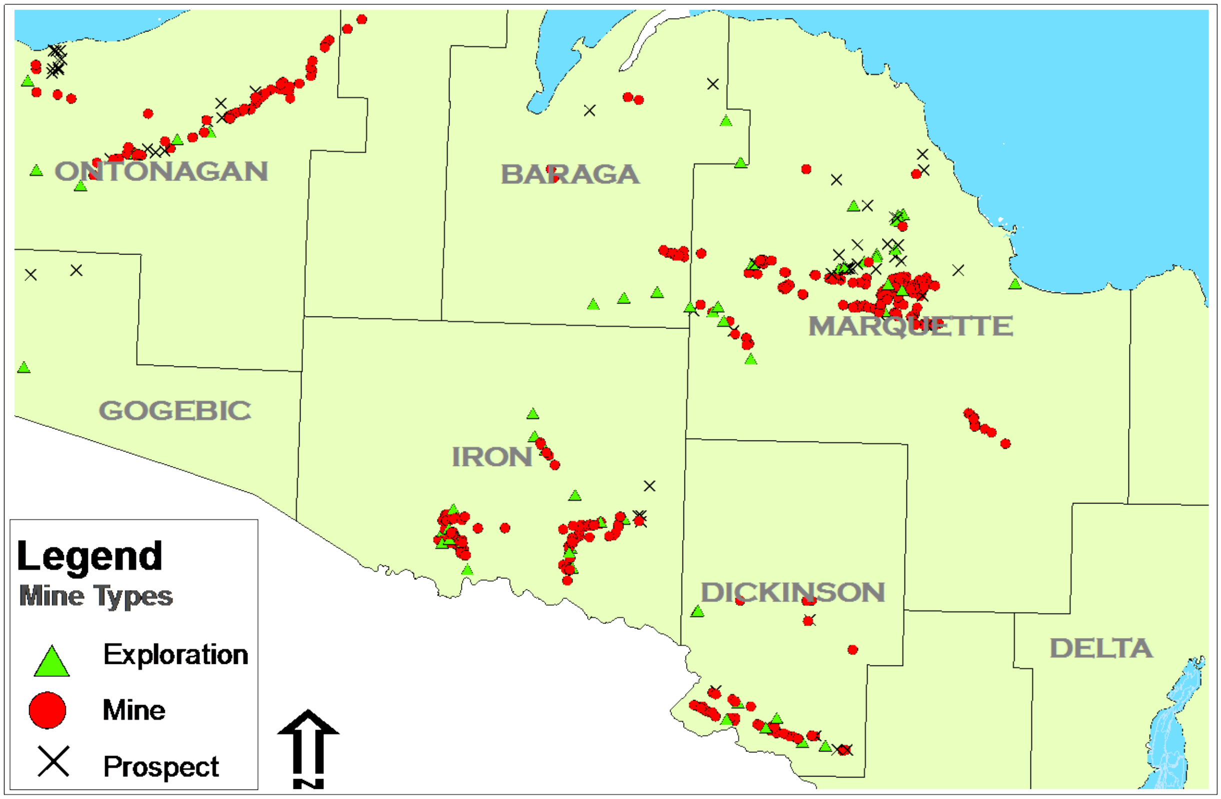


County selection for compiling a data set should be based on availability of data provided by the NRCS, or similar reliable source, and proximity to the site of interest. Soil surveys developed by the NRCS are generated after years of data collection and released as a county based document. Although this research uses entire counties to develop data sets, it is possible to create models based on specific geological, climatological, social, or other identified boundaries.

The area of study is located in the western Upper Peninsula of Michigan. 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.

Marquette County is of particular interest to reclamationists as it currently hosts a large-scale iron ore mining operations 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.

Figure 1.2 Locations of mines and mine exploration sites in the Michigan's western Upper Peninsula. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this thesis.



Historically, all three counties have been mined. Figure 1.4 illustrates the locations of mines and exploration sites. 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.

2.2a 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 know 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 the 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, characterize as fine sands to sandy loams in texture (Albert, 1995). Linsemier (1997) describes the taxonomic classification of each soil type examined in this study.

2.2b 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).

2.3 VARIABLES INVESTIGATED

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 1.4.

Table 1.4 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	Inches/inch
BD	Moist Bulk Density	g/cc
CL	% Clay	Proportion by weight
FR	% Rock Fragments	Proportion by weight of particles >3 inches
HC	Hydraulic Conductivity	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)

There were a total of 95 soils investigated between Dickinson and Iron Counties. 45 applicable soils were investigated from Iron County, while 50 applicable soils were examined 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.

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 analysis are included in Table 1.5. These specific plants were selected for investigation due to the availability of information of these plants in both counties.

Table 1.5 Dependent variable crop and woody plant units and abbreviations as they appear in the eigenvector analysis.

<u>Agronomic Crops</u>

Abbreviation	Crop Type	Measured Average Yield
CO	Corn	Bushels/acre
CS	Corn Silage	Tons/acre
OA	Oats	Bushels/acre
IP	Irish Potatoes	Hundredweights/acre, 100lbs/acre
AH	Alfalfa Hay	Tons/acre

Table 1.5 (cont'd)

Woody Plants

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

RESULTS

Table 2.1 illustrates the eigenvalues of the combined Iron County and Dickinson County crop and woody plant data set. There were 4 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 percent, 16.15 percent and 10.94 percent of the variance respectively. The first four principal components together comprised 79.21 percent of the variance in the data set.

Table 2.1 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 2.2 Principal component analysis eigenvectors for Iron County and Dickinson County, Michigan dependent variables. See Table 1.5 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

3.1 PRINCIPAL COMPONENT 1

As illustrated in Table 2.2 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.

Figure 2.1 illustrates the best suitable model developed for the first principal component. The model was found to explain 87.93 percent 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, 2012), therefore further validating the strength of this model.

Figure 2.1 Best model found for the Stepwise Maximum R-squared Improvement for Principal Component 1. Refer to Table 1.4 for an explanation of independent variable soil parameters.

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

3.2 PRINCIPAL COMPONENT 2

Table 2.2 shows 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 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.

Figure 2.2 illustrates the best equation derived for the second principal component. 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.

Figure 2.2 Best model found for the Stepwise Maximum R-squared Improvement for Principal Component 2. Refer to Table 1.4 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

Figure 2.2 (cont'd)

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

3.3 PRINCIPAL COMPONENT 3

Table 2.2 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 2.3 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 percent 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 & Thomsen,1987), others suggest that the relativity of the values is what should be considered (Agresti, 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 2.3 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 1.4 for an explanation of independent variable soil parameters.

