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Ecological Indicator Development, Integration and Knowledge Mapping

Aaron Dean Peacock
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Aaron Dean Peacock entitled "Ecological Indicator Development, Integration and Knowledge Mapping." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Plants, Soils, and Insects.

Michael Essington, Major Professor

We have read this dissertation and recommend its acceptance:

Virginia Dale, Arnold Saxton, Daniel Yoder

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

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ECOLOGICAL INDICATOR DEVELOPMENT,

INTEGRATION AND KNOWLEDGE MAPPING

A Dissertation

Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Aaron Dean Peacock

May 2007

Dedication

This dissertation is dedicated to David Cleveland White, who was tragically taken from our laboratory family by an auto accident on October 25, 2006. I could write a book about my boss and friend, there were so many stories.

Acknowledgements

The author would like to acknowledge Michael Essington, for all of the great conversations over the years, and for helping an unconventional student negotiate the UT system. The author acknowledges Virginia Dale, for her encouragement to pursue a Ph.D., and for all of her support in this project, without her guidance this work would not have been possible. The author would like to thank Arnold Saxton for all of the statistical help (since 1998), and Daniel Yoder for his perspective on tough issues. The author also acknowledges Sarah MacNaughton for assistance in the early part of this project and her comments on the draft, James Cantu for all of his efforts in the field, in the lab, and pinch hitting at a presentation when the author was ill. Thanks go to Taryn Arthur for collecting and organizing much of the data used in this work, without her efforts the author would still be chasing numbers. The author would like to acknowledge the help of Suzanne Beyeler and Patty Kosky in the field and Jonas Almeida for suggestions regarding artificial neural networks. The author would like to thank Chuck Garten for his insight into soil systems and data analysis, and David B. Hedrick for science and editing assistance. The author would also like to thank everyone at the Center for Biomarker Analysis, they will be missed. The project was funded by a contract from the Conservation Program of the Strategic Environmental Research and Development Program (SERDP) with Oak Ridge National Laboratory (ORNL) under subcontract 4500012011, *Indicators of Ecological Change*. ORNL is managed by UT-Battelle, LLC for the U. S. Department of Energy under contract DE-AC05-00OR22725.

Abstract

The overall goals of this project were: (1) to develop a microbiological ecological indicator that would describe military land disturbance, (2) integrate previously collected ecological indicator data from five separate research teams, and (3) produce knowledge maps with the resulting information that illustrates how the selected indicators are involved in ecosystem processes. To address goal one, soil samples were obtained from four levels of military traffic (reference, light, moderate, and heavy) with an additional set of samples taken from previously damaged areas. Using the soil microbial biomass and community composition as ecological indicators, reproducible changes showed increasing traffic disturbance decreases soil viable biomass, biomarkers for microeukaryotes and Gram-negative bacteria, while increasing the proportions of aerobic Gram-positive bacterial and actinomycete biomarkers. To address the second goal, ecological indicator data was collected by five separate research teams. Land-management categories (LMCs) were developed that described the uses or causes of the ecological effect from military use(s) of land. A mechanism of multiple solutions was developed that combined the results and tested the efficacy of the proposed indicators. Results from the integration effort showed that Soil A horizon depth and soil compaction were important soil physical indicators of military land disturbance. Soil Nitrogen and Carbon content were important soil chemical indicators of land use. Soil mineralization rate, soil respiration, microbial composition and Beta Glucosidase activity were important microbiological indicators. Important plant indicators included tree stand age, canopy

cover, understory cover, plant life form and legumes. To address the third goal several knowledge maps were developed, and the results from the integration of indicator data were pooled and studied for the relationships between them. By displaying the indicators in this fashion, it was hoped that the knowledge of what the indicators represent to the functioning of the ecological system could be understood. For the practitioner, this knowledge should lead to actionable products or at least a better understanding of what is being measured and how it relates to broader ecosystem dynamics.

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Abbreviations

ANN	Artificial Neural Network
ANOVA	analysis of variance
DoD	U.S. Department of Defense
LMC	land management category
PLFA	Phospholipid (Polar Lipid) Fatty Acids
SERDP	Strategic Environmental Research and Development Program,
SEMP	SERDP Ecosystem Management Project

Chapter 1

Background and Introduction

Background

Lester Brown, president of the Earth Policy Institute, states that the global economy is outgrowing the capacity of the earth to support it (Brown, 2006). Brown goes on to state that as a result of the world's preoccupation with output, humanity is consuming renewable resources faster than they can regenerate. Falling water tables, shrinking forests, deteriorating grasslands, collapsing fisheries and eroding soils are combining to challenge the human capability to understand and interact with the environment in a sustainable way. Whether or not people agree with the motives or tactics of people like Mr. Brown, there is a level of truth to his message. As a result of increasing population and other pressures, there has been a steady increase in the intensity and use of land resources. The use of the land resources can take many forms, from agriculture and mining to recreation. However, because of the increased intensity of land use and the realization that the land is a finite resource, it is incumbent upon society to manage the land in a sustainable way. This concern may be all the more important when and if oil becomes more limited and humanity must then rely on the land to provide not only food, fiber, and clean water, but also fuel for our economies.

If humanity expects those who are responsible for managing land to do so in a sustainable manner, then society must provide the tools they need to perform the job. This work describes the exploration and validation of terrestrial ecosystem ecological indicators that can be used in sustainable land management programs. The focus of the work is on ecological indicators, defined as the parameters that can inform about the condition of the environment, provide early warning signals of changes, and diagnose the cause of problems (Dale and Beyeler, 2001). This work is intended to have broad application to terrestrial environments and land usage. A decision was made to conduct this study using military land-use sustainability and monitoring because the military is dealing with many land use problems that are reflective of land use challenges in general.

Military trainers and land managers are responsible for the planning, use and maintenance of lands designated for the preparation of military personnel for war. In the conduct of war there is, by definition, destruction of property and resources. In order to simulate war for training purposes, some land resources are often used in ways that are not environmentally sustainable. Recently, issues related to base realignment and closure (BRAC) policies have had the effect of concentrating more military training on fewer installations. In addition to the loss of bases for training, The US Army Corp of Engineers states that "*Heavier and faster vehicles, longer combat engagement distances, increased mechanization, combined armed exercises, and testing for advanced weapons systems and other materiel have increased environmental impacts on U.S. Army installations*" (USCERL, 2006). The reduction in training area and environmental degradation due to overuse of remaining land resources lessen the realism of a natural environment in combat training situations (USCERL, 1997). In extreme cases, heavily eroded land can become dangerous for use by tactical vehicles and may need to be remediated by various means at great expense. During remediation activities, the land resources are not available for military training. The loss or mismanagement of land resources on military bases can result in criticism from the public that the Armed Forces are not capable stewards (Lindsey-Poland, 2000), but the most dangerous result for the country is inadequately trained troops.

According to the Range and Training Land Assessment Technical Reference Manual (Bern et al., 2006) military training can cause several types of land disturbance and environmental degradation. Some examples of environmental problems associated with military training include:

- Soil compaction.
- Soil erosion.
- Siltation of waterways and wetlands.
- Increased flooding.
- Loss of wildlife habitat.
- Loss of biodiversity.
- Loss of groundcover.
- Invasion by non native plant species.
- Impacts on Threatened and Endangered Species (TES) and other species of concern.

The Army and other services are required under the National Environmental Policy Act of 1969 (NEPA) to avoid short- and long-term impacts to the environment caused by military training. The Army has also set its own regulation, Army Regulation 200-2, to deal with environmental impacts of military training, and it essentially seconds the NEPA regulation. Regardless of any regulation, it is in the best interest of the Department of

Defense to preserve and even enhance land resources for the use and realistic training of military personnel.

The Army realizes the importance of managing land use in order to provide training and has established the Sustainable Range Program (SRP). The SRP serves as the executive program and defines methods for how the Army manages and uses land resources to meet training responsibilities. At the present time, the Range and Training Land Program (RTLP) and the Integrated Training Area Management Program (ITAM) are the central programs within the SRP. These central programs are, in turn, integrated with facilities management, environmental management, munitions management and other functions such as safety programs in order to provide availability and accessibility of Army training lands (Bern et al., 2006).

The ITAM program includes the Range and Training Land Assessment (RTLA) program. The RTLA and its predecessor, the Land Condition Trend Analysis (LCTA) program (Diersing et al., 1992), have been the Army's designated technical authority for ecological monitoring on military lands since 1984. Originally the RTLA program was established as a top-down program that provided national level assessments of land condition and inventories of natural resources on military lands. The emphasis was on long-term monitoring of ecological trends and on data collection activities. Although one of the original objectives of the RTLA was that "*The data would be able to evaluate the capability of lands to support sustained military use*" (Bern et al., 2006), in practice this goal was not achieved. Many installations collected data, but these data were not used for management decisions (Dale, personal communication). Those working with the RTLA have recognized this problem, as in section 1.2 of the current RTLA technical manual it states: “*Since its inception, the emphasis of the RTLA has been on data collection. Prior to 2000, on most installations RTLA data was not used extensively for reporting, problem solving, and adaptive management. Few or no reporting requirements partially resulted in a high proportion of the RTLA being expended on data collection, rather than on data management, evaluation, analysis, and site-specific applications. As a result, data collected provided limited feedback to support adaptive resource management, mission sustainability, and evaluation of the monitoring design and methods*” (Bern et al., 2006).

Recently, the RTLA program managers have focused on providing a decentralized installation-level approach to monitoring, and there is evidence that individual installations are adapting the approaches described in the RTLA to specific problems such as sustainability. Currently the RTLA provides a wealth of highly detailed information on many ecological methods such as resource monitoring, sampling, data management, and data interpretation.

In order to address the knowledge gaps that had arisen from the current standard operating procedure for the sustainable use of military lands, the Strategic Environmental Research and Development Program (SERDP) hosted a workshop in 1997 titled “*The Management-Scale Ecosystem Research Workshop*.” Participants at the workshop were tasked with identifying critical issues related to understanding ecosystem status and military use. The main issues identified included:

- Ecosystem health or change indicators.
- Thresholds of disturbance.
- Biogeochemical cycles and processes.

- Ecosystem processes as they relate to multiple temporal and spatial scales.

As a consequence of the workshop, SERDP's Ecosystem Management Program (SEMP) was established. The purpose of SEMP was to address relevant Department of Defense (DoD) ecosystem sustainability research. SEMP developed a Statement of Need (SON) based on the results of the ecosystem workshop and solicited competitive responses. After scientific peer review and a Technical Advisory Committee (TAC) review, five research teams representing several universities and two government research institutions were selected to perform research. The research was divided into two main categories, with the first being "*Determination of Indicators of Ecological Change*." The main objective for these projects was to identify indicators signaling ecological change on military bases along disturbance gradients caused by military training. The second research category was titled "*Ecological Disturbance in the Context of Military Landscapes*." The main objective of this group was to develop the knowledge base that identified ecological thresholds required to implement adaptive ecosystem management approaches for military lands and waters (SERDP, 2002). The present research integrates and extends the results from the SEMP program by distilling the ecological indicator data and investigating the role the indicators play in the ecosystem.

Introduction

Ecological Indicators for Environmental Monitoring

Ecological indicators are parameters that can be used to assess the condition of an environment (Dale and Beyeler, 2001). Ecological indicators can take many forms and can provide information about several different aspects of the environment, such as function or response to stresses. Some examples of ecological indicators that have been used for military land management include percent bare ground, soil surface loss or degradation, annual biomass production, and plant functional or structural groups (Pyke et al., 2002). Perhaps the most critical decision for land managers is choosing the right indicators for the ecosystem they are trying to understand and manage. An important point to consider is that "Ecosystem management requires the identification of ecological attributes that are indicative of critical processes of an ecosystem and that can be altered by management actions".

There are some general and overarching princples for land management that can aid in the selection of candidate indicators. In an Ecological Society of America report, Dale et al. (2000) describe five ecological princples and their implications for land use. Each of these is described in detail below.

1. Time Principle: Ecological processes function at many time scales, some long and some short, and ecosystems change through time.

Ecological succession is a good illustration of this principle. Originally a landscape is colonized by species that dominate for a time, and then give way to another group of species. Eventually, a climax community is established that can be supported by, and is reflective of, the constraints of that ecosystem. During succession, there are ecologically relevant reactions occurring at different time scales; e.g., microbial metabolic reactions in the soil and rhizosphere may be accomplished in minutes or seconds, but soil formation can take centuries.

2. Species Principle: Particular species and networks of interacting species have key, broad-scale ecosystem level effects.

There are several different types of species including indicator, keystone, ecological engineers, umbrella, and linkage species. Each of these species types can interact with the environment in different ways. Ecological monitoring based on a particular species type provides different information for the management of military lands. It follows that identifying the important species (as indicators) can aid in the exposition of ecosystem function or lack thereof.

3. Place Principle: Local climatic, hydrologic, edaphic, and geomorphologic factors as well as biotic interactions strongly affect ecological processes and the abundance and distribution of species at any one place.

Niche spaces are influenced or controlled by the available resources provided by the environment in a particular location. In most cases, the environment dictates what types of species can exist. At a geochemical level, carbon, nutrient, and energy cycles are highly influenced by the particular environment. For example, a Boreal forest is very different in production and structure from a forest located in a temperate zone, and any monitoring program must take this princple into account.

4. Disturbance Principle: The type, intensity and duration of disturbance shape the characteristics of populations, communities, and ecosystems.

This princple is most important when considering the management of military lands. Small and temporary disturbances may interfere with ecological systems, whereas large and/or chronic disturbances can completely reshape them and result in a loss of sustainability.

5. Landscape Principle: The size, shape and spatial relationships of land-cover types influence the dynamics of populations, communities and ecosystems.

This principle also has relevance to military land use. Military bases are usually discrete land areas with arbitrary borders. Within the bases there may be training areas that are not conducive for a given purpose due to the size and or shape of the property.

Taken together, these five princples provide a framework for understanding those processes (in a general sense) that a robust set of ecological indicators should measure and ultimately describe; namely structure, function and composition. The identification, development and application of ecological indicators for a given purpose such as military land use will be extremely complex. As such, the value of any set of ecological indicators will vary depending on management goals and strategies.

There are also several challenges when considering specific ecological indicators for monitoring purposes. Dale and Beyeler (2001) list several attributes of effective ecological indicators for monitoring programs:

- Are easily measured.
- Are sensitive to stresses on the system.
- Respond to stress in a predictable manner.
- Are anticipatory, i.e., signify an impending change in key characteristics of the ecological system.
- Predict changes that can be averted by management actions
- Are integrative: the full suite of indicators provides a measure of coverage of the key gradients across the ecological system (e.g. soils, vegetation types, temperature, etc.)

- Have a known response to natural disturbances, anthropogenic stresses, and changes over time.
- Have a low variability in response.

Identifying an indicator that would satisfy all of these criteria would be extremely difficult if not impossible. However, it is not expected that any single indicator can or will be able to meet all criteria, so a suite of indicators should be employed that best addresses management needs. It is also important to state at this time that not all relevant indicators have been assessed in this dissertation. For example, as this work progressed it became apparent that soil erosion was a critical process at Fort Benning. Jawdy (2003) measured erosion rate and found it was a useful ecological indicator of soil quality, because when soils are eroding quickly it is impossible to maintain the healthy status of other indicators. When the soil is eroding the support of all of the primary production and nutrient cycling are likewise degraded, and then other measured indicators decline in quality, as an example soil organic matter declines with more erosion.

Data Analysis for Environmental Monitoring

Another important issue in ecological indicator development for monitoring programs is to decide what ecological indicators to use and how to integrate them into land management. As an example, at several Army installations there already exist extensive ecological data collected from past and current monitoring programs and various scientific efforts. Although these efforts may provide good data, they may not relate to the management goals established by land managers. Data, models and information produced by scientists and others often fail to meet the needs of land managers (Jones et al., 1999; Rayner et al., 2001; Steel et al., 2001), so a program or method that can relate ecological indicators to management goals for land use is paramount to program success and sustainability.

In order to address the disconnect between ecological indicators, land management, and land management goals, Wolfe and Dale (2006a; 2006b) developed an approach that identifies a series of land management categories for military installations that encompass land-management goals and are relevant to the management of military lands. The creation of land-management categories was a necessary step in the establishment of land-use goals and, once specified, have provided land managers with the data they need to allocate resources.

The work of Wolfe and Dale was only the first step in a process to identify and validate ecological indicators that would have meaning for military land managers. What remained to be developed was a method to identify and integrate the relevant ecological indicators from a pool of candidate indicators. The data for these indicators can originate from several different data sources and were, in a word, 'disordered'. The structure and shape of the data make the use of basic statistical models unreliable. New thought as to how data integration should take place was needed.

Data Visualization and Validation

Once ecological indicators that are relevant to the management and sustainability of military lands have been identified and integrated, there remains a need to justify and present the results in a manner that the managers can identify. There are several different methods one could choose to accomplish this. Conceptual Ecological Models can be very helpful in synthesizing what is known about an ecosystem and also in identifying attributes to monitor changes in those systems over time (Bern et al., 2006). The type of model that is developed depends upon the management goals for the site. Information provided in a Nature Conservancy Report (The Nature Conservancy, 1994), and papers from Peacock et al., (2001a) and Gross (2003) allowed the authors of the Bern et al. (2006) to state that conceptual models can:

- Store information and capture institutional knowledge.
- Provide users with predictive capabilities and scenario-building information.
- Identify priority conservation targets, processes, stressors, and threats (actual or potential) affecting them.
- Help managers and scientists understand ecosystem dynamics, responses to stressors (natural and anthropogenic), and ranges of natural variability.
- Identify links between state/ecosystem components, drivers, stressors, system responses, and monitoring attributes.
- Facilitate evaluation of monitoring data.
- Provide a framework for interpreting monitoring results in an adaptive management context and for prioritizing actions.
- Document assumptions, knowledge, experience, and unknowns/information gaps.
- Be valuable tools for a variety of audiences.
- Help identify thresholds of condition that may be difficult or impossible to reverse.

Conceptual models do not need to be complex, and management-oriented conceptual models are routinely used to help direct management and monitoring activities. Perhaps one of the most important aspects of a conceptual model is the ability to illustrate the relationship between an indicator and the ecosystem. Models can also provide context for monitoring activities, development and land-management.

Another way to validate data is to use a technique known as Knowledge Mapping. The purpose of Knowledge Mapping is to visualize a network of operational relationships between objects in a complex system, in our case indicators within the ecosystem under study. This visualization aids in the charting of cause-and-effect connections within a given system. For military land management, we can consider the measured ecological indicators as facts, the definition of which is an assertion or measurement that can be proven by experiment, observation or demonstration (Van Warren, 2004). These facts lead to a more holistic ecosystem view that combines what is known about an indicator and how that indicator relates to the ecosystem in the context of military use.

According to Rewerts et al. (2004) the primary processes of ecosystem knowledge and mapping are:

- Inventory knowledge and data.

Development of knowledge inventory can be done through direct observation, literature review or by other means that compiles known facts about the ecosystem under study.

- Map relationships.

Visualization tools such as dynamic concept maps, tree graphs, and thematic branching can be used as a way to interact with the ecosystem knowledge and data. Information and knowledge derived from the indicators in varying ordinations and dimensions can include the usual fundamental types of visualization, such as spatial data displayed in two, three, or temporal dimensions, tabular and statistical data, and process types of concepts.

- Capture processes into computable components.

This feature provides mechanisms and protocols for modeling efforts and also show where more data or knowledge is needed for modeling to be successful.

- Provide a framework for adaptive management.

The computable components and the models that are generated from them can provide land managers with the ability to implement adaptive management practices and other functions that aid in the stewardship of military lands.

As was stated previously, there is too often a disparity in connecting the science of ecology with those who need to apply it. Knowledge Mapping can be a way to display data so that relationships may be explored and adaptive management enhanced. Knowledge Mapping of ecological indicators may also be used as a tool to bridge knowledge gaps and enhance the understanding of those whose job it is to manage land resources. With a good knowledge map managers can visualize ecological system properties and relate those properties to ecological principles of land management.

Research Objectives

There has been extensive research on the development and use of ecological indicators for military land management and sustainability (Bern et al., 2006 and references therein; Diersing et al., 1992 and references therein). However, there are still many gaps in the identification, integration and application of indicators for monitoring purposes as evidenced by the establishment of SERDPs Ecosystem Management Program. Previously, the majority of ecological indicators for monitoring programs have focused on biodiversity of terrestrial macroorganisms that have a long period of recovery and require professionals to identify and assess the data. Microorganisms that can be quantitatively monitored with chemical biomarkers have been largely overlooked despite their complete integration into and dependency with the macro-world (Zak et al., 1994; Lee, 1991). Also, Current monitoring programs rely on indicators from published studies that may not deal directly with the causes of military disturbance or may not be applicable because of differences in ecosystem function or land management goals. Specific knowledge of the impacts of military disturbance to land resources and the relationship to land management goals are therefore needed to close the gaps in current monitoring systems. Additionally, there is a need to present ecological data in a way that military land managers and trainers can understand in order to connect the ecological indicators with ecosystem function and sustainability for military training.

These observations have produced several questions and have led to the following study objectives:

1. To test the hypothesis that a suite of microbial ecological indicators would distinguish between the management of military lands.
2. To develop a method for the integration of disparate or legacy ecological indicator data for the management of military lands.

3. To extract relevant facts from the preceding two objectives and develop a Knowledge Map/Conceptual Model that illustrates and explores the relationships between the ecological indicators and military training impacts.

Although these objectives are closely related, they are quite distinct, and in order to accomplish them a phased approach to the research was necessary. In Phase I, a series of field sites was selected that were representative of several different environmental impacts caused by military use, as well as reference control areas. Representative soil samples were taken from each of the selected sites. The soil was extracted and analyzed for phospholipid fatty acid (PLFA) content, which provided an index of the soil microbial community biomass, composition and metabolic status. The aim of the experiment was to discover if soil PLFA (soil microbial community) could provide indicators to ultimately predict different types of military land use. We chose lipid biomarkers to assay the soil microbial community because lipids can be quantitatively extracted from almost any sample matrix, and analyzed by the mature techniques of chromatography and mass spectroscopy. Accurate quantitative data representative of an entire microbial community allows the application of statistics or other models to authenticate differences across an environment or between treatments.

In Phase II, ecological indicator data previously collected by the five SEMP research teams was compiled, integrated as far as possible, and then screened through a data mining approach that used variable selection techniques combined with a multiple models solution to elucidate ecological indicators (predictors) that were best able to discriminate between different military land uses. In Phase III, the indicators that made it through the relevance screen were used as inputs in a Knowledge Map/Conceptual

Model. The purpose of this effort was to validate the chosen indicators by the use of innovative visualization, presentation, and modeling capabilities in order to gain a better understanding of ecosystem dynamics on military managed landscapes.

Questions of Scale

There were two critical questions relating to scale in this study. The first question was over what time scale are military impacts important for management and indicators, and second, at what physical scale is land management important? For this study we assessed indicators over several different temporal and physical scales. Figure 1-1 illustrates the types of indicators that were assessed and the relevant scales. For our purposes it was considered that the military would require sustainability, and in that case relevant time scales would be in years, not decades. Moreover as a matter of design this work focused on plot-level indicators. Other researchers have focused on watershed or landscape-level indicators.

Chapter Organization

The objectives of this study were fairly diverse and required a broad approach, so each chapter deals with particular objectives separately. The present chapter has addressed the background, justification and objectives for this work. The second chapter addresses the first objective and details the development and testing of soil microbial PLFA as a source of ecological indicators of military training disturbances. The third chapter focuses on the development of a method to extract useable ecological indicators

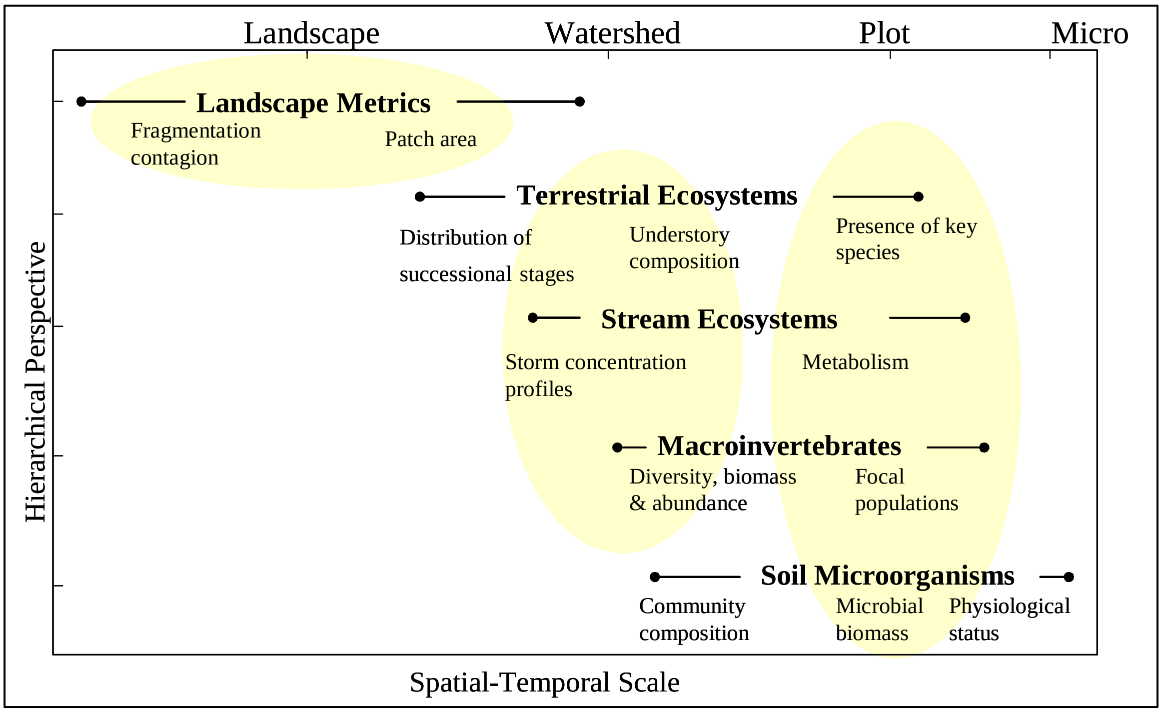

Figure 1-1. Spacial-temporal scaling of ecological indicators.

from legacy and other relevant data. In chapter four the indicators that have been researched and validated are incorporated into a Knowledge Map/Conceptual Model.

Chapter 2

Development of Ecological Indicators

This chapter is a revised version of the paper "*Soil Microbial Biomass and Community Composition Along an Anthropogenic Disturbance Gradient Within a Longleaf Pine Habitat*" published in the journal *Ecological Indicators* in 2001 by Aaron D. Peacock, Sarah J. Macnaughton, James M. Cantu, Virginia H. Dale and David C. White:

> Peacock, A.D., S.J. Macnaughton, J.M. Cantu, V.H. Dale, and D.C. White. 2001. Soil Microbial Biomass and Community Composition Along an Anthropogenic Disturbance Gradient Within a Longleaf Pine Habitat. *Ecological Indicators* 1:113-121.

My use of the term "we" in this chapter denotes myself and coauthors. My primary contributions to this paper included (1) selection of the topic and development of the problem into a work relevant to my study of ecological indicators, (2) microbial PLFA chemical, biological and statistical analyses, (3) most of the gathering and interpretation of literature, (4) the cartographic work, (5) compiling my co-author's inputs, (6) most of the writing, and (7) addressing comments from reviewers.

Introduction

As was discussed in the preceding chapter, managers at military installations provide land for training of military personnel. Often, such activities are inconsistent with sustainable land use practices. Therefore, an effective ecological monitoring program capable of quantifying and predicting land use status is essential to ensuring the long-term viability of these training areas. Further, the identification and development of ecological indicators that can be used in monitoring programs is critical to the success of monitoring efforts. To that end, the first objective of this effort is to identify and develop a suite of microbiological ecological indicators useful for the management of military lands that encompasses the ecological principles and guidelines set forth in the Ecological

Society of America Report "*Ecological Principles and Guidelines for Managing the Use of Land*" (Dale et al., 2000).

Previously, the majority of ecological indicators for monitoring programs have focused on biodiversity of terrestrial macroorganisms that have a long period of recovery and require professionals to identify and assess the data. Microorganisms that can be quantitatively monitored with chemical biomarkers have been largely overlooked despite their complete integration into and dependency with the macro-world (Zak et al., 1994; Lee, 1991). Soil microbial biomarkers satisfy the five ecological principals of land use management as described by Dale et al. (2000), and are listed in the previous chapter.