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

Figure 2.3 (cont'd)

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 2.4 illustrates a second model for the third principal component. This equation was found to explain 87.68 percent of the variance, which is comparable to the r-square value of the first principal component. In contrast to the model shown in Figure 2.3, the number of terms in this model shown in Figure 3.4 (38 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 Table R.5.

Figure 2.4 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 1.4 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

Figure 2.4 (cont'd)

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

3.4 PRINCIPAL COMPONENT 4

Although the eigenvalue for the fourth principal component, as shown in Table 2.1 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. The best model found had a R-squared value of 0.3133. Because the model explained such a small portion (31.33 percent) of the variation in the crop and woody plant axis, it was not considered for further analysis. No equation was produced for this model.

Figure 2.5 Best model found for the Stepwise Maximum R-squared Improvement for Principal Component 4. Refer to Table 1.4 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

DISCUSSION

There were a total of 5 equations developed for the three principal component investigated. Figures 3.1, 3.2, 3.3, 3.4, and 3.6 display the equations 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 way 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 (1995) 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 specialist 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 (Linsemier, 1989; Linsemier, 1997) characteristics. 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 study area of this study.

4.1 PRINCIPAL COMPONENT 1: Mesic Model

Figure 3.1 presents the equation developed from the stepwise maximum r-squared improvement for the first principal component. 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-mine 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.

Figure 3.1 Best equation found for the Stepwise Maximum R-squared Improvement for Principal Component 1. This equation is best described as a mesic model.

$$
\begin{aligned}
\text{Plant} = -0.872 &+ [((TP-3.121)*1.267^{-1})*(0.505)] \\
&+ [((SL-8.00)*7.765^{-1})*(-2.073)] \\
&+ [((CL-8.915)*4.138^{-1})*(0.803)] \\
&+ [((HC-5.227)*4.302^{-1})*(-0.966)] \\
&+ [((AW-0.122)*0.040^{-1})*(-2.374)] \\
&+ [((PH-5.971)*0.671^{-1})*(0.406)] \\
&+ [((SL-8.00)*7.765^{-1})* ((SL-8.00)*7.765^{-1})*(0.398)] \\
&+ [((FR-4.571)*6.760^{-1})* ((FR-4.571)*6.760^{-1})*(-0.263)] \\
&+ [((AW-0.122)*0.040^{-1})* ((AW-0.122)*0.040^{-1})*(0.882)] \\
&+ [((TP-3.121)*1.267^{-1})* ((CL-8.915)*4.138^{-1})*(0.370)] \\
&+ [((TP-3.121)*1.267^{-1})* ((BD-1.506)*0.084^{-1})*(-0.595)] \\
&+ [((TP-3.121)*1.267^{-1})*((HC-5.227)*4.302^{-1})*(-0.488)] \\
&+ [((TP-3.121)*1.267^{-1})*((OM-1.995)*1.201^{-1})*(2.067)] \\
&+ [((SL-8.00)*7.765^{-1})* ((OM-1.995)*1.201^{-1})*(-1.454)] \\
&+ [((FR-4.571)*6.760^{-1})*((BD-1.506)*0.084^{-1})*(-0.768)] \\
&+ [((CL-8.915)*4.138^{-1})* ((HC-5.227)*4.302^{-1})*(-0.747)] \\
&+ [((CL-8.915)*4.138^{-1})* ((PH-5.971)*0.671^{-1})*(-0.429)] \\
&+ [((BD-1.506)*0.084^{-1})*((OM-1.995)*1.201^{-1})*(-0.674)] \\
&+ [((HC-5.227)*4.302^{-1})* ((PH-5.971)*0.671^{-1})*(-0.761)] \\
&+ [((AW-0.122)*0.040^{-1})*((PH-5.971)*0.671^{-1})*(-1.201)]
\end{aligned}
$$

This points to an inherent concern when comparing the finds of Curtis's and similar naturalized community observation studies to the findings of this research. The study conducted by Curtis was an inventory of tree stands in natural settings with the influence of interspecies competition, while the soils surveys this research used to develop its data set measured trees grow under more controlled circumstances that limited this interaction. This could account for discrepancies between findings of these studies. Despite the manner in which data sets were derived, the Curtis study gives useful insight into the tree species that exist in a natural community setting, which revegetation reclamation efforts are most likely going to attempt to replicate.

All species investigated in this study have unique ranges of soil conditions in which they are able to grow. For instance, white spruce is usually associated with more wet soil conditions, whereas red pine is most commonly associated with dry sites. However, the range of both species as well as all others investigated reaches into more moderate conditions. This common range of conditions that satisfies the growth needs of species would imply that all species would covary in one axis, as was found for the first principal component. The first model can therefore best be described as a mesic model.

4.2 PRINCIPAL COMPONENT 2 EQUATION: Northern Dry Forest Model

Figure 3.2 presents the equation developed from the stepwise maximum r-squared improvement for the second principal component. The eigenvector analysis of this principal component (refer to Table 2.2) 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" (Curtis, 1959 pg. 537) in this community. This finding coincides 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 (refer to Table 2.2).

Figure 3.2 Best equation found for the Stepwise Maximum R-squared Improvement for Principal Component 2. This equation is best described as a northern dry forest model.

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

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 like 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.

4.3 Principal Component 3 Equation: Wet Mesic Model

Figures 3.3 and 3.4 show the equations developed for the third principal component. Two separate equations were derived due to possible divergences in statistical interpretations, as previously discussed. Figure 3.4 illustrates the second equation developed from the stepwise maximum r-squared improvement, which is considered to be more conservative than the equation shown in Figure 3.3. The equations explain 91.79% and 87.68% of the variance. Considering the small amount of explanation of the variance that is lost by selecting the second equation and its more conservative nature, the second equation is considered to be the most reliable model for the third principal component.