Microbial biomass in soil has a turnover time of less than a year and reacts quickly to changes in nutrients, moisture, temperature and soil organic matter content and quality (Paul, 1984). Viable microbial biomass is integral for nutrient storage and cycling (Rice et al., 1996), soil aggregate formation (Tisdall and Oades, 1982; Blanco-Canqui and Lal, 2004), and other ecological factors such as filtering, buffering, and gene reserves (Blum, 1998). Soil microbial biomass and community composition have been shown to be sensitive indicators of changes in nutrient type (Peacock et al., 2001b; Kirchner et al., 1993), botanical composition (Borga et al., 1994), pollutant toxicity (Stephen et al., 1999), and climate change (Zogg et al., 1997). Because the microbial community integrates the physical and chemical aspects of the soil and responds to anthropogenic activities, it can be considered a biological indicator of soil quality (Rice et al., 1996). The viable microbial biomass, community composition, and nutritional status of soil can be readily measured by analysis of extracted lipid biomarkers, providing rational endpoints for many disturbance/recovery processes (White et al., 1998).

We chose lipid biomarkers to assay the soil microbial community because lipids can be quantitatively extracted from almost any sample matrix, and analyzed by the mature techniques of chromatography and mass spectroscopy. Accurate quantitative data representative of an entire microbial community allows the application of statistics or other models to authenticate differences across an environment or between treatments.

Total viable biomass is an important parameter in describing microbial communities. The viable microbial biomass increases with the availability of metabolizable substrates (such as litter) and may decrease after their exhaustion. The rates of biogeochemical transformations such as carbon dioxide production, carbon sequestration, or contaminant detoxification in soils are all proportional to the viable microbial biomass.

The viable biomass is simply the total weight of the living organisms. In macro-ecology (non-microbial ecology), the technology for the enumeration of organisms can be as simple as a pen and notepad to record the number of plants or animals observed within a defined area. In microbial ecology, however, the very small size of the organisms, their huge numbers and relative absence of defining morphology require more sophisticated techniques.

Polar Lipid Fatty Acids

All intact cell walls contain polar lipids, which in microbes are primarily phospholipids. With cell death, exogenous and endogenous phospholipases rapidly transform the polar lipids in the cell membranes to neutral lipid diglycerides by removing polar phosphate-containing head groups (Tollefson and McKercher, 1983). Studies have shown that diglycerides disappear in soils less rapidly than phospholipids, as diglycerides are detectible in many natural environments (White and Ringelberg, 1996). Since the lipid recovery procedure involves extensive solvent extraction and product concentration, there are few environments to which the biomass measurement cannot be applied. Samples from an enormous variety of matrices have been analyzed for microbial lipid content, including soils (Bossio and Scow, 1998; Bossio et al., 1998; Cox et al., 1994; Frostegaard et al., 1991), soil rhizosphere (Tunlid et al., 1985), clinical specimens (Nichols et al., 1985), ice cores (Palmisano et al., 1988), sediments (Federle et al., 1983; Findlay et al., 1989; Findlay et al., 1990; Guckert et al., 1985; Kieft et al., 1994; Parkes et al., 1992; Smith et al., 1989; White, 1995), subsurface materials (Balkwill et al., 1988; Smith et al., 1986; White and Ringelberg 1995; 1996), bioprocessing units (Hedrick et al., 1991; Mikell et al., 1987), rocks (Amy et al., 1994), estuarine fungi (White et al., 1980), and groundwater well collection devices (Peacock et al., 2004).

In this phase of the study, we investigated the soil microbial biomass and community composition (as measured by PLFA) as ecological indicators of change along an anthropogenic disturbance gradient. The disturbance gradient included the duration and type of traffic in military training areas in a longleaf pine habitat. The hypothesis was that duration and intensity of disturbance (traffic) in the longleaf pine ecosystem would be reflected in changes in the soil microbial community biomass and composition.

Disturbance effects between transects were identified with 2 different data analysis techniques - a linear discriminant analysis based on 17 PLFA variables, and a non-linear artificial neural network analysis which used all 61 PLFA variables and the biomass. Herein we compare these two computational analyses and assess the use of PLFA as an ecological indicator for use in a monitoring program.

Materials and Methods

Study Site

The study was conducted at the Fort Benning Army Installation located in the lower Piedmont Region of central Georgia and Alabama, six miles southeast of Columbus, Georgia. The post consists of approximately 73,650 hectares of river valley terraces and rolling terrain. The climate at Fort Benning is humid and mild, with rainfall occurring regularly throughout the year. Annual precipitation averages 105 cm, with October being the driest month.

Soils at Fort Benning

Soils at Fort Benning are highly weathered Ultisols (Jones and Davo, 1997). Most of these soils are of Coastal Plain origin, however the base includes some minor inclusions of alluviums derived from the Piedmont ecological unit to the north. The two dominant Coastal Plain ecological units that cover most of the installation are Sand Hills and Upper Loam Hills. The major soil series associated with these soil units are Ailey loamy coarse sand (loamy, kaolinitic, thermic arenic kanhapludults), Cowarts loamy sand (fine-loamy, kaolinitic, thermic arenic kanhapludults), Nankin sandy clay loam (kaolinitic, thermic arenic kanhapludults), Pelion loamy sand (fine-loamy, kaolinitic, thermic fragiaquic kanhapludults), Troup and Troup loamy sand (loamy, kaolinitic, thermic grossarenic kandiudults), Vaucluse and Vaucluse sandy loam (fine-loamy, kaolinitic, thermic fragic kanhapludults). Sands and loamy sands are common on upland sites while sandy loams and sandy clay loams are commonly found in the valleys and riparian areas (Garten, 2004). A detailed soil cover map is provided in Appendix 1, and a companion file (Soils.pdf) contains additional soils information.

This study encompassed training areas that have been subjected to a range of military traffic. Disturbance of the soil ecosystem due to training includes the direct removal or damage of vegetation, digging, and soil dislocation and compaction from vehicles, erosion, and sedimentation. The degree and extent of the impacts of training activities within a compartment are dependent upon the type of activity, number of personnel being trained, and how frequently the compartment is exposed to activity. Furthermore, training activity typically occurs irregularly throughout a compartment, creating localized gradients of disturbance within individual compartments.

Soil Sampling

Soils for this study were collected from upland sites. The sites were chosen specifically because that is where most of the military training and disturbances occur. Soil cores were collected in the Autumn of 1999. To avoid cross contamination, the soil corers were washed in solvent (methanol) and sterile distilled water, and dried prior to each sampling. Cores were approximately 20 cm in depth and 2 cm in diameter. For each core, the depth of sample and the presence/absence of an A horizon was recorded. Five samples were taken from separate plots at each transect (14 transects x 5 = 70 samples, Table 2.1). Of the transects selected, three were reference transects (with stand ages of 28, 68, and 74 years); three were heavy usage (undergoing tracked vehicle

Table 2-1. Experimental Design.

Transect	# of Samples	Disturbance
A	5	Reference
E	5	Reference
M	5	Reference
D	5	Light
L	5	Light
N	5	Light
C	5	Moderate
I	5	Moderate
K	5	Moderate
B	5	Heavy
H	5	Heavy
J	5	Heavy
F	5	Remediated
G	5	Remediated

training); three were moderate usage (areas adjacent to tracked vehicle training); three were light usage (infantry training), and two came from a site currently undergoing remediation (previous heavy disturbance, currently trees and groundcover planted and no usage). Samples were stored at –80°C prior to analysis.

PLFA Analysis

PLFA analysis was performed using previously reported precautions (White and Ringelberg, 1998). Soil samples (5 g) were extracted with the single-phase chloroform-methanol-buffer system of Bligh and Dyer (1954), as modified by White et al. (1979). The total lipid extract was fractionated into neutral lipids, glycolipids, and polar lipids by silicic acid column chromatography (Guckert et al., 1985). All results presented in this chapter are for the polar lipid fraction. The polar lipids were transesterified to the fatty acid methyl esters (FAMEs) by a mild alkaline methanolysis (Guckert et al., 1985).

The FAMEs were analyzed by capillary gas chromatography with flame ionization detection on a Hewlett-Packard 5890 Series 2 chromatograph with a 50 m non-polar column (0.2 mm I.D., 0.11 µm film thickness). Preliminary peak identification was by comparison of retention times with known standards. Definitive identification of peaks was accomplished by gas chromatography/mass spectroscopy of selected samples using a Hewlett-Packard 6890 series gas chromatograph interfaced to a 5973 mass selective detector using a 20 m non-polar column (0.1 mm I.D., 0.1 µm film thickness).

Fatty acids were named according to the convention of Gunstone and Herslöf (1992), X:YωZ, where “X” stands for the number of carbon atoms in the chain, “Y” for the number of unsaturations, and “Z” the number of carbon atoms from the terminal methyl end of the molecule to the first unsaturation encountered. Prefixes: “i” = iso-branched, “a” = anteiso-branched, “10me” = methyl branch on the tenth carbon from the carboxylate end, “Br” = branched at unknown location, and “Cy” = cyclopropyl. The suffixes “c” and “t” stand for the cis and trans geometric isomers of the unsaturation respectively. When different fatty acids had the same designation, they were distinguished by lower-case letters suffixes; a, b, etc.

Statistical Analysis

Biomass (pmol/g PLFA) and relative proportion (mol%) of specific PLFA were used to test the null hypothesis that degree of land disturbance would not influence the composition of the soil microbial communities. To test that hypothesis, an analysis of variance (ANOVA) using the General Linear Model STATISTICA procedure (Statsoft Inc. Tulsa, OK) was used for a completely randomized design with five treatments. The values reported are least square means of 15 replicates, except in the case of the transect undergoing remediation, which contained 10 replicates (total n=70). Standard errors of the means were determined. Differences in the mean proportions of PLFA in each treatment were tested using Tukey’s Honest-Significant-Difference procedure. A hierarchical cluster analysis (Ward’s method, 1-Pearson r) was used to discover how the PLFAs that differed significantly with treatment were clustered.

A linear discriminant analysis with cross-validation (SAS Institute Cary, NC) was chosen to classify the observations into one of the 4 usage classes (n=60, 15 observations in each group) based on the degree of land disturbance. Only those PLFA that comprised at least 1% of any profile were included in the analysis. Therefore, fatty acids that may have been unreliably quantified were not included. Before statistical analysis, arcsine square root transformation was applied to the mole percent PLFA data. After truncation, a one-way ANOVA was conducted on the remaining PLFAs, and those that differed significantly with usage were included in the model.

Artificial Neural Network Analysis:

Neural network (NN) identification was performed with early stopping by cross-validation and topology optimization by bootstrapping (selection criteria: median cross-validated error) using the microCortex web-based neural computing environment (www.microCortex.com) (Almeida, 2002). The relative importance of each input parameter in predicting the target values was calculated by performing sensitivity analysis on the trained NN (Masters, 1993). In this study, sensitivity of an output parameter $Out_{j=1,2,\ldots,nj}$ (for nj output parameters) to an input parameter $In_{i=1,2,\ldots,ni}$ (for ni input parameters) was defined as the normalized ratio between variations caused in Out_j by variations introduced in In_j and is represented by the following equation:

$$NS_{i,jc} = (dOut_{j,c} / d\, In_{i,c})(In_{i,c} / Out_{j,c})$$

$$S_i = [\, \Sigma_{j=1,2,\ldots,nj;\, c=1,2,\ldots,nc} (NS_{i,jc}) \,] / [\Sigma_{i=1,2,\ldots,ni;\, j=1,2,\ldots nj;\, c=1,2,\ldots,nc} (NS_{i,jc}) \,]$$

(eq. 1)

i= 1, 2, ..., ni; input index

j= 1, 2, ..., nj; output index

c= 1, 2, ..., nc; sample (case) index

The normalized sensitivity for an individual profile c, $NS_{i,jc}$ was calculated for every combination of input, i, and output parameters, j, and for every profile (for nc profiles). The overall sensitivity to an input, S_i, was determined by taking the average over all profiles and all binary outputs used to classify them. Finally, the sensitivity values obtained were represented as relative values, calculated as a percent of the sum of all sensitivities (Eq1, S_i) (Masters, 1993).

Results

Degree of military land use significantly influenced the microbial biomass estimates (PLFA). Specifically, the microbial biomass for the highly-trafficked soil was reduced relative to other disturbance categories ($p<0.05$, Figure 2-1). If it is assumed that 1 pmole of PLFA is equivalent to 2.5×10^4 bacterial cells (Balkwill et al., 1988; Pinkart et al., 2000), then bacterial density in the soils ranged from approximately 7.7×10^8 cells g^{-1} in the reference soil to 3.8×10^7 cells g^{-1} in the heavily trafficked soil. The soil currently undergoing restoration contained an average of 5.8×10^8 cells g^{-1} with a corresponding high variability. PLFA analysis identified 61 fatty acids, all of which are commonly found in soil environments (Peacock et al., 2001a). Of the 61 fatty acids detected and quantified, 28 were highly significant according to a one-way ANOVA ($p<0.001$), illustrating differences between land use. Mean separations were conducted on the 28 PLFAs using Tukey's Honest-Significant-Difference procedure and the results are presented in Table 2-2. Generally, the short-chain normal saturated PLFA (14:0, 15:0, and 16:0) decreased with increasing traffic, while the longer chain normal saturated PLFA (18:0 and 20:0) increased with increasing traffic.