Figure 3.3 First equation found for the Stepwise Maximum R-squared Improvement for Principal Component 3. Comparison of number of terms in the equation and C(p) value indicates that this equation may be over specific.

$$
\begin{aligned}
PLANT = -0.582 &+ [((TP-3.121)*1.267^{-1})*(-0.635)] \\
&+ [((SL-8.000)*7.765^{-1})*(0.950)] \\
&+ [((FR-4.571)*6.760^{-1})*(-1.987)] \\
&+ [((AW-0.122)*0.040^{-1})*(-0.479)] \\
&+ [((PH-5.971)*0.671^{-1})*(-0.311)] \\
&+ [((OM-1.995)*1.201^{-1})*(0.831)] \\
&+ [((TP-3.121)*1.267^{-1})*((TP-3.121)*1.267^{-1})*(0.466)] \\
&+ [((SL-8.000)*7.765^{-1})*((SL-8.000)*7.765^{-1})*(-0.235)] \\
&+ [((FR-4.571)*6.760^{-1})*((FR-4.571)*6.760^{-1})*(-0.562)] \\
&+ [((CL-8.915)*4.138^{-1})*((CL-8.915)*4.138^{-1})*(-1.668)] \\
&+ [((BD-1.506)*0.084^{-1})*((BD-1.506)*0.084^{-1})*(0.844)] \\
&+ [((HC-5.227)*4.302^{-1})*((HC-5.227)*4.302^{-1})*(-2.746)] \\
&+ [((TP-3.121)*1.267^{-1})*((FR-4.571)*6.760^{-1})*(-1.999)] \\
&+ [((TP-3.121)*1.267^{-1})*((BD-1.506)*0.084^{-1})*(-1.798)] \\
&+ [((TP-3.121)*1.267^{-1})*((HC-5.227)*4.302^{-1})*(-2.129)] \\
&+ [((TP-3.121)*1.267^{-1})*((AW-0.122)*0.040^{-1})*(-1.453)] \\
&+ [((TP-3.121)*1.267^{-1})*((PH-5.971)*0.671^{-1})*(-0.648)] \\
&+ [((SL-8.000)*7.765^{-1})*((FR-4.571)*6.760^{-1})*(0.597)] \\
&+ [((SL-8.000)*7.765^{-1})*((BD-1.506)*0.084^{-1})*(0.523)] \\
&+ [((SL-8.000)*7.765^{-1})*((HC-5.227)*4.302^{-1})*(0.554)] \\
&+ [((SL-8.000)*7.765^{-1})*((AW-0.122)*0.040^{-1})*(0.552)] \\
&+ [((SL-8.000)*7.765^{-1})*((PH-5.971)*0.671^{-1})*(0.215)] \\
&+ [((FR-4.571)*6.760^{-1})*((CL-8.915)*4.138^{-1})*(-7.305)] \\
&+ [((FR-4.571)*6.760^{-1})*((BD-1.506)*0.084^{-1})*(-0.477)] \\
&+ [((FR-4.571)*6.760^{-1})*((HC-5.227)*4.302^{-1})*(-4.554)] \\
&+ [((FR-4.571)*6.760^{-1})*((PH-5.971)*0.671^{-1})*(0.531)] \\
&+ [((FR-4.571)*6.760^{-1})*((OM-1.995)*1.201^{-1})*(2.867)] \\
&+ [((CL-8.915)*4.138^{-1})*((HC-5.227)*4.302^{-1})*(-5.842)]
\end{aligned}
$$

Figure 3.3 (cont'd)

$$
\begin{aligned}
&+ [((CL-8.915)*4.138^{-1})*((AW-0.122)*0.040^{-1})*(-1.163)] \\
&+ [((CL-8.915)*4.138^{-1})*((PH-5.971)*0.671^{-1})*(0.723)] \\
&+ [((BD-1.506)*0.084^{-1})*((PH-5.971)*0.671^{-1})*(-0.524)] \\
&+ [((BD-1.506)*0.084^{-1})*((OM-1.995)*1.201^{-1})*(-0.668)] \\
&+ [((HC-5.227)*4.302^{-1})*((PH-5.971)*0.671^{-1})*(0.909)] \\
&+ [((HC-5.227)*4.302^{-1})*((OM-1.995)*1.201^{-1})*(1.583)] \\
&+ [((AW-0.122)*0.040^{-1})*((PH-5.971)*0.671^{-1})*(-0.489)] \\
&+ [((AW-0.122)*0.040^{-1})*((OM-1.995)*1.201^{-1})*(1.207)] \\
&+ [((PH-5.971)*0.671^{-1})*((OM-1.995)*1.201^{-1})*(-0.340)]
\end{aligned}
$$

Figure 3.4 Second equation found for the Stepwise Maximum R-squared Improvement for Principal Component 3. Comparison of number of terms in the equation and C(p) value indicates that this equation is most likely not over specific. This is considered the more conservative equation for this principal component when compared to the equation in Figure 3.3. Best described as a wet mesic model.

$$
\begin{aligned}
PLANT = -0.648 &+ [((TP-3.121)*1.267^{-1})*(-0.566)] \\
&+ [((SL-8.000)*7.765^{-1})*(0.854)] \\
&+ [((FR-4.571)*6.760^{-1})*(-1.422)] \\
&+ [((AW-0.122)*0.040^{-1})*(-0.538)] \\
&+ [((TP-3.121)*1.267^{-1})*((TP-3.121)*1.267^{-1})*(0.671)] \\
&+ [((SL-8.000)*7.765^{-1})*((SL-8.000)*7.765^{-1})*(-0.243)] \\
&+ [((CL-8.915)*4.138^{-1})*((CL-8.915)*4.138^{-1})*(-1.518)] \\
&+ [((BD-1.506)*0.084^{-1})*((BD-1.506)*0.084^{-1})*(0.664)] \\
&+ [((HC-5.227)*4.302^{-1})*((HC-5.227)*4.302^{-1})*(-1.334)] \\
&+ [((AW-0.122)*0.040^{-1})*((AW-0.122)*0.040^{-1})*(0.577)] \\
&+ [((PH-5.971)*0.671^{-1})*((PH-5.971)*0.671^{-1})*(-0.240)] \\
&+ [((TP-3.121)*1.267^{-1})*((FR-4.571)*6.760^{-1})*(-1.906)] \\
&+ [((TP-3.121)*1.267^{-1})*((BD-1.506)*0.084^{-1})*(-1.634)] \\
&+ [((TP-3.121)*1.267^{-1})*((HC-5.227)*4.302^{-1})*(-2.135)] \\
&+ [((TP-3.121)*1.267^{-1})*((AW-0.122)*0.040^{-1})*(-1.530)] \\
&+ [((TP-3.121)*1.267^{-1})*((PH-5.971)*0.671^{-1})*(-0.803)] \\
&+ [((SL-8.000)*7.765^{-1})*((FR-4.571)*6.760^{-1})*(0.538)] \\
&+ [((SL-8.000)*7.765^{-1})*((BD-1.506)*0.084^{-1})*(0.471)] \\
&+ [((SL-8.000)*7.765^{-1})*((HC-5.227)*4.302^{-1})*(0.548)] \\
&+ [((SL-8.000)*7.765^{-1})*((AW-0.122)*0.040^{-1})*(0.612)] \\
&+ [((SL-8.000)*7.765^{-1})*((PH-5.971)*0.671^{-1})*(0.280)] \\
&+ [((FR-4.571)*6.760^{-1})*((CL-8.915)*4.138^{-1})*(-8.013)] \\
&+ [((FR-4.571)*6.760^{-1})*((HC-5.227)*4.302^{-1})*(-1.469)] \\
&+ [((FR-4.571)*6.760^{-1})*((AW-0.122)*0.040^{-1})*(2.057)] \\
&+ [((FR-4.571)*6.760^{-1})*((PH-5.971)*0.671^{-1})*(1.270)] \\
&+ [((FR-4.571)*6.760^{-1})*((OM-1.995)*1.201^{-1})*(0.631)] \\
&+ [((CL-8.915)*4.138^{-1})*((HC-5.227)*4.302^{-1})*(-5.909)] \\
&+ [((CL-8.915)*4.138^{-1})*((AW-0.122)*0.040^{-1})*(-1.469)]
\end{aligned}
$$

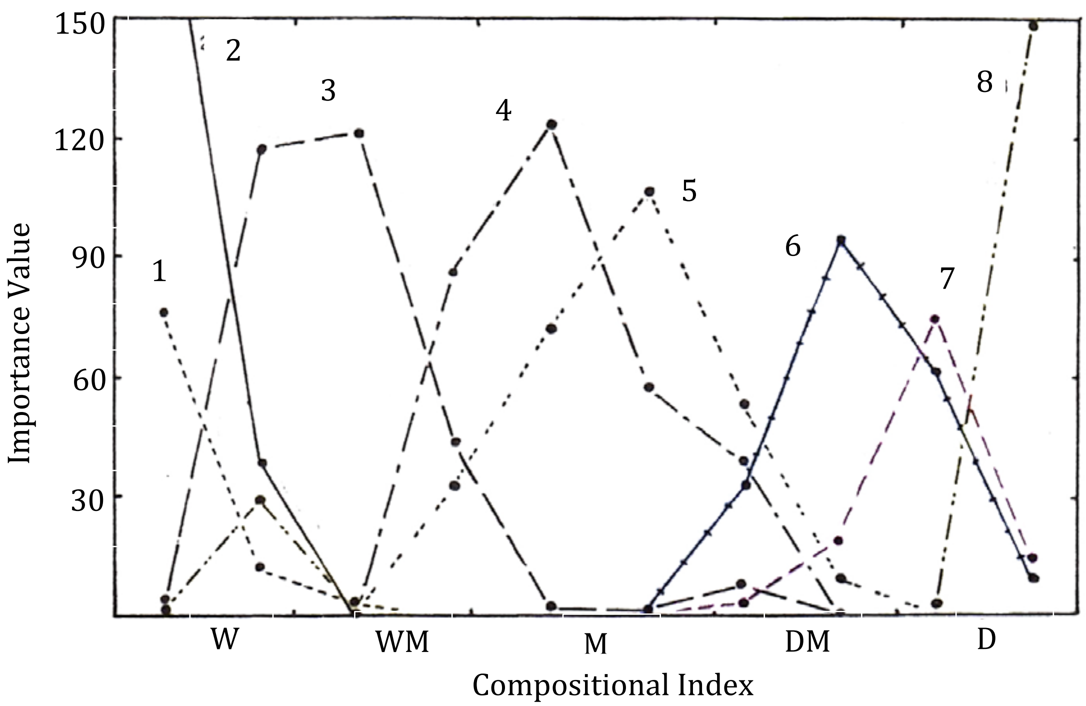
Figure 3.4 (cont'd)

$$+ [((BD-1.506)*0.084^{-1})*((OM-1.995)*1.201^{-1})*(-1.134)]$$
$$+ [((HC-5.227)*4.302^{-1})*((AW-0.122)*0.040^{-1})*(1.504)]$$
$$+ [((HC-5.227)*4.302^{-1})*((PH-5.971)*0.671^{-1})*(1.082)]$$

The eigenvector coefficients that were strongly associated with the third principal component were red maple and white spruce (refer to Table 2.2). 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 & 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. 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.

Figure 3.5 "Behavior of major tree species on the combined ordination of northern upland and lowland forests. 1, tamarack (*Larix laricina*); 2, black spruce (*Picea mariana*); 3, white cedar (*Thuja ocidentalis*); 4, hemlock (*Tsuga canadensis*); 5, sugar maple (*Acer saccharum*); 6, white pine (*Pinus strobus*); 7, red pine (*Pinus resinosa*); 8, jack pine (*Pinus banksina*)" (Curtis, 1959 pg. 180).



One concern with naming the third principal component model the wet mesic model is that Curtis found that jack pine (*Pinus banksiana* Lamb.) to show a spike in occurrence in the wet mesic range as illustrated in Figure 3.5. 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 2.2). 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.

4.4 JACK PINE MODEL

An equation was developed specifically for jack pine due to the findings of the principal component analysis. As illustrated in Table 2.2, 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 a 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 3.6 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.

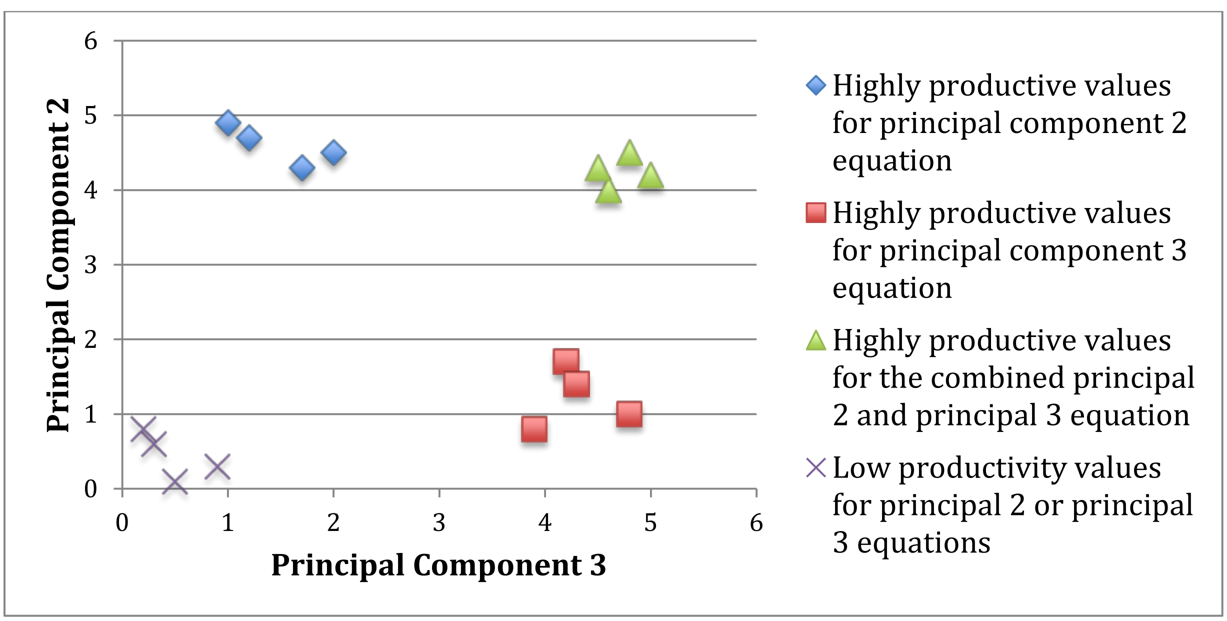


Figure 3.6 illustrates a plotting of hypothetical findings of equations that could be derived from the second and the third principal components. The values plotted are not derived from any developed equation, but rather are used to illustrate that combining the principal component 2 axis with the principal 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 are 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.