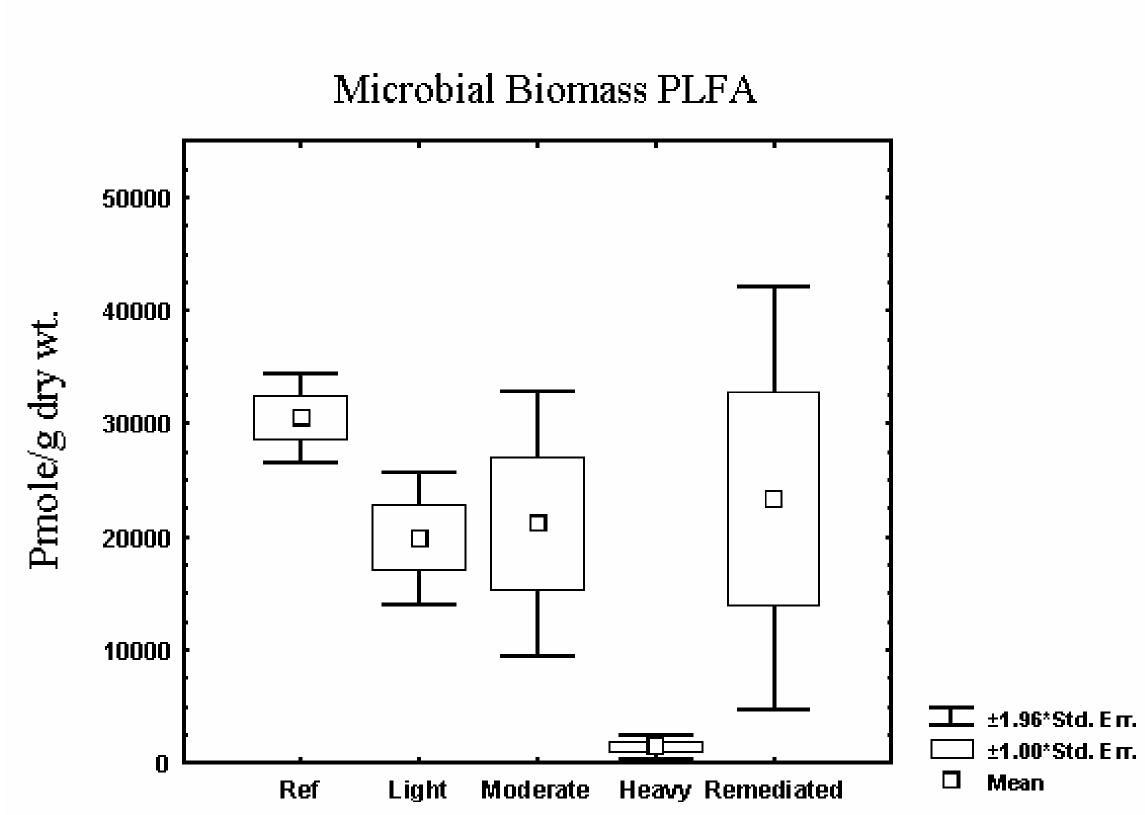

Figure 2-1. Microbial biomass PLFA. Samples were taken from four disturbance categories and areas undergoing remediation. $P < 0.05$.

Table 2-2. Mean Relative Proportions (Mole %) of PLFA's by Treatment. In each row treatments followed by the same letter are not different at $\alpha = 0.05$.

PLFA	Reference		Light		Moderate		Heavy		Remediated	
General										
14:0	0.53	a	0.50	a	0.46	a	0.18	b	0.40	a
15:0	0.65	a	0.57	a	0.58	a	0.26	b	0.51	a
16:0	12.8	a	12.81	a	13.31	a	10.08	b	13.31	a
18:0	3.04	c	3.47	c	4.20	b	5.12	a	3.42	c
20:0	0.96	b	0.81	b	1.06	b	1.63	a	0.76	b
Gram-negative bacteria										
15:1	0.08	a	0.09	a	0.09	a	0.02	b	0.06	ab
16:1ω7c	2.79	a	2.57	ac	2.29	bc	1.99	b	2.73	ac
16:1ω5c	1.90	a	1.82	a	1.96	a	1.52	a	2.49	b
17:1	0.16	ab	0.18	a	0.10	b	0.06	c	0.11	abc
18:1ω5c	0.89	a	0.96	a	0.89	a	0.35	b	0.95	a
Cy19:0	12.84	a	13.53	a	10.33	b	11.34	ab	8.92	b
Eukaryote (plant and fungal)										
18:2ω6	5.74	a	5.90	a	3.63	b	1.00	c	6.51	a
18:1ω9c	8.49	a	8.32	a	7.79	a	6.08	b	8.71	a
20:3ω3	0.08	a	0.09	a	0.07	ab	0.01	b	0.08	a
20sat	2.08	a	2.08	a	1.32	b	0	b	0.01	b
poly20a	0.13	a	0.16	a	0.03	b	0.02	b	0.02	b
poly20b	0.18	ab	0.34	a	0.28	a	0.07	b	0.35	a
Actinomycetes type										
i14:0	0.19	a	0.13	a	0.15	a	0.03	b	0.19	a
Br16:0a	0.80	b	1.06	b	1.23	b	3.89	a	0.92	b
Br16:0b	0.16	a	0.12	a	0.07	ab	0.01	b	0.07	ab
i16:0	3.22	ab	2.84	b	3.86	a	3.36	ab	3.51	ab
i17:1ω7c	1.44	b	1.49	ab	1.82	a	1.73	ab	1.60	ab
10Me16:0	3.87	b	3.96	b	4.46	ab	4.82	a	4.13	ab
i17:0	2.17	c	2.24	c	3.76	b	4.79	a	2.95	c
a17:0	2.14	b	2.10	b	2.70	a	2.96	a	2.67	a
17:0	0.64	c	0.71	bc	0.76	b	0.88	a	0.67	bc
i10Me16:0	1.26	c	1.34	c	3.35	b	6.04	a	1.93	c
12Me18:0	0.68	c	0.66	c	1.45	b	2.43	a	1.48	b

Monounsaturated and polyunsaturated PLFAs decreased with increasing traffic, whereas the methyl-branched saturated PLFAs increased with increasing traffic. An exploratory hierarchical cluster analysis (Ward's method, 1-Pearson r) was conducted using the 28 PLFAs that are significantly different by disturbance category (Figure 2.2). Two primary clusters emerged. The first contained predominantly short-chain saturated, monounsaturated, and polyunsaturated PLFA, while the second contained long-chain saturates, methyl-branched monounsaturated, and saturated PLFA. A secondary cluster derived from the first primary cluster contained short-chain normal saturated and 16 carbon monounsaturates. The remaining secondary clusters contained mostly 18 to 20 carbon mono and polyunsaturates. Secondary clusters derived from the second primary cluster included long-chain normal saturates and methyl branched fatty acids.

A linear discriminant analysis with cross-validation was chosen to classify the observations into one of four classes (n=60, 15 observations in each group) based on the degree of land disturbance. The first task was to reduce the number of variables to be included in the model. Only those PLFA that comprised at least 1% of any profile were included in the analysis, so fatty acids that may have been unreliably quantified were not included. Before statistical analysis, an arcsine square root transformation was applied to the mole percent PLFA data. Arcsine square root transformations have been used for many years to transform proportions to make them more suitable for statistical analysis (Studebaker, 1985). After this truncation, a one-way ANOVA was conducted on the remaining PLFAs, and those that differed significantly with disturbance category were included in the model. The resulting model included 17 descriptor variables (Table 2-3). Wilks' Lambda for the model was .032 ($P<.001$). Overall, the error estimates for the

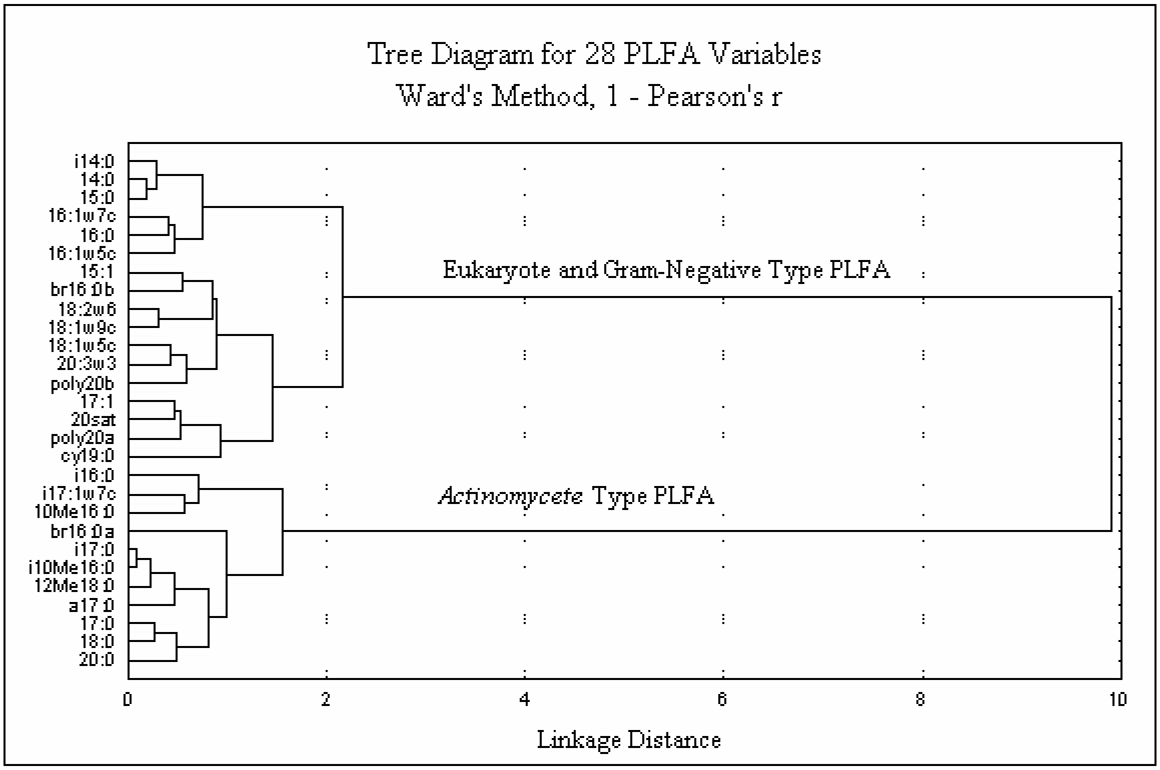

Figure 2-2. Cluster analysis of significant PLFA variables (mol%). Two primary clusters emerged, the first contained primarily PLFAs indicative of eukaryote microorganisms (polyunsaturates) and Gram-negative bacteria (monounsaturates); While the second contained PLFA indicative of *Actinomycetes* (methyl-branched saturates).

Table 2-3. PLFA included in the discriminant model.

Normal Saturates	Terminally Branched	Mono-unsaturated	Cyclopropyl	Mid-Chain Branched	Other
17:0	a15:0	16:1ω7c	Cy17:0	br16:0a	i17:1ω7c
18:0	i16:0	18:1ω9c	Cy19:0	10Me16:0	18:2ω6
20sat	i17:0			i10Me16:0	
	a17:0			10Me18:0	

model were 33%, and the generalized distance between groups is reported in Table 2-4. Only the reference and trafficked treatments were used to construct the model. Once the model was complete, the ten observations taken from the remediated transects were classified. One observation was classified as a reference, three as lightly trafficked, and six as moderately trafficked.

A non-linear Artificial Neural Network discriminant analysis (ANN) was performed using the biomass estimates and all of the 61 PLFA variables. Ninety percent of the data was used to train the ANN and the remaining ten percent for validation. The resulting ANN included five hidden nodes and resulted in an r^2 of 0.97. The correct classification of profiles for this model was 66%, and six of the PLFAs had sensitivity values above 3%. As with the linear discriminant model, once the ANN model was complete, it was used to classify the observations from the remediated transects. Four of the observations were classified as reference, two as moderate, and four as heavily trafficked.

Discussion

The four categories of military traffic in this study has been previously shown to vary in the amount and diversity of the floristic component (Dale et al., 2002). In addition, soil carbon and nitrogen concentrations and stocks, as well as the carbon to nitrogen ratios, differed significantly with degree of traffic (Garten et al., 2003). Soil compaction due to the amount of traffic was also significantly different along the disturbance gradient (Garten et al., 2003).

Table 2-4. Number of observations and percent classified into usage based on 17 PLFAs that were significantly affected by disturbance category.

	Reference	**Light**	**Moderate**	**Heavy**	**Total**
Reference	11	4	0	0	15
%	73.33	26.67	0	0	100
Light	6	8	1	0	15
%	40	53.33	6.67	0	100
Moderate	0	2	11	2	15
%	0	13.33	73.33	13.33	100
Heavy	0	1	4	10	15
%	0	6.67	26.67	66.67	100
Error Count Estimates					
	Reference	Light	Moderate	Heavy	
Rate %	26.6	46.6	26.6	33.3	33.3
Priors %	25	25	25	25	
Generalized Squared Distance					
	Reference	Light	Moderate	Heavy	
Reference	0	5.65	40.47	77.8	
Light	5.65	0	23.22	52.95	
Moderate	40.47	23.22	0	11.85	
Heavy	77.8	52.95	11.85	0	

Myers et al., (2001) states, "Microbial metabolism in soil is limited by the availability and types of organic substrates, and therefore it is plausible that ecosystems which differ floristically will produce litter with chemically distinct substrates that will differentially foster microbial growth." Soil microbial community composition and biomass differed along the gradient as measured by the PLFA analysis. Biomass content in these soils decreased with increasing traffic and was significantly lower in highly trafficked soil (Figure 2-1). Specific PLFA components can be related to certain subsets of the microbial community, and PLFA patterns can be used to monitor changes in the community composition. Using the ANOVA results (Table 2.2), the reference and the lightly trafficked soil contained on average more PLFAs indicative of Eukaryotes (including plant associated PLFAs) and Gram-negative bacteria (Wilkinson, 1988), while the more trafficked soils contained relatively more PLFAs associated with actinomyctes (O'Leary and Wilkinson, 1988; Verma and Khuller, 1983). The cluster analysis (Figure 2.2), using variable clustering, illustrates this point. Over the disturbance gradient, when PLFA markers for eukaryotes and Gram-negative bacteria were high, the PLFAs indicative of the actinomycetes were low. Monounsaturated PLFAs are indicative of predominantly Gram-negative bacteria (White et al., 1996). An increase in the amount and type of carbon sources has been shown to increase monounsaturated PLFAs (Peacock et al., 2001a; Bossio and Skow, 1998; Macnaughton et al., 1999). The loss of monounsaturated PLFAs with traffic indicates a loss of these types of bacteria. Terminally branched saturated PLFA in aerobic environments are indicative of Gram-positive bacteria, including Arthrobacter and Bacillus spp. (White et al., 1996). Many of these types of bacteria are spore formers and can exist in environments that are lower in overall organic carbon content and higher metabolic refractiveness (Boylen and Ensign, 1970; Keynan and Sandler, 1983). Mid-chain branched saturated PLFA are primarily indicative of actinomycete type bacteria in surface soils. It has been stated that since these bacteria grow conidia, they are able to better survive in relatively harsh soil environments (desiccation and heat). This may give these bacteria a competitive advantage in the heavily trafficked areas (Alexander, 1998). Polyunsaturated PLFA shows significant decreases due to traffic and indicates the loss of fungi and microbial grazers that follows the loss of bacterial microorganisms.