Figure 3.7 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 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.

Figure 3.7 Jack pine model derived from multiplying the second principal component model by the most reliable model for the third principal component.

$$
\begin{aligned}
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)]\} \\
* \ \{[&-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}
$$

4.5 INTERPRETATION OF MODELS

Interpretation of models developed using this methodology is often difficult. It may be most beneficial to select one equation for further analysis to demonstrate the methods of interpreting such equations. The equation developed for the second principal component has been selected as the example for equation interpretation due to its relative simplicity in comparison to other equations in this study (refer to Figure 3.8). As previously mentioned, the equation is best described as a northern dry forest or xeric model. The woody plant species that are strongly, positively associated with this equation grow well in well drained, sandy soils that are dry or seasonally dry, which is consistent with the findings of the stepwise regression analysis.

Figure 3.8 Best equation developed from the Stepwise Maximum R-squared Improvement of Principal Component 2. This equation has been selected as an example to illustrate methods of interpreting vegetative productivity equations.

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

The equation is comprised of a combination of main-effect terms, squared terms, and interaction terms. Main-effect terms are those associated with a single soil parameter. Main-effect terms included in the second principal component equation are percent slope, percent rock fragment, and available water content. The coefficient for the first main-effect term, percent slope, is positive meaning that an increase in slope will add to the productivity of the described species. Similarly, percent rock fragment also increases the productivity of these plants. As expected, available water is negatively associated with the model meaning that the plants of the xeric model grow well in dry soils. However, this term is complicated by its interaction with the available water squared term.

Squared terms describe variables that increase or decrease productivity to a limit then reverse their trends, forming parabolic trend lines. Available water content multiplied by available water content is the only squared term in this equation. This term shows that available water content increases productivity to a certain point then begins to decrease its positive influence on growth after its peak. This implies that the species described the equation can survive in conditions with low availability of water, but growth rates are reduced when soils become overly saturated or extremely dry. Although the availability of water soil parameter is only represented in this equation by a main-effect and a square term, many other parameters found in other equations of this study are further complicated by their relations with interaction terms.

The interaction terms are often much more difficult to draw intuitive conclusions from when compared to main-effect and squared terms. Interaction terms are those terms that multiply two different soil parameters together. For instance, the term that multiples topographic position with percent clay is positively associated with the model. This means that these plants grow well in steeply sloped soils with high clay content. This interaction could possibly be interpreted as; soils that are steeply sloped may be less likely to erode if they have strongly cemented clay-bond soils. However, no research has been found that suggests such finds are related to productivity of the described plant species. This term is further complicated by other terms that are associated with topographic position, such as those that combine topographic positions with percent rock fragments and bulk density. When analyzing the terms individually, all associations may not be intuitive. It is therefore necessary to analyze all terms concurrently to fully comprehend the meaning of these interactions. However, analysis of all terms can be very complicated, especially in equations with many terms.

Some terms in the resulting equation may be considered tempering terms, there to set limits upon other interactions within the equation. This could possibly be true for the two terms; topographic position multiplied by percent clay, which show a positive association, and topographic position multiplied by bulk density, which is negatively associated with the model. It is difficult to draw definitive conclusions from such interactions because one may think that soils with high percent clay would have high bulk densities, yet the opposing trends of these terms contradict this assumption. In many cases such contradictions cannot be intuitively explained as the terms are present in the equation to set limits on one another.

An alternative rationalization for this specific contradiction may possibly be explained by the presence of bedrock under shallow soils. Bulk density numbers can be drastically increased in cases of shallow soils, in which the bulk density bedrock, having a relatively high bulk density compared to soils, is measured within the first 48 inches of soil. These high bulk density values could drastically change the overall bulk density value reported for a soil and thus lower the resulting productivity score. This explanation would also allow for the possibility for soils with high clay content to be along ridgelines.

Regardless of such speculation, all soil parameter interactions must be field tested before any definitive conclusions are drawn from such equations. As illustrated in this discussion it is difficult to decipher the actual edaphic interactions, as they relate to vegetative productivity, that these equations describe. Complications associated with analyzing such equations are exacerbated as the number of terms is increased and the number of times a given soil parameter presents itself within the equation. Despite difficulties, it is important for researches to review and analyze such equations to identify issues that may be presented in developed predictive models.

4.6 LIMITATIONS OF STUDY

Although the models investigated in this study all explained significant amounts of the 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 and other (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 and others (2011) identified soils 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.

To initiate the processes post-mined soils are often planted with cover crops to avoid nutrient loss, prevent erosion of topsoil, and help to initiate sustainable nutrient cycles. Until plants are established reclamationists often fertilize areas to augment nutrient deficient soils. When this occurs the availability of the nutrient is most likely not dependent upon its concentration in the soil, but rather on the pH level of the soil as it pertains to nutrient absorption. Brady and Weil (2002) related many other chemical and biological properties to pH and considered it a master variable in determining nutrient availability. In this way, the equation does account for at least a component of what is necessary for nutrient cycling, as it relates to a plant's ability to uptake nutrients from the soil. However, it may be beneficial to explore variables that account for the concentrations of nutrients in the soil.

The most significant soil parameter investigated in this study that relates to soil nutrient concentration is percent organic matter. Three major macronutrients, nitrogen, phosphorus and potassium, which are generally deficient in post-mined soils (Coppin and Bradshaw, 1982; Sheoran et al., 2008) have been related directly to soil organic content (Sheoran et al., 2010).

Although these factors have been correlated with soil organic content, exact concentrations of individual nutrients have not been identified in the equations. It may be beneficial to investigate variables to accurately assess effects of specific nutrients to account for further explanation of the variance.

Microorganism populations in post-mined soils are often much smaller when compared to undisturbed soils and restoration of populations takes time. Chodak and others (2009), Harris (2003,2009), Jasper (2007), 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 like be used to assess soil quality in arid regions such as the southwestern United States (Scholl, 1986).

Some regional factors that have not 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 profile. 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 than all soils types in this region and would therefore produced 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 makes 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, I consider the measured properties used to create the data set adequate for accounting for the influence of them. The texture of the soil is partially accounted for by the parameters percent clay and percent rock fragments, although could be strengthen 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 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 instance in which industrial use could have contaminated soils prior to mine 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 regionally basis if 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 associated with copper mining depends on the ore being mined, it is possible if some or all of these contaminants are present in post-mined soils from this operation. Bech (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 affects 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.

4.7 ADDITIONAL USES OF EQUATIONS

The models in this study can be used in two main ways. The primary intent of these equations is to establish accurate models that predict growth potentials of crop and woody species on reconstructed soils. However, these equations can also be analyzed as a means of identifying post-mine soil treatments. For instance, cases in which plant species are described by an equation that identifies bulk density as a major limiting factor to plant growth and the sampled soil receives an insufficient score, reclamationists may recommend a tilling regime to reduce the bulk density of the measured soil. This post-mine soil treatment would be expected to decrease bulk density and therefore raise the soil index score. In this way the equations can be view not only as a way to identify the applicability of a species or set of species to a soil, but also a way to identify problematic conditions of the equation.

Similarly, the influence of soil amendments or alternative growth medias could be more accurately predicted by the equations developed by this methodology. A considerable amount of research has investigated the applications of various alternative substrates as growth media or soil amendments (Zornoza et al., 2012; Watts et al., 201 apparent. The models developed in this study can be used to assess these interactions and assist reclamationists in making amendment application decisions.

APPENDIX

Table A.1 Iron County Independent Variables

	TP	SL	FR	CL	BD	HC	AW	PH	OM
IR1OCA	1.5	1.5	0.138	10.842	1.54	1.848	0.148	7.061	1.5
IR2OCB	1.5	4	0.138	10.842	1.54	1.848	0.148	7.061	1.5
IR3OCD	2	12	0.138	10.842	1.54	1.848	0.148	7.061	1.5
IR4PAA	2.5	1.5	4.5	9.583	1.536	3.503	0.139	5.523	1.25
IR5PAB	2.5	4	4.5	9.583	1.536	3.503	0.139	5.523	1.25
IR6PAD	2.5	12	4.85	9.583	1.536	3.503	0.139	5.523	1.25
IR7TRB	2	3.5	2.85	11.238	1.488	2.38	0.154	6.332	2
IR8TRD	3	12	2.85	11.238	1.488	2.38	0.154	6.332	2
IR9SOA	1	1.5	7.2	14.25	1.533	1.3	0.152	7.27	2
IR10CHA	1	1.5	5.583	6.35	1.482	6.91	0.107	5.415	2
IR11KAB	2	3.5	0	8.591	1.484	5.05	0.114	5.213	1.25
IR12KAD	2	12	0	8.591	1.484	5.05	0.114	5.213	1.25
IR13GAA	1.5	1.5	0.479	12.967	1.534	0.985	0.19	5.655	3.5
IR14FEA	2	1.5	0	12.541	1.532	0.46	0.19	5.114	1.5
IR15FEB	2.5	4	0	12.541	1.532	0.46	0.19	5.114	1.5
IR16FED	2.5	12	0	12.541	1.532	0.46	0.19	5.114	1.5
IR17PEB	3.5	3.5	9.233	6	1.505	6.05	0.099	5.545	2
IR18PED	3.5	12	9.233	6	1.505	6.05	0.099	5.545	2
IR19KEB	2.5	3.5	12.252	8.25	1.624	3.948	0.092	5.523	1.25
IR20KED	3	12	12.252	8.25	1.624	3.948	0.092	5.523	1.25
IR21ESB	2.5	3.5	10	8.6	1.478	3.73	0.101	6.287	1.75
IR22STA	1.5	1.5	5.013	10.675	1.416	2.365	0.205	5.291	2
IR23STB	2	4	5.013	10.675	1.416	2.365	0.205	5.291	2
IR24STD	3	12	5.013	10.675	1.416	2.365	0.205	5.291	2
IR25SAB	3.5	3.5	8.383	8.267	1.601	1.3	0.118	5.528	2
IR26SAD	4	12	8.383	8.267	1.601	1.3	0.118	5.528	2
IR27SUB	3.5	3.5	4.366	6.263	1.541	7.845	0.127	5.638	2
IR28SUD	4	12	4.366	6.263	1.541	7.845	0.127	5.638	2
IR29SUA	3.5	1.5	3.934	7.058	1.541	6.599	0.142	5.621	2
IR30MAA	1.5	1.5	4.646	7.238	1.568	4.533	0.108	5.647	2
IR31PEB	2	3.5	5.65	8.429	1.607	1.005	0.146	6.05	2
IR32PED	2.5	12	5.65	8.429	1.607	1.005	0.146	6.05	2
IR33SAB	2.5	3.5	11.05	8.5	1.384	4	0.128	6.43	2
IR34SAD	3	12	11.05	8.5	1.384	4	0.128	6.43	2
IR35ALB	2.5	3	1.5	16.113	1.596	1.255	0.175	6.147	3.5

Table A.1 Iron County Independent Variables (Cont'd)

	TP	SL	FR	CL	BD	HC	AW	PH	OM
IR36MOA	1	1.5	7.5	6.417	1.678	1.3	0.111	6.037	2.5
IR37PEB	3.5	3.5	7.5	6.133	1.507	6.217	0.099	5.535	2
IR38PED	3.5	12	7.5	6.133	1.507	6.217	0.099	5.535	2
IR39MOA	1	1.5	7.5	6.417	1.678	1.3	0.111	6.037	2.5
IR40BEA	1	1	3.5	11	1.28	1.3	0.212	5	3
IR41STB	3	4	4.517	10.675	1.395	1.661	0.214	5.268	2
IR42LOB	2.5	3.5	7.5	7.583	1.314	4.728	0.139	5.351	1.25
IR43LOD	2.5	12	7.5	7.583	1.314	4.728	0.139	5.351	1.25
IR44MOA	1	1	7.5	8.396	1.616	1.3	0.135	5.798	2.5
IR45PEB	3.5	3.5	4.475	6	1.505	6.05	0.099	5.545	2