Analysis of the soil microbial community PLFA in a predictive linear discriminant model was successful in distinguishing the amount of traffic a soil received. Inspecting the generalized squared distance results from the linear discriminant analysis revealed that the reference and lightly trafficked soils were very close in terms of the microbial community composition (Table 2.4). In comparison, the moderate and heavily trafficked soils were very different. Indeed, when observations were classified during model validation, most of the misclassifications were between the reference and lightly trafficked soils.

To more fully explore the relationships between the soil disturbance and the microbial community composition, without assumptions of normal distributions or linear relationships, a non-linear artificial neural network discriminant model was applied to the data. The overall predictive effectiveness for correct profile classification for the model was 66%, which was the same as for the linear discriminant model. However, the ANN was constructed and optimized using all of the 61 PLFAs and included the biomass parameter. As with the linear analysis, most of the misclassifications occurred between traffic categories that were close (i.e., moderate being more similar in disturbance to heavy). However, when the ANN was used to predict the status of the remediated transects, eight of the ten samples were classified as either reference or heavy traffic. Inspection of the novelty indexes from the prediction outputs showed that the input vectors from the remediated transects were very different from the data used to train the ANN. This result is not surprising, as when the soil is remediated it does not escalate through states of succession in the same way it descended by disturbance. In other words, in this case there is not a sliding scale on which the ecosystem recovery can be measured, but a new community succession is taken, initiated by the remediation efforts (planting of groundcover and trees).

The subtlety of the hysteresis between disturbance and recovery was not detected with the linear discriminant model, which showed no bias toward extreme classifications. With the linear discriminant analysis, most samples undergoing remediation were classified as either moderate or light usage, with one sample being classified as reference. Since this analysis was linear and only used 17 descriptor variables, the resultant predictions may be of a more general nature, whereas the ANN used the complete matrix in which to base predictions. The amount of data available for the parametric statistical analysis constrained the number of descriptors used. Regardless, the predictions of the linear analysis could be accepted and used to aid stakeholders in management of the land use.

The collection, processing and analysis of the PLFA data allowed us to assess the use of soil microbial community as effective indicators for monitoring programs. As mentioned in the Introduction, Dale and Beyeler (2001) list several attributes of effective ecological indicators for monitoring programs, and we will discuss each in turn.

- *Are easily measured*. The collection of samples required for the soil microbial PLFA analysis is straightforward and does not require any special training. Laboratory analysis requires a gas chromatograph and mass spectrometer and provides confidence in the identification of PLFAs.
- *Are sensitive to stresses on the system.* The results of this phase of the research indicate that soil microbial PLFAs are sensitive to stresses on land use due to military disturbance.
- *Respond in a predictable manner*. There have been several published journal articles listed in this work as well as others that demonstrate a consistent response to disturbance of the soil microbial community as measured by PLFA. Generally with a reduction in soil quality there is a reduction in the amount of monounsaturated PLFA and a corresponding increase in terminally branched saturated PLFA as well as other specific biomarkers. However it is impossible to know if this response is universal.
- *Are anticipatory, i.e., signify an impending change in key characteristics of the ecological system.* The models presented in this work show that it is possible to use soil microbial PLFA to predict without prior knowledge the degree of military land use. However, more study would be needed in order to verify the applicability of these techniques to signify impending change.

- *Predict changes that can be averted by management actions.* The response to the criteria here is similar to the above. More research is needed to see if PLFA can predict and respond to change.
- *Are integrative: the full suite of indicators provides a measure of coverage of the key gradients across the ecological system (e.g. soils, vegetation types, temperature, etc.).* All of the soils across the spectrum of military land uses at Fort Benning contain microbial communities and as such are fully integrated across all of the key ecological gradients in these systems.
- *Have a known response to natural disturbances, anthropogenic stresses and changes over time.* In the case of disturbance, soil PLFA has been shown to be a sensitive ecological indicator, but elucidation of the nature of the disturbance (whether natural or anthropogenic) will require more research.
- *Have a low variability in response.* Soil microbial PLFA responds in a predictable manner to land disturbance and results have shown the responses to be consistent across many environments such as those listed in the introduction. The magnitude of the response both in biomass and community composition correlate with the amount of the disturbance.

Conclusion

The goal of this project was to explore the possibility of using the soil microbial community as an ecological indicator signaling the degree of environmental degradation along a military disturbance gradient. The analysis based on the soil PLFA was successful, reflected above-ground changes, and provided an index of the degree of land disturbance (traffic) the soil received.

Both linear discriminant and non-linear ANN analysis were able to adequately classify the degree of disturbance. However, there were drawbacks when the ANN and linear discriminant models were used to predict stages of soil recovery in remediated transects. The linear discriminant model was shown to be a fairly robust but perhaps coarse measure of remediative efforts. The ANN was sufficiently sensitive to detect subtleties in recovery not detected with the linear discriminant analysis, but in current form could not be relied on to classify remediated samples. The inclusion of data reflecting remediation in these models could make them capable of monitoring the more complex process of soil degradation and recovery.

Chapter 3

Integration of Ecological Indicators

Introduction

Land use has been defined as "*the purpose to which land is put to use by humans*" (Dale et al., 2000). Some general land-use categories include agriculture, forestry, mining and settlement. The way a given land asset is administered by humans is defined as land management (Dale et al., 2000). Some examples of land management decisions include tillage versus no-till agriculture, open cast versus drift mining, and various forestry harvesting methods. In each of these examples, the people responsible for the administration of the land assets decide how to use limited and often non-renewable resources. Central to the management of land resources are the management goals (or endpoints) for which the land resource is to be used (Dale and Haeuber, 2000). However, there has often been a disconnect between land management, land use, and land management goals (Wolfe and Dale, 2006a). Frequently this disconnect is exacerbated by the methods and procedures used for monitoring the land resources.

A major challenge for land managers is to decide what ecological variable or variables to measure to indicate that land is being used commensurate with land management goals, or in other words, how to monitor degradation or improvement in land resources (Dale and Beyeler, 2001). Much data has been and is currently being collected that relates to land management, such as the Environmental Protection Agency (EPA) requirements for various land resources, or the Land Condition Trend Analysis

(LCTA) data collected for military bases (Diersing et al., 1992), but this information is not always appropriate or useful in the context of land use or land-management goals. There are several reasons why this information collected under various mandates may not be suitable for coherent land management. Many of the programs that are currently used were not designed to answer questions about land-management goals. For example, the LCTA used at military installations was established to assess long-term trends in ecological data, but the LCTA approach does not address the day-to-day or month-to-month land-use issues that arise at these installations, and is not flexible. In order to address the disconnect between land management, land use, and land management goals, we have developed a two-step approach that (1) identifies land management categories that encompass land management goals and (2) selects ecological variables that best predict these management categories. The creation of land-management categories is a necessary step in the establishment of land-use goals and, once specified, provide land managers with the data they need to allocate resources. The approach is first described and then illustrated by an example of its use at Fort Benning, Georgia. This chapter focuses specifically on the procedure used to select indicators that differentiate the land-management categories.

Overview of Approach

Data, models, and information (peer reviewed publications) produced by scientists often fail to meet the needs of land managers (Jones et al., 1999; Steel et al., 2001; Rayner et al., 2001), and this usually occurs because the goals of the groups are not compatible. In order to connect land management with accurate data about current land conditions we developed a method to select specific indicators of land suitability. The overall approach was to screen the indicators that best discriminated between the land-management categories and involved three steps:

1. Use a Delphi approach to establish land-management categories.
2. Collect potential indicator data by category.
3. Screen selected indicators against the land-management categories.

Figure 3-1 illustrates the steps of this method. The first step involves the use of a modified Delphi process to query resource managers and scientists regarding current land use and land-management practices. In order to address the disconnect and to set the groundwork for future integration and screening efforts, Wolfe and Dale (2006a; 2006b) developed an iterative Delphi process to facilitate integration between ecological scientists and land managers. The Delphi method is an approach that seeks to establish a group opinion, and was originally developed in the 1960s (Soderstrom, 1981; Fontana and Frey 1994). Participants were asked a round of questions to elicit information. This process was iterated until a consensus was achieved. The participants were queried separately to avoid problems with group interactions. The goal of the Delphi process in this case was to identify Land-Management Categories. These categories were derived from land use goals coupled with the current impact from diverse uses. Because the categories were initially set by the perspective of the resource managers, it was anticipated that the results would then have meaning to these managers.

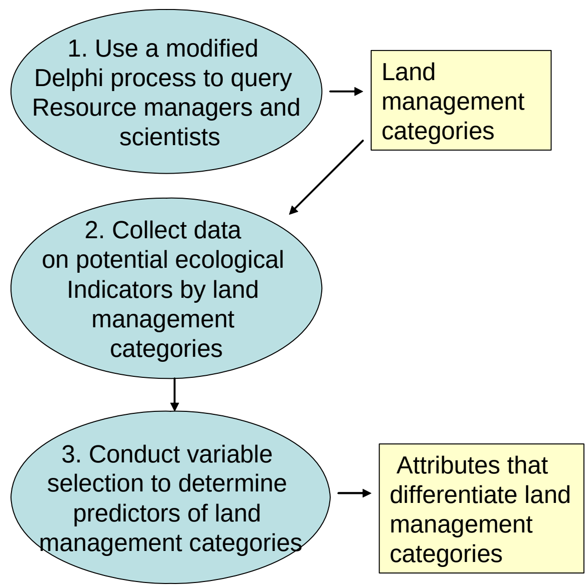

Figure 3-1. The three steps in determining which ecological attributes best differentiate Land Management Categories using the Dephi Method.

Once the Land-Management Categories had been established, the second step in the process was to collect ecological indicator data by category. The type of data collected may differ from region to region, but would most likely include soil physical and chemical parameters, plant abundance and diversity, animal abundance and diversity, and other data that are known to be useful to land managers in a given ecosystem. In our case, the choice of potential indicators drew from the hypothesis that a suite of indicators could best explain land-use conditions (Dale et al., 2004).

The third part of the approach was to take the assembled indicator data describing the different Land-Management Categories, and to distill the collected information into a suite of indicators that best described the particular category. One of the basics of science is to seek the simplest solution, and we used a multiple solutions approach (Lee et al., 2002) to elucidate important indicators as they relate to Land Management Categories. Using the distilled data, a manager would be able to monitor degradation or improvement within Land-Management Categories and hence be able to better manage the land. Herein we describe this selection process for data appropriate for differentiating between Land-Management Categories that can be used by resource managers at Fort Benning, GA.

Land-Management Categories at Fort Benning, Georgia

Managers at military installations are responsible for allocating a finite amount of land resources for the use and training of military personnel. Military training often requires the use of ordnance or engineering activities that are inconsistent with sustainable land-use practices, therefore an effective monitoring program that accurately assesses the status of land resources becomes integral to ensuring the long-term viability of those lands for training purposes. In a broad sense, managers at military installations must address the issue of competition for limited resources and provide the stewardship necessary to the continued mission of troop readiness.

Several ecological disturbances occur at Fort Benning, including military training and testing, timber harvest and thinning, natural and anthropogenic fire, insect outbreaks, and the spread of introduced invasive species (USAIC, 2001). External activities also impact Fort Benning, including changes in surrounding land-use, encroachment, and general climatic changes (heating or cooling) that may lead to changes in precipitation or other climatic effects (Turner and Meyer, 1994; Efroymson et al., 2005). A viable and relevant set of ecological indicators could provide managers with early warning of abnormal conditions of resources, data to better understand the dynamic nature and condition of installation ecosystems, data to meet legal and Congressional mandates, and a means of measuring suitability of land for training purposes or for a go/no-go decision for continued training in a certain area (Davis, 1997).

Methods

Study Site

The studies were conducted at the Fort Benning Army Installation located in the lower Piedmont Region of central Georgia and Alabama, six miles southeast of Columbus, Georgia. The installation consists of approximately 736 square kilometers of river valley terraces and rolling terrain. The climate at Fort Benning is humid and mild, with rainfall occurring regularly throughout the year. Annual precipitation averages 105 cm, with October being the driest month. Most of the soils at the base are heavily weathered Ultisols, as detailed in chapter 2 (USAIC, 2001).

Land Management Categories

Land-Management Categories were established for the base according to the work of Wolfe and Dale (Wolfe and Dale, 2006a; 2006b). Table 3-1 (reprinted from Wolfe and Dale, 2006a) summarizes the Land-Management Categories as defined from the matrix consisting of goals and endpoints, impacts from use, and frequency of use. This matrix shows the three major land management goals and endpoints for Fort Benning and subgoals as compared to the cause of predominant ecological effect from military use of the land. Each element in the matrix denotes a Land-Management Category. The Land-Management Categories are not in themselves land management goals, but are determined by them. The Land-Management Categories are further delineated by the frequency of use each category may receive. The establishment of Land-Management Categories allowed the assessment of the ecological indicators for this project. The end result of the effort of Wolfe and Dale (2006a) was a multidimensional matrix of Land-Management Categories that included the cause of predominant ecological impact of military land use, land management goals and endpoints, and frequency of use. The Land-Management Categories provided a common framework for synthesizing diverse data from several research projects, and the approach allowed specific field plots to be assigned to a unique Land-Management Category, regardless of whether those plots had been used differently or were currently used for multiple purposes.

Table 3-1. Land-management categories as determined by military training and land management practices. (From Wolfe and Dale, 2006a) Key '0' = military uses do NOT occur in areas managed in specified ways. 'I' and 'F' = the relative frequency with which military uses occur in areas managed in specified ways (I = infrequent and F = frequent). '+' = land management options in areas not used by the military.

Land management goals and endpoints	Cause of predominant ecological effect from military use(s) of land								
	Tracked vehicles	Wheeled vehicles	Foot traffic	Designated bivouac areas	Firing ranges	Impact areas	Drop or landing zones	No military effect	Admin-strative use
1. Minimally managed areas									
1.1 Wetlands	I,F	I, F	I	0	0	0	0	+	0
1.2 Vegetation on steep slopes	I, F	I, F	I	0	0	0	0	+	0
1.3 Forests in impact zones	0	0	0	0	0	I,F	0	+	0
2. Managed to restore and preserve upland forest									
2.1 Upland forests									
2.1.a Long leaf dominance	I	I,F	I, F	0	0	0	0	+	0
2.1.b Mixed pine									
2.1.c Scrub oak pine mix									
2.2 RCW mgmt clusters	I	I	I,F	0	0	0	0	+	0
2.3 Sensitive area designated by signs	0	0	I,F	0	0	0	0	+	0
3. Managed to maintain an altered ecological state									
3.1 Intensive military use areas	F	F	0	I,F	F	0	0	0	0
3.2 Wildlife openings	0	I	I	0	0	0	I	+	0
3.3 Mowed fields	0	I	I,F	0	I,F	0	I,F	+	0
3.4 Roads (paved and unpaved)	I, F	I, F	I, F	0	0	0	0	+	0
3.5 Built environment	0	0	0	0	0	0	0	0	+

Table 3-1. Continued. Wet = Wetland, Ste = Steep Slope, For = Forest, Up = Upland, Rcw = Red Cockaded Woodpecker, Mil = Military, Rd = Road, Wld = Wildlife openings, Mow = Mowed, Tr = Tracked vehicle, Wh = Wheeled, Ft = Foot, Imp = Impact, Fir = Firing, F = Frequent, I= Infrequent

Land management goals	Cause of predominant ecological effect from military use(s) of land								
	Tracked vehicles	**Wheeled vehicles**	**Foot traffic**	**Designated bivouac areas**	**Firing ranges**	**Impact areas**	**Drop zones**	**No effect**	**Admini-strative use**
1. Minimally managed areas									
1.1 Wetlands	WetTrI WetTrF	WetWhI WetWhF	WetFtI	0	0	0	0	Wet+	0
1.2 Vegetation on steep slopes	SteTrI SteTrF	SteWhI SteWhF	SteFtI	0	0	0	0	Ste+	0
1.3 Forests in impact zones	0	0	0	0	0	ForImpI ForImpF	0	For+	0
2. Actively managed to restore and preserve upland forest									
2.1 Upland forest	UpltrI	UplWhI UplWhF	UplFtI UplFTF	0	0	0	0	Upl+	0
2.2 RCW mgmt clusters	RcwTrkI	RcwWhI	RcwFtI RcwFtF	0	0	0	0	Rcw+	0
2.3 Sensitive area designated by signs	0	0	SenFtI SenFtF	0	0	0	0	Sen+	0
3. Managed to maintain an altered ecological state									
3.1 Intensive military use areas	MilTrkF	MilWhF	0	MilBivI MilBivF	MilFirF	0	0	0	0
3.2 Wildlife openings	0	WldWhI	WldFI	0	0	0	WldDrpI	Wld+	0
3.3 Mowed fields	0	MowWhI	MowFtI MowFtF	0	MowFirI MowFirF	0	MowDrpI	Mow+	0
3.4 Roads (paved and unpaved)	RdtrI RdTrF	RdWhI RdWhF	RdFtI RdFtF	0	0	0	0	Rd+	0
3.5 Built areas	0	0	0	0	0	0	0	0	Ba

Data Collected on Ecological Attributes

The data consisted of environmental indicators representing soil, plant, and microbial data at the plot level from various plot and point locations at Fort Benning. Strategic Environmental Research Development Programs, Ecosystem Management Program (SERDP SEMP, defined in Chapter 1) sponsored the projects that produced the data used in this analysis. Environmental indicator data were available from the SEMP Data Repository (https://sempdata.erdc.usace.army.mil/) and consisted of 13 separate datasets containing 4,283 total observations on 112 indicators. Each indicator is characterized by descriptive statistics in Table 3-2 Parts A to C. The details on all indicators including methods of collection, measurement units, and investigator justification are provided in Appendix 1.

Variable Selection Approach

From the pool of candidate indicators, several variable selection techniques were used to identify a subset of important ecological indicators that best discriminated the Land-Management Categories. The selection method had 4 steps: (1) data exploration, using descriptive and general statistics; (2) matrix conditioning, including filtering outliers, imputing missing values and transforming variables where necessary; (3) variable selection using Regression, Neural Network and Decision Tree models; and (4) the assessment and scoring of output to identify common traits of important indicators that were strong discriminators of the Land-Management Categories.

Table 3-2 Indicator properties as collected by the SEMP research teams. N = number of observations, Min. = minimum value, Max. = maximum value, Std. Dev. = standard deviation.

Data Set[1]	Indicator[2]	N	Mean	Min.	Max.	Lower Quartile	Median	Upper Quartile	Range	Std. Dev.	Shapiro-Wilk W	Trans-formation
P1	Soil Depth (cm)	216	0.8	0	4	0	0.5	1.5	4	0.9	0.844	
P2	Lang	1,080	8	0	20	4	7	11	20	5	0.965	
P3	NO3-N	144	3.24	1.11	7.74	1.93	3.08	4.42	6.63	1.45	0.938	
P3	NH4-N	108	10.35	4.87	32.51	7.14	8.96	12.70	27.64	4.71	0.851	
P3	MBC	144	163.7	4.3	1,308.9	49.9	106.4	216.0	1,304.6	182.8	0.720	
P3	SOM	144	3.08	0.43	26.70	1.60	2.27	3.51	26.27	2.99	0.606	log
P4	ftac	252	69.8	30.3	148.4	58.3	67.4	78.3	118.1	16.3	0.955	
P4	fdiv	252	78.9	54	95	74	80	84	41	7.6	0.983	
P4	btac	252	40.1	0.6	114.8	21.5	39.5	54.9	114.2	22.1	0.978	
P4	bdiv	252	54.5	2	90	44	57	68	88	18.5	0.962	
P5	ammonium	414	0.04	0.00	4.84	0.00	0.00	0.00	4.84	0.30	0.122	Binary
P5	nitrate	414	0.32	0.00	25.94	0.00	0.00	0.00	25.94	1.73	0.174	Binary
P5	phosphorus	414	0.03	0.00	2.66	0.00	0.00	0.00	2.66	0.21	0.101	Binary
P5	sulfate	414	27.8	2.7	233.2	10.6	19.4	34.3	230.4	28.9	0.667	
S1	SoilDEPTH	384	0.65	0.00	6.50	0.00	0.00	1.00	6.50	0.96	0.724	
S1	OrgLMass	256	47.4	2.6	238.7	24.3	37.7	56.5	236.1	37.5	0.762	
S1	Massm2	256	957	53	4,823	491	761	1,142	4,770	757	0.762	
S1	treesha	35	336	132	822	219	278	440	690	162	0.885	
S1	treesacre	35	136	53	333	89	112	178	280	66	0.885	
S1	Percover	32	0.413	0.120	0.657	0.340	0.392	0.511	0.537	0.138	0.965	
S1	OrgLayerN	221	0.703	0.176	1.230	0.556	0.700	0.821	1.054	0.195	0.995	
S1	NO3	128	0.052	0.000	0.830	0.000	0.021	0.063	0.830	0.120	0.402	log
S1	NH3	128	0.82	0.00	6.13	0.15	0.52	1.14	6.13	1.00	0.755	

(continued next page)

Table 3-2, continued.

Data Set[1]	Indicator[2]	N	Mean	Min.	Max.	Lower Quartile	Median	Upper Quartile	Range	Std. Dev.	Shapiro-Wilk W	Trans-formation
S1	NO32	128	0.88	0.00	15.32	0.00	0.06	0.81	15.32	2.03	0.478	log
S1	NH32	128	1.94	0.00	19.68	0.12	0.70	2.54	19.68	2.84	0.682	log
S1	NO3M1	128	0.83	-0.17	14.49	0.00	0.04	0.74	14.66	1.95	0.488	log
S1	NH3M1	128	1.12	-1.72	17.60	-0.09	0.29	1.64	19.32	2.50	0.700	log
S1	NO33	128	4.51	0.00	29.60	0.00	1.75	6.92	29.60	6.10	0.759	log
S1	NH33	128	2.90	0.00	26.97	0.28	0.99	4.23	26.97	4.27	0.683	log
S1	NO3M2	128	4.46	-0.17	28.76	0.00	1.71	6.91	28.93	6.05	0.761	log
S1	NH3M2	128	2.07	-2.93	24.90	-0.21	0.64	3.03	27.83	3.90	0.738	log
S1	totalN	128	6.53	-0.69	28.82	2.18	5.18	9.26	29.51	6.18	0.864	
O1	O-HORgN/m2	119	6.2	0.0	28.4	2.8	5.2	9.1	28.4	5.2	0.908	
O1	0-10gN/m2	123	61	0	213	39	55	84	213	35	0.957	
O1	0-10g/cm3	123	1.24	0.83	1.71	1.06	1.20	1.41	0.88	0.23	0.957	
O1	00-10[C]%	123	1.45	0.04	4.69	0.91	1.34	1.81	4.65	0.92	0.926	
O1	O-HORgC/m2	119	336	0	1,064	164	352	477	1,064	230	0.950	
O1	0-10gC/m2	123	1,620	63	4,030	1,153	1,546	2,089	3,967	830	0.968	
O1	0-20gPOM-C/m2	123	795	25	2,225	506	762	1,060	2,200	453	0.968	
O1	0-20gMOM-C/m2	123	1,622	92	4,146	1,174	1,484	1,999	4,054	853	0.942	
O1	0-10[N]%	123	0.05	0.00	0.20	0.03	0.05	0.07	0.20	0.04	0.926	
O1	O-HORC:N	101	61.2	25.1	145.9	45.4	53.6	71.4	120.8	25.3	0.869	
O1	0-10C:N	119	29.3	3.1	123.0	22.0	28.5	34.1	119.9	13.4	0.773	log
O1	T0ugNO3N/g	123	0.16	-0.09	1.84	0.00	0.07	0.20	1.93	0.29	0.573	log
O1	T0ugNH4N/g	123	2.23	0.05	19.31	0.93	1.46	2.45	19.26	2.52	0.628	log
O1	T0ugTOTN/g	123	2.39	0.26	19.97	1.10	1.68	2.67	19.71	2.51	0.608	log
O1	MOM[C]%	123	2.78	0.22	10.17	1.12	2.16	3.95	9.95	2.10	0.887	

(continued next page)

Table 3-2, continued.

Data Set[1]	Indicator[2]	N	Mean	Min.	Max.	Lower Quartile	Median	Upper Quartile	Range	Std. Dev.	Shapiro-Wilk W	Trans-formation
O1	MOM[N]%	123	0.14	0.02	0.41	0.07	0.12	0.17	0.39	0.08	0.909	
O1	fPOM-C	123	0.32	0.14	0.60	0.26	0.33	0.39	0.47	0.10	0.989	
O1	O-HORg/cm2	118	0.09	0.00	0.31	0.04	0.09	0.13	0.31	0.06	0.962	
O1	NMINRATE	123	4.44	-13.56	40.30	0.57	2.43	6.55	53.86	7.21	0.777	log
O2	Acanthaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.202	None/Binary
O2	Aizoceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.098	None/Binary
O2	Amaranthaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.314	None/Binary
O2	Anacardiacea	70	0.007	-0.003	0.090	0.000	0.005	0.005	0.093	0.014	0.528	None/Binary
O2	Aquifoliaceae	70	0.009	0.000	0.625	0.000	0.000	0.000	0.625	0.075	0.106	None/Binary
O2	Boraginaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.098	None/Binary
O2	Cactaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.158	None/Binary
O2	Campanulaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.158	None/Binary
O2	Caryophyllaceae	70	0.000	0.000	0.010	0.000	0.000	0.000	0.010	0.001	0.201	None/Binary
O2	Cistaceae	70	0.001	0.000	0.005	0.000	0.000	0.000	0.005	0.002	0.519	None/Binary
O2	Compositae	70	0.116	0.000	0.885	0.010	0.033	0.120	0.885	0.194	0.635	None/Binary
O2	Convolvulaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.282	None/Binary
O2	Cyperaceae	70	0.001	0.000	0.030	0.000	0.000	0.000	0.030	0.005	0.195	None/Binary
O2	Ebenaceae	70	0.004	0.000	0.030	0.000	0.005	0.005	0.030	0.007	0.509	None/Binary
O2	Ericacae	70	0.038	-0.073	0.380	0.000	0.000	0.015	0.453	0.086	0.559	None/Binary
O2	Euphorbiaceae	70	0.001	0.000	0.005	0.000	0.000	0.000	0.005	0.002	0.473	None/Binary
O2	Fagaceae	70	0.006	0.000	0.185	0.000	0.000	0.005	0.185	0.023	0.249	None/Binary
O2	Graminae	70	0.427	0.000	5.005	0.040	0.200	0.440	5.005	0.845	0.439	None/Binary
O2	Hamamelidaceae	70	0.020	-0.008	0.625	0.000	0.000	0.000	0.633	0.084	0.260	None/Binary
O2	Hypericaceae	70	0.004	0.000	0.060	0.000	0.000	0.005	0.060	0.010	0.484	None/Binary

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Table 3-2, continued.

Data Set[1]	Indicator[2]	N	Mean	Min.	Max.	Lower Quartile	Median	Upper Quartile	Range	Std. Dev.	Shapiro-Wilk W	Transformation
O2	Juglandaceae	70	0.001	0.000	0.030	0.000	0.000	0.000	0.030	0.004	0.229	None/Binary
O2	Lamiaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.098	None/Binary
O2	Lauraceae	70	0.002	0.000	0.085	0.000	0.000	0.000	0.085	0.010	0.175	None/Binary
O2	Leguminosae	70	0.025	0.000	0.130	0.000	0.015	0.035	0.130	0.033	0.741	None/Binary
O2	Liliaceae	70	0.009	0.000	0.380	0.000	0.000	0.005	0.380	0.045	0.154	None/Binary
O2	Loganiaceae	70	0.001	0.000	0.005	0.000	0.000	0.000	0.005	0.002	0.505	None/Binary
O2	Myricaceae	70	0.001	0.000	0.030	0.000	0.000	0.000	0.030	0.005	0.213	None/Binary
O2	Passifloraceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.098	None/Binary
O2	Pinaceae	70	0.008	0.000	0.195	0.000	0.000	0.005	0.195	0.028	0.324	None/Binary
O2	Polypodiaceae	70	0.019	0.000	0.375	0.000	0.000	0.000	0.375	0.070	0.301	None/Binary
O2	Rosaceae	70	0.014	0.000	0.085	0.000	0.005	0.015	0.085	0.019	0.682	None/Binary
O2	Rubiaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.098	None/Binary
O2	Scopulariaceae	70	0.001	0.000	0.010	0.000	0.000	0.000	0.010	0.002	0.425	None/Binary
O2	Solanaceae	70	0.001	0.000	0.005	0.000	0.000	0.000	0.005	0.002	0.490	None/Binary
O2	Violaceae	70	0.000	0.000	0.008	0.000	0.000	0.000	0.008	0.001	0.209	None/Binary
O2	Vitaceae	70	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.001	0.205	None/Binary
O3	BD	70	1.43	1.02	1.72	1.32	1.45	1.54	0.70	0.16	0.977	
O3	SOIL-C	70	175	20	511	95	176	229	491	101	0.960	
O3	SOIL-N	70	6.6	0.9	14.8	4.4	6.0	8.0	13.9	2.9	0.925	
O3	C:N	70	28	4	68	18	26	37	64	14	0.967	
O3	DepthA	70	2.1	0.0	12.0	0.0	0.0	4.0	12.0	3.1	0.721	
O3	oldtree	70	35.7	0.0	120.0	0.0	7.5	80.0	120.0	43.1	0.768	
O3	Ccover	70	13.8	0.0	44.5	0.0	2.2	27.3	44.5	16.3	0.774	
O3	Ucover	70	48.9	0.0	100.0	23.0	57.0	69.0	100.0	28.1	0.911	

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Table 3-2, continued.