Table A.2 Iron County Dependent Variables

	CO	CS	OA	IP	AH	RM	WS	RP	EP	JP	LI
IR1OCA	70	11	60	0	0	0	0	30.5	30.5	30.5	11.5
IR2OCB	70	11	60	0	0	0	0	30.5	30.5	30.5	11.5
IR3OCD	50	8	40	0	0	0	0	30.5	30.5	30.5	11.5
IR4PAA	70	11	70	0	0	0	0	30.5	30.5	30.5	11.5
IR5PAB	70	11	70	0	0	0	0	30.5	30.5	30.5	11.5
IR6PAD	55	9	55	0	0	0	0	0	0	0	0
IR7TRB	0	14	75	350	0	0	0	0	0	0	0
IR8TRD	0	0	60	0	0	0	0	0	0	0	0
IR9SOA	85	14	75	0	0	0	0	0	0	0	0
IR10CHA	0	0	60	0	0	0	20.5	0	30.5	0	11.5
IR11KAB	70	13	60	0	0	0	0	20.5	20.5	20.5	11.5
IR12KAD	0	0	50	0	0	0	0	20.5	20.5	20.5	11.5
IR13GAA	0	0	85	0	0	0	20.5	0	30.5	0	0
IR14FEA	75	12	75	0	0	30.5	20.5	30.5	30.5	0	11.5
IR15FEB	70	11	75	0	0	30.5	20.5	30.5	30.5	0	11.5
IR16FED	60	10	70	0	0	30.5	20.5	30.5	30.5	0	11.5
IR17PEB	60	10	55	0	0	0	0	30.5	30.5	30.5	11.5
IR18PED	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
IR19KEB	0	10	60	250	3	0	20.5	30.5	30.5	20.5	11.5
IR20KED	0	0	0	0	2.4	0	20.5	30.5	30.5	20.5	11.5

A.2 Iron County Dependent Variables (cont'd)

	CO	CS	OA	IP	AH	RM	WS	RP	EP	JP	LI
IR21ESB	75	12	70	350	3.5	0	20.5	30.5	30.5	20.5	11.5
IR22STA	0	14	80	350	4	0	20.5	20.5	30.5	20.5	0
IR23STB	0	14	80	350	4	0	20.5	20.5	30.5	20.5	0
IR24STD	0	0	60	0	3	0	20.5	20.5	30.5	20.5	0
IR25SAB	80	13	65	0	0	0	0	0	0	0	0
IR26SAD	0	0	0	0	0	0	0	0	0	0	0
IR27SUB	0	0	55	275	0	0	0	20.5	20.5	20.5	0
IR28SUD	0	0	0	0	0	0	0	20.5	20.5	20.5	0
IR29SUA	0	0	60	275	0	0	0	20.5	20.5	20.5	0
IR30MAA	0	10	50	0	0	0	0	30.5	30.5	30.5	11.5
IR31PEB	80	13	75	0	3.5	0	0	0	0	0	0
IR32PED	0	0	65	0	3.5	0	0	0	0	0	0
IR33SAB	0	0	60	275	0	20.5	20.5	30.5	30.5	0	0
IR34SAD	0	0	0	0	0	20.5	20.5	30.5	30.5	0	0
IR35ALB	90	15	70	0	0	30.5	20.5	0	30.5	0	11.5
IR36MOA	0	12	60	0	0	30.5	20.5	0	30.5	0	11.5
IR37PEB	60	10	55	0	0	0	0	30.5	30.5	30.5	11.5
IR38PED	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
IR39MOA	0	12	60	0	0	30.5	20.5	0	30.5	0	11.5
IR40BEA	0	0	70	0	0	0	20.5	0	30.5	0	0
IR41STB	0	14	75	350	4	0	20.5	20.5	30.5	20.5	0
IR42LOB	0	0	75	0	3.5	0	0	0	0	0	0
IR43LOD	0	0	0	0	2.5	0	0	0	0	0	0
IR44MOA	0	12	60	0	0	30.5	20.5	0	30.5	0	11.5
IR45PEB	60	10	55	0	0	0	0	30.5	30.5	30.5	11.5

Table A.3 Dickinson County Independent Variables

	TP	SL	FR	CL	BD	HC	AW	PH	OM
DI1PEB	4	3	7.5	10.265	1.394	3.825	0.138	5.82	1.75
DI2PED	4.5	12	7.5	10.265	1.394	3.825	0.138	5.82	1.75
DI3PEF	5	26.5	7.5	10.265	1.394	3.825	0.138	5.82	1.75
DI4FEB	3.5	3	0	12.2	1.477	0.64	0.2	5.05	1.5
DI5FED	3	12	0	12.2	1.477	0.64	0.2	5.05	1.5

Table A.3 Dickinson County Independent Variables (cont'd)

	TP	SL	FR	CL	BD	HC	AW	PH	OM
DI6KAB	4	3	0	5.817	1.489	5.65	0.087	6.005	1.25
DI7KAD	4.5	12	0	5.817	1.489	5.65	0.087	6.005	1.25
DI8KAF	5	26.5	0	5.817	1.489	5.65	0.087	6.005	1.25
DI9ESB	3.5	3	2.625	8.879	1.484	3.64	0.105	6.253	1.75
DI10ESD	4	12	2.625	8.879	1.484	3.64	0.105	6.253	1.75
DI11EMB	3.5	3	2.5	15.417	1.624	3.055	0.13	6.968	2
DI12EMD	4	12	2.5	15.417	1.624	3.055	0.13	6.968	2
DI13EMF	5	26.5	2.5	15.417	1.624	3.055	0.13	6.968	2
DI14PEB	3.5	3	4.683	5.5	1.522	4.5	0.09	5.421	2
DI15PED	4	12	4.683	5.5	1.522	4.5	0.09	5.421	2
DI16PEF	5	26.5	4.683	5.5	1.522	4.5	0.09	5.421	2
DI17DE	1	0	0	5.8	1.515	13	0.064	6.94	8
DI18ROA	3.5	1.5	0	5	1.468	13	0.079	5.505	1.5
DI19NAB	4	3	8.5	7.675	1.414	5.04	0.125	6.884	2
DI20NAD	4.5	12	8.5	7.675	1.414	5.04	0.125	6.884	2
DI21NAF	5	26.5	8.5	7.675	1.414	5.04	0.125	6.884	2
DI22ROB	4	3	0	5	1.468	13	0.07	5.611	1.5
DI23ROD	4.5	12	0	5	1.468	13	0.07	5.611	1.5
DI24ROF	5	26.5	0	5	1.468	13	0.07	5.611	1.5
DI25OCB	3.5	3	1.275	9.775	1.556	2.475	0.12	7.098	1.5
DI26OCD	4.5	12	1.275	9.775	1.556	2.475	0.12	7.098	1.5
DI27WAA	1	1.5	0	6.55	1.401	13	0.082	5.528	3
DI28MAB	4	3	3.417	7.625	1.375	12.633	0.083	6.883	1.75
DI29MAD	4.5	12	3.417	7.625	1.375	12.633	0.083	6.883	1.75
DI30MAF	5	26.5	3.417	7.625	1.375	12.633	0.083	6.883	1.75
DI31KI	1	0	0	5	1.45	13	0.05	5.29	9.5
DI32VIB	4	3	0	2.983	1.579	13	0.08	5.54	1
DI33VID	4.5	12	0	2.983	1.579	13	0.08	5.54	1
DI34VIF	5	26.5	0	2.983	1.579	13	0.08	5.54	1
DI35CHA	1.5	1.5	4.563	6.3	1.491	7.378	0.103	5.429	2
DI36ZIB	4	3	0	4.75	1.595	13	0.08	6.61	1.5
DI37ZID	4.5	12	0	4.75	1.595	13	0.08	6.61	1.5
DI38ZIF	5	26.5	0	4.75	1.595	13	0.08	6.61	1.5
DI39RUB	4	3	0	4.437	1.443	13	0.061	5.297	0.75
DI40RUD	4.5	12	0	4.437	1.443	13	0.061	5.297	0.75

Table A.3 Dickinson County Independent Variables (cont'd)

	TP	SL	FR	CL	BD	HC	AW	PH	OM
DI41RUF	5	26.5	0	4.437	1.443	13	0.061	5.297	0.75
DI42UD	2	0	0	0	0	0	0	0	0
DI43SOB	1.5	2	1.5	13.354	1.55	1.3	0.138	7.344	2
DI44ENB	1	0	5	14.65	1.515	3.189	0.12	7.335	5.5
DI45ALB	3.5	3	0.075	16.637	1.599	1.255	0.175	6.415	3
DI46HE	1	0	0	31.3	1.525	0.432	0.173	7.467	3.5
DI47LOB	3.5	3	43.75	8.083	1.445	1.263	0.089	6.45	2
DI48LOD	4	12	43.75	8.083	1.445	1.263	0.089	6.45	2
DI49UVB	4	4	4.125	18.125	1.664	0.92	0.167	6.093	2
DI50UVD	4.5	12	4.125	18.125	1.664	0.92	0.167	6.093	2

Table A.4 Dickinson County Dependent Variables

	CO	CS	OA	IP	AH	RM	WS	RP	EP	JP	LI
DI1PEB	70	11	60	300	3	0	20.5	30.5	30.5	0	11.5
DI2PED	0	0	50	0	0	0	20.5	30.5	30.5	0	11.5
DI3PEF	0	0	0	0	0	0	20.5	30.5	30.5	0	11.5
DI4FEB	90	15	80	362.5	4	30.5	20.5	30.5	30.5	0	11.5
DI5FED	0	0	70	0	3.5	30.5	20.5	30.5	30.5	0	11.5
DI6KAB	70	13	60	300	3	0	0	30.5	30.5	0	11.5
DI7KAD	0	0	55	0	2.5	0	0	30.5	30.5	0	11.5
DI8KAF	0	0	0	0	0	0	0	30.5	30.5	0	11.5
DI9ESB	75	12	70	312.5	3.5	0	20.5	30.5	30.5	30.5	11.5
DI10ESD	0	0	55	0	3.1	0	20.5	30.5	30.5	30.5	11.5
DI11EMB	75	15	75	337.5	3.5	30.5	20.5	30.5	30.5	0	11.5
DI12EMD	0	0	70	0	3.2	30.5	20.5	30.5	30.5	0	11.5
DI13EMF	0	0	0	0	0	30.5	20.5	30.5	30.5	0	11.5
DI14PEB	70	10	60	300	3	0	0	30.5	30.5	30.5	11.5
DI15PED	0	0	55	0	2.7	0	0	30.5	30.5	30.5	11.5
DI16PEF	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
DI17DE	0	0	0	0	0	0	30.5	0	30.5	0	11.5

Table A.4 Dickinson County Dependent Variables (cont'd)

	CO	CS	OA	IP	AH	RM	WS	RP	EP	JP	LI
DI18ROA	70	10	60	300	3	0	20.5	30.5	30.5	30.5	0
DI19NAB	70	11	70	312.5	3	0	20.5	30.5	30.5	0	11.5
DI20NAD	0	0	65	0	2.6	0	20.5	30.5	30.5	0	11.5
DI21NAF	0	0	0	0	0	0	20.5	30.5	30.5	0	11.5
DI22ROB	60	10	50	287.5	2.8	0	20.5	30.5	30.5	30.5	0
DI23ROD	0	0	45	0	2.2	0	20.5	30.5	30.5	30.5	0
DI24ROF	0	0	0	0	0	0	20.5	30.5	30.5	30.5	0
DI25OCB	70	11	70	312.5	3	0	0	30.5	30.5	30.5	11.5
DI26OCD	50	8	65	0	2.5	0	0	30.5	30.5	30.5	11.5
DI27WAA	70	14	60	0	3	0	11.5	0	30.5	0	0
DI28MAB	70	13	60	300	3	0	20.5	30.5	30.5	30.5	11.5
DI29MAD	0	0	55	0	2.7	0	20.5	30.5	30.5	30.5	11.5
DI30MAF	0	0	0	0	0	0	20.5	30.5	30.5	30.5	11.5
DI31KI	0	0	0	0	0	0	0	0	0	0	0
DI32VIB	50	8	40	262.5	2.5	0	0	30.5	30.5	30.5	11.5
DI33VID	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
DI34VIF	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
DI35CHA	70	11	65	0	3	0	20.5	0	30.5	30.5	11.5
DI36ZIB	70	10	60	300	3	0	0	30.5	30.5	30.5	11.5
DI37ZID	0	0	55	0	2.7	0	0	30.5	30.5	30.5	11.5
DI38ZIF	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
DI39RUB	0	0	0	0	2	0	0	30.5	30.5	30.5	11.5
DI40RUD	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
DI41RUF	0	0	0	0	0	0	0	30.5	30.5	30.5	11.5
DI42UD	0	0	0	0	0	0	0	0	0	0	0
DI43SOB	80	14	80	0	3.5	30.5	20.5	0	30.5	0	11.5
DI44ENB	0	0	0	0	0	0	0	0	0	0	0
DI45ALB	90	14	85	0	4	30.5	20.5	0	30.5	0	11.5
DI46HE	0	0	0	0	0	0	0	0	0	0	0
DI47LOB	70	11	70	312.5	3	0	0	0	0	0	0
DI48LOD	0	0	65	0	2.7	0	0	0	0	0	0
DI49UVB	80	15	65	362.5	3.8	0	20.5	30.5	30.5	30.5	11.5
DI50UVD	70	14	60	0	3.8	0	0	30.5	30.5	30.5	11.5

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