Data Set[1]	Indicator[2]	N	Mean	Min.	Max.	Lower Quartile	Median	Upper Quartile	Range	Std. Dev.	Shapiro-Wilk W	Trans-formation
O3	Urich	70	20.6	0.0	39.0	11.0	24.0	29.0	39.0	11.1	0.920	
O3	Thero	70	4.16	0.00	17.00	2.00	3.00	5.00	17.00	3.92	0.827	
O3	Cypto	70	19.94	0.00	44.00	10.00	20.50	30.00	44.00	11.78	0.955	
O3	Hemic	70	8.19	0.00	24.00	2.00	8.50	13.00	24.00	6.94	0.921	
O3	Chamae	70	3.11	0.00	11.00	0.00	3.00	5.00	11.00	2.75	0.896	
O3	Phanero	70	12.24	0.00	56.00	1.00	10.50	20.00	56.00	11.93	0.878	
O4	pmolgram	70	19,027	152	106,024	2,402	16,925	27,770	105,871	19,137	0.790	
O4	Nsats	70	21.2	16.7	28.3	20.0	21.0	22.0	11.6	1.9	0.955	
O4	MBSats	70	17.4	9.9	35.5	13.6	15.8	20.1	25.6	5.1	0.901	
O4	TBSats	70	15.9	10.1	22.3	14.3	15.8	17.7	12.3	2.5	0.994	
O4	Bmonos	70	3.6	2.4	7.4	3.2	3.5	3.9	5.0	0.7	0.818	
O4	Monos	70	36.4	24.6	44.4	34.2	36.5	39.1	19.8	4.0	0.975	
O4	Polys	70	5.6	0.6	13.5	3.1	5.6	7.5	12.9	3.0	0.973	
FL1	TC	298	36.8	0.5	290.1	5.3	10.6	51.7	289.6	56.0	0.656	
FL1	SoilResp	220	2.62	0.00	18.79	0.27	0.67	4.25	18.79	3.95	0.678	
FL1	BetaGlActiv	230	7.6	-0.2	46.4	3.4	4.9	9.8	46.6	7.7	0.740	
FL2	A Horizon	40	2.4	0.0	8.3	0.7	2.2	3.4	8.3	2.2	0.900	

[1]Data set: P = Prescott College Group, S = Savannah River Ecology Laboratory Group, O = Oak Ridge National Laboratory Group, FL = University of Florida Group. Numbers after the group designation are specific data set identifiers. For example Prescott College provided five data sets P1 to P5.

[2]Indicator denotes the type of ecological indicator. Indicator definition, units of measure and justification are defined in Appendix 1.

Although the framework of Land-Management Categories facilitated the comparison of multiple indicators across research teams, there were concerns about how to perform the indicator (variable) selection. Concerns included: (1) Land-Management Categories were retroactively applied to the plots at Fort Benning, and the data collected were not intended to explain Land-Management Categories; (2) Land-Management Categories were not equally distributed across the base, and the sampling across Land-Management Categories was not even; (3) not all indicators were equally reasonable for all Land-Management Categories; and (4) all Land-Management Categories were not equally important to resource managers.

In order to compensate for the shortcomings in the data, a strategy was implemented using multiple solutions by employing several parametric and nonparametric indicator selection techniques. The underlying assumptions of this approach were that a combination of indicators would give more reliable guidance than any single indicator, and that multiple selection techniques would make the best use of the data available. The hypothesis was that certain important ecological indicators would discriminate between Land-Management Categories with different levels of military activity and associated ecological impacts. Once organized, the important indicators could be identified for each Land-Management Category and used in a management program.

Descriptive Statistics and Matrix Conditioning

Each indicator was assessed with a series of descriptive statistics to ascertain the shape of the distribution and frequency of values. Histograms were plotted and a Shapiro-Wilk W statistic was computed for each variable. If the Shapiro-Wilk W test result was < 0.7, showing non-normality (A. Saxton, Personal Communication), then a transformation of the variable was performed and the distribution of the variable was again assessed until a suitable transformation was found (Table 3-2 Parts A-C). Outliers were filtered at five standard deviations from the mean. If it was found that values representing acceptable data were beyond the first filter, then the filter was broadened to accommodate that data. Mean imputation was used in two of the datasets in order to keep as many observations as possible for model generation and assessment.

Regression

Logistic Regression (Dreiseitl and Ohno-Machado, 2002) was performed using SAS Enterprise Miner 4.2 software (SAS Cary, NC). Forward, stepwise, and standard variable selection were used to screen indicators against the Land-Management Categories. All regression models used LOGIT as the link function and deviation coding. Forward and Stepwise selection criteria were set at the significance level of 0.05 for entry and/or to stay in the model. Indicators from the regression analysis were considered important if the overall predictive model was significant at 0.05 and the individual indicator was also significant at 0.05.

Neural Network

Neural network (NN) identification was performed with early stopping by cross-validation and topology optimization by bootstrapping (selection criteria: median cross-validated error) using the microCortex web-based neural computing environment (www.microCortex.com) (Almeida, 2002). NN models were considered relevant if the r^2 statistic for any trained NN (for any Land-Management Category) was greater than 0.6. The relative importance of each input parameter in predicting the target values was calculated by performing sensitivity analysis on the trained NN (Masters, 1993). In this study, sensitivity of an output parameter $Out_{j=1,2,\ldots,nj}$ (for nj output parameters) to an input parameter $In_{i=1,2,\ldots,ni}$ (for n_i input parameters) was defined as the normalized ratio between variations caused in Out_j by variations introduced in In_j and is represented by the following equation:

$$NS_{i,jc} = (dOut_{j,c} / d\, In_{i,c})(In_{i,c} / Out_{j,c})$$

$$S_i = [\, \Sigma_{j=1,2,\ldots,nj;\, c=1,2,\ldots,nc} (NS_{i,jc}) \,] / [\, \Sigma_{i=1,2,\ldots,ni;\, j=1,2,\ldots nj;\, c=1,2,\ldots,nc} (NS_{i,jc}) \,]$$

(eq. 1)

i= 1, 2, ..., ni; input index

j= 1, 2, ..., nj; output index

c= 1, 2, ..., nc; sample (case) index

The normalized sensitivity for an individual profile c, $NS_{i,jc}$ was calculated for every combination of input i and output parameter j, and for every profile (for nc profiles). The overall sensitivity to an input S_i was determined by taking the average over all profiles and all binary outputs used to classify them. Finally, the sensitivity values obtained were represented as relative values, calculated as a percent value of the sum of all sensitivities (eq.1, S_i) (Masters, 1993). If the indicator sensitivity was greater than 10%, then it was considered important and scored.

Decision Tree

The Tree-growing algorithms (Answer Tree v3.1 SPSS Chicago, IL), Exhaustive Chi-squared Automatic Interaction Detector (Kass 1980; Biggs et al., 1991), and Classification and Regression Trees (C&RT) (Breiman et al., 1984) were used to select a subset of predictors from the indicator data that predicted the Land-Management Category. Indicators resulting from the decision rules from Tree models were considered relevant if the model had a misclassification rate less than or equal to 40%.

Results Scoring

A strategy of multiple solutions employing several parametric and nonparametric indicator selection techniques as described above was used to elucidate which indicators best discriminate the Land-Management Categories. In order to summarize the indicator selection outcomes, a selection score was calculated from the union of or intersection between indicator results. If a given indicator was significant (as defined above) within a given overall significant model, then it was scored. The selection score was calculated as the sum of the number of models (union of or intersection between) for which a given indicator was significant. The maximum selection score an indicator could receive was six, because that was the number of indicator selection techniques used. Higher selection scores for indicators within data sets are interpreted as meaning those indicators are more robust in regards to defining the Land-Management Categories.

Results

Variable Selection

The variable selection analyses resulted in several strong ecological indicators describing the Land-Management Categories. Table 3-3 shows the results of the indicator selection techniques. Three types of ecological indicator data were available for this analysis and included: (1) soil physical, chemical and microbiological parameters; (2) plant family and life form; and (3) cover data (individual indicators are described in Appendix 1). Soil physical and chemical variables that received high selection scores (>3) included soil "A" horizon depth, compaction, organic matter, organic layer N, NH_3, Total N, N mineralization rate, total carbon and % carbon. Soil microbiological indicators that received high selection scores included biomarkers for fungi, Gram-negative Eubacteria, soil microbial respiration and beta-glucosidase activity. Plant family and life form indicators that received high selection scores were the family Leguminosae, possibly Rosaceae, and the plant life forms Therophyte, Cyptophyte, Hemicryptophyte and

Table 3-3 Indicator selection scores for Land-Management Categories (LMCs) adequately represented by each research team.

[1]Data Set (LMC)		[2]Indicator	Regression			ANN	Tree		[4]Score
			Standard	Backward	Step		CHAID	C&RT	
P1	(UplFtI, RcwFtI, MilTrF)	Soil A Horizon Depth	[3]X	NA	NA	~	X	X	5
P2	(UplFtI, RcwFtI, MilTrF)	Soil Compaction	X	NA	NA	~	X	X	5
P3	(UplFtI, RcwFtI, MilTrF)	Soil Nitrate				X	X	X	3
P3		Soil Ammonium	X		X		X	X	4
P3		Soil Organic Matter	X	X	X	X	X	X	6
P4	(UplFtI, RcwFtI, MilTrF)	Bacteria Ttl Activity	X	X	X	~	~	~	3
P4		Bacteria Func. Div.	X	X	X	~	~	~	3
P4		Fungi Func. Div.	X	X	X	~	~	~	3
P5	(UplFtI, RcwFtI, MilTrF)	NL: nitrate			X	~	~	~	1
P5		NL: sulfate	X			~	~	~	1
S1	(UplWhI, UplTrI)	SoilDEPTH	X	X	X		X	X	5
S1		treesacre				X			1
S1		OrgLayerN	X	X	X	X			4
S1		NH3	X	X	X		X	X	5
S1		totalN	X	X	X	X	X	X	6
S2	(UplWhI, UplTrI)	NMINRATE	X	NA	NA	~	X	X	5
O1	(MilTrF, UplTrI, WetFtI)	O-HORgN/m2	X	X					2
O1		0-10g/cm3	X			X			2
O1		00-10[C]%	X	X				X	3
O1		O-HORgC/m2	X	X					2
O1		0-10gC/m2	X	X					2
O1		0-20gPOM-C/m2						X	1
O1		0-20gMOM-C/m2	X	X			X		3
O1		0-10[N]%		X					1
O1		O-HORC:N				X			1
O1		0-10C:N	X			X			2
O1		T0ugNH4N/g			X				1
O1		MOM[C]%	X						1
O1		MOM[N]%	X	X					2
O1		fPOM-C				X	X		2
O1		O-HORg/cm2	X						1
O1		NMINRATE	X	X		X			3
O2	(Upl+, MilTrF, MilWhF, WldDrpI, UplFtF)	Cistaceae		~	~	X			1
O2		Compositae		~	~	X		X	2
O2		Ericacae		~	~			X	1

(continued next page)

Table 3-3, continued.

[1]Data Set (LMC)		[2]Indicator	Regression			ANN	Tree		[4]Score
			Standard	Backward	Step		CHAID	C&RT	
O2		Graminae	X	~	~	X			2
O2	(Upl+, MilTrF,	Hypericaceae		~	~		X		1
O2	MilWhF, WldDrpI,	Leguminosae	X	~	~	X	X	X	4
O2	UplFtF)	Loganiaceae		~	~	X			1
O2		Rosaceae	X	~	~	X			2
O3		BD		X	X	X			3
O3		SOIL-C			X				1
O3		SOIL-N	X	X	X				3
O3		C:N		X					1
O3		DepthA						X	1
O3		oldtree		X			X	X	3
O3	(Upl+, MilTrF,	Ccover	X	X		X		X	4
O3	MilWhF, WldDrpI,	Ucover	X	X	X	X		X	5
O3	UplFtF)	Urich	X	X					2
O3		Thero	X	X	X	X			4
O3		Cypto	X	X	X	X	X		5
O3		Hemic	X	X	X	X	X		5
O3		Chamae	X	X	X	X			4
O3		Phanero	X	X	X				3
O4		pmolgram	X	X	~			X	3
O4	(Upl+, MilTrF,	Nsats			~	X			1
O4	MilWhF, WldDrpI,	TBSats			~	X		X	2
O4	UplFtF)	Bmonos			~	X			1
O4		Monos	X	X	~	X		X	4
O4		Polys	X	X	~	X	X	X	5
FL1	(MilWhF, MilTrkF,	TC	X	X	X	X	X		5
FL1	UplFtI, WetTrkF,	SoilResp	X	X	X	X	X	X	6
FL1	Wet+, Upl+)	BetaGlActiv	X	X	X	X	X	X	6
FL2		A Horizon	X	N/A	N/A	~	~	~	1

[1]Abbreviations for data set codes in legend to Table 3-2, and for LMCs in Table 3-1B.
[2]Indicator definitions, units of measure and justification are defined in Appendix 1.
[3]X = selected indicator was significant in a significant model. ~ = selected model was not stable and calculation not possible. N/A = model was not applicable. A blank space means that indicator was not significant for that model.
[4]Score = The total number of significant models in which a given indicator was significant. The maximum score an indicator can receive is six.

Chamaephyte. Understory cover, overstory cover and tree stand characteristics also scored well in the ability to discriminate between Land-Management Categories.

Discussion

Circumstances necessitated an uncommon approach for the selection of indicators that best discriminated Land-Management Categories. There were two key components to this work, (1) the development of Land-Management Categories and (2) variable screening by multiple solutions. Although the data for this effort were not collected in a fashion compatible with traditional statistical techniques, variable screening by multiple solutions meant it was possible to integrate the separate research efforts and score the results. The use of selection scores provided a straightforward method to compare indicators, which was important in obtaining unambiguous results.

Similar indicators were measured by several different research teams, which provided an internal control for the method. Similar indicators measured by different teams scored similarly in the indicator selection process, which supported the validity of the selection process. Soil "A" horizon depth scored high in two out of three data sets where it was measured. Soil horizons are layers of soil or soil material that are approximately parallel to the land surface and differ from adjacent related layers by chemical, physical or biological properties. The soil "A" horizon is a mineral horizon in which the emphasized feature is the accumulation of humified organic matter intimately associated with the mineral fraction, and develops partially from organic matter accumulation (Boul et al., 1994).

Soil compaction was found to be an important indicator of Land Management Categories and is defined as the volume change produced by momentary load application on the soil (Bradford and Peterson, 2000). Many of the LMC's at Fort Benning are defined by the amount of military traffic they receive. The traffic consists of dismounted infantry (foot traffic), wheeled vehicles, and tracked vehicles. Soil compaction decreases void space, increases bulk density, and decreases compressibility and permeability. Soil compaction may also alter the growth of trees in forest systems and affect the water regime and organic matter content (Greacen and Sands, 1980).

Soil organic matter (SOM) is defined as the sum of all natural and thermally altered biologically derived organic material found in the soil or on the soil surface irrespective of its source, whether it is living or dead, or stage of decomposition, but excludes the aboveground portion of living plants (Baldock and Nelson, 2000). As defined, the amount and quality of SOM is determined by the inputs of the plant and animal community and has been linked to the resilience of ecosystems to disturbance (Szabolcs, 1994). SOM serves as a reservoir of metabolic energy, a source of macronutrients, and stabilizes soil structure. The amount and quality of SOM in the soils at Fort Benning were found to be important in discriminating the Land-Management Categories. Several measures of soil carbon and nitrogen, which are integral parts of the SOM, were also diagnostic for discriminating Land-Management Categories at Fort Benning.

Soil microbiological properties were also found to be good indicators of Land-Management Categories (Peacock et al., 2001a). Soil microbiological activity as defined by Soil Respiration, although shown to be variable (Raich and Tufekciogul, 2000), is directly related to nutrient cycling and photosynthetic activity (Högberg et al., 2001) and was important in discriminating Land-Management Categories. Additionally, N mineralization rate (the transformation of organic to inorganic N forms (Norten, 2000)) was also found to be a good predictor of Land-Management Categories. Beta glucosidase activity was assessed at several point and plot locations at Fort Benning. Beta glucosidase activity has been linked to soil microbial activity and numbers (Taylor et al., 2002) and has been studied as a potential indicator for effects of agriculture on ecological systems (Bandick and Dick, 1999).

Several plant-associated indicators were also very useful in discriminating the Land-Management Categories. Understory cover, overstory cover, and tree stand characteristics were indicative of differences in these categories. That these measures are important is not surprising, as cover data are intuitive and have been widely used as indicators (Thysell and Carey, 2000, and references therein). The plant family Leguminosae, which support nitrogen fixation, has been shown to add to the quality and amount of soil organic matter (Robles and Burke, 1997) and was an important indicator. Plant life form (Therophyte, Cryptophyte, Hemicryptophyte and Chamaephyte) was also a good predictor of land use (Dale et al., 2002).

Conclusions

Data limitations required a new approach to integrating disparate data from several research teams at Fort Benning. In order to solve the particular problem of relating land management to current challenges, Wolfe and Dale (2006a; 2006b) developed a matrix of Land-Management Categories that enabled a statistical multiple solutions approach to assess which ecological indicators would be the best candidates for inclusion in a relevant monitoring program. Since the ecological indicator information was spread over several data sets, a method had to be established to integrate and compile the results. The approach of multiple solutions with scoring allowed us to compare the fitness of each indicator for the prediction of Land-Management Categories without the limitations of other more traditional statistical methods. Ecological indicator data available for this analysis included: (1) soil physical, chemical and microbiological parameters; (2) plant family and life form; and (3) cover data. Soil physical and chemical variables that received high selection scores included soil "A" horizon depth, compaction, organic matter, organic layer N, NH_3, total N, N mineralization rate, total carbon and % carbon. Soil microbiological indicators that received high selection scores included biomarkers for fungi, Gram-negative Eubacteria, soil microbial respiration and β-glucosidase activity. Plant family and life form indicators that received high selection scores were the family Leguminosae, possibly Rosaceae, and the plant life forms Therophyte, Cyptophyte, Hemicryptophyte and Chamaephyte. Understory cover, overstory cover and tree stand characteristics also scored well in the ability to discriminate between Land-Management Categories. The results and insights gained from this effort appear to be consistent with other work in ecological indicators.

This approach fulfilled the expectations for these data and it is assumed the same approach could be used at other sites where there are existing data that were not collected in a way commensurate with traditional statistical methods.

Chapter 4

Ecological Knowledge Management:

Visualization of Ecological Indicators

Background

Knowledge or knowledge management can be defined as turning data (raw material) into information (finished products) and from there into knowledge (actionable products) (Spiegler, 2000). The objective of this part of the work was to use the results from the soil microbial analysis (Chapter 2) and legacy data integration (Chapter 3) to extend the understanding of the ecological dynamics and management impacts as they relate to the screened ecological indicators. The outcome is intended as a framework for visualizing and distilling the ecological indicators. This approach is, in a broad sense, defined as ecological knowledge management. The purpose of ecological knowledge management is to improve our ability to bring to bear general scientific knowledge, combined with available specific facts and data, to the decision maker to illuminate their choices and improve their ability to share their opinions with others. There are several steps to the knowledge management method:

1. Identify the relevant ecological indicators.
2. Define the identified relevant indicators and provide context.
3. Describe how the indicators respond to stress in the given ecosystem.
4. Define the relationships between relevant indicators.

Once these steps have been taken, a visual display of the information and mapping of the relationships between the indicators can take place. The mapping has the potential to increase the understanding of ecosystem functioning and corresponding ecosystem management decisions.

In chapters two and three, several ecological indicators were identified that are potentially useful in land management. That effort accomplished the first step in the knowledge management system. The relevant identified indicators were grouped into four categories as described:

1. Soil physical indicators. The identified indicators in this group included soil compaction and the depth of the 'A' horizon.
2. Soil chemical indicators. The identified indicators in this group included soil nitrogen (several measured forms), organic carbon (several measured forms) and organic matter.
3. Soil microbial/biochemical indicators. This group of indicators included microbial community biomass and composition, soil respiration, nitrogen mineralization rate and β-glucosidase activity.
4. Floristic/vegetative indicators. Indicators in this group are comprised of canopy cover, understory cover, plant life forms and one plant family (legumes).

To continue with the knowledge management process, each identified ecological indicator is addressed in turn.

Soil Physical Indicator; Soil Compaction

Definition and background. Soil compaction is defined as the process by which the soil grains are rearranged by mechanical means, resulting in decreased void space and increased bulk density (Soil Science Society of America, 2006). Compaction literally squeezes out pore space (the part of the soil that is occupied by water and gas). Generally, larger pores that best carry air and water are lost first. Stiegler (2006) states that the result of compaction on the soil is slower water infiltration, poor aeration, and more erosion. Any texture of soil is susceptible to compaction, but soils made up of a mixture of grain sizes will compact more than a soil of a single grain size. Soil moisture has the most influence on the amount of compaction a soil can receive under a given pressure. When a soil is wet, the water acts as a lubricant, facilitating the movement of soil particles, so generally the higher the soil moisture content the lower the pressure needed to cause compaction. The amount of organic matter in soils also plays a part in the compaction, as generally the more organic matter a soil contains the less susceptible it is to compaction.

Response to Stress. There is an increase in soil compaction with increased military traffic and training intensity. Figure 4-1 shows the measured amounts of soil compaction for three different land management categories. These land management categories are on the extreme ends of the land use spectrum, with frequent tracked vehicle use having a mean measure of just over 10, while the infrequent upland foot traffic mean value is about 6.5. Since not all traffic was measured, it is assumed the other land management categories fall somewhere between these values for the same soil type.

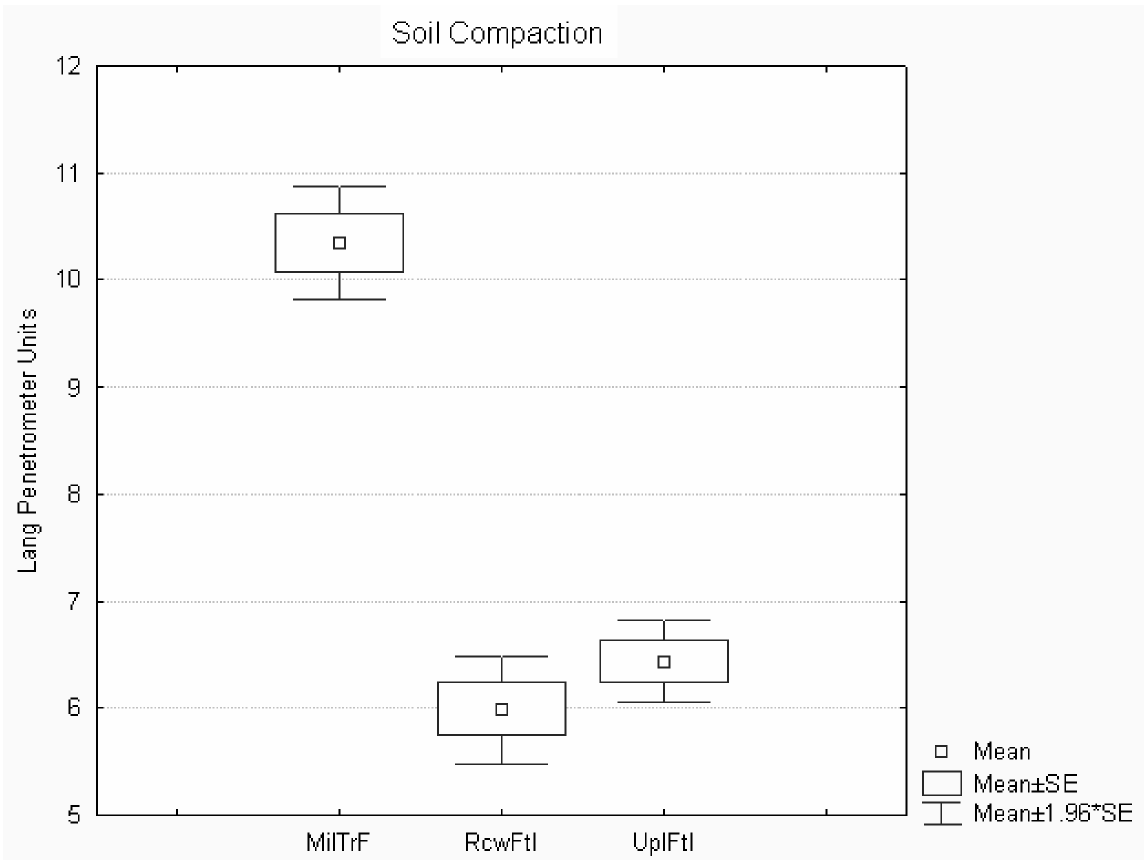

Figure 4-1. Soil compaction for three land use categories. Higher values indicate more soil compaction, n = 240 for each point and the x axis is treatment. Confidence limits for mean: 95%. MilTrF = frequent military tracked vehicles, RcwFtI = RCW managed infrequent foot traffic, and UpFtI = upland with infrequent foot traffic.

Relationships and feedback to other identified measured indicators. Increased soil compaction can have many effects on ecosystem properties,

- Reduced leaf litter (Waltert et al., 2002).
- Lower amount of fine roots and soil organic matter (Waltert et al., 2002).
- Loss of ground cover vegetation (Waltert et al., 2002).
- Lower rate of decomposition of organic matter and N mineralization (Breland and Hansen, 1996).
- Increase in gaseous losses of N (Breland and Hansen, 1996).
- Loss of plant species diversity (Dale et al., 2002).

In a sense, the soil compaction measure is more a cause of differences in our measured indicators rather than an indicator in and of itself.

Soil Physical Indicator; Soil "A" Horizon Depth

Definition and Background. Soil horizons are layers of soil or soil material that are approximately parallel to the land surface and differ from adjacent related layers by chemical, physical or biological properties. The soil "A" horizon is a mineral horizon directly under an organic horizon (litter), and the emphasized feature is the accumulation of humified organic matter intimately associated with the mineral fraction and developed partially from organic matter accumulation (Boul et al., 1994).

Soils scientists use five soil forming factors to explain how soils are developed (Boul et al., 1994).

1. Parent material: Parent material is the starting component of a soil, it may be rock, volcanic emissions, silt carried onto a floodplain, or derived from other sources. The parent material influences soil formation by its composition, rate of weathering, nutrients and particle size.
2. Climate: Soil formation varies depending upon temperature, moisture and wind.
3. Topography: Slope and aspect can effect soil formation. Steep soils are more susceptible to erosion and may be thinner. Soils at the bottom of a slope may be thicker due to deposits from upslope. Steep slopes facing the sun are warmer then those not so situated, which may increase organic matter decomposition rates.
4. Biological Factors: Plants, animals, microbes and humans effect soil formation. Plants open channels in the soil with root formation and add carbon, nitrogen and other nutrients. Microbes in many cases can control chemical exchanges in soils. Animals and humans mix soils and add organic matter through their wastes.
5. Time: The development of soils is continuous and the interplay of the other soil forming factors over time constitutes soil formation.

The development of soil horizons proceeds faster in warm, humid and forested conditions where there is enough water to move material through soil profiles. The depth of the soil “A” horizon is influenced by additions of organic matter and suspended particulates, and through soil loss by leaching and erosion. Figure 4-2 shows an illustration of standard soil horizons.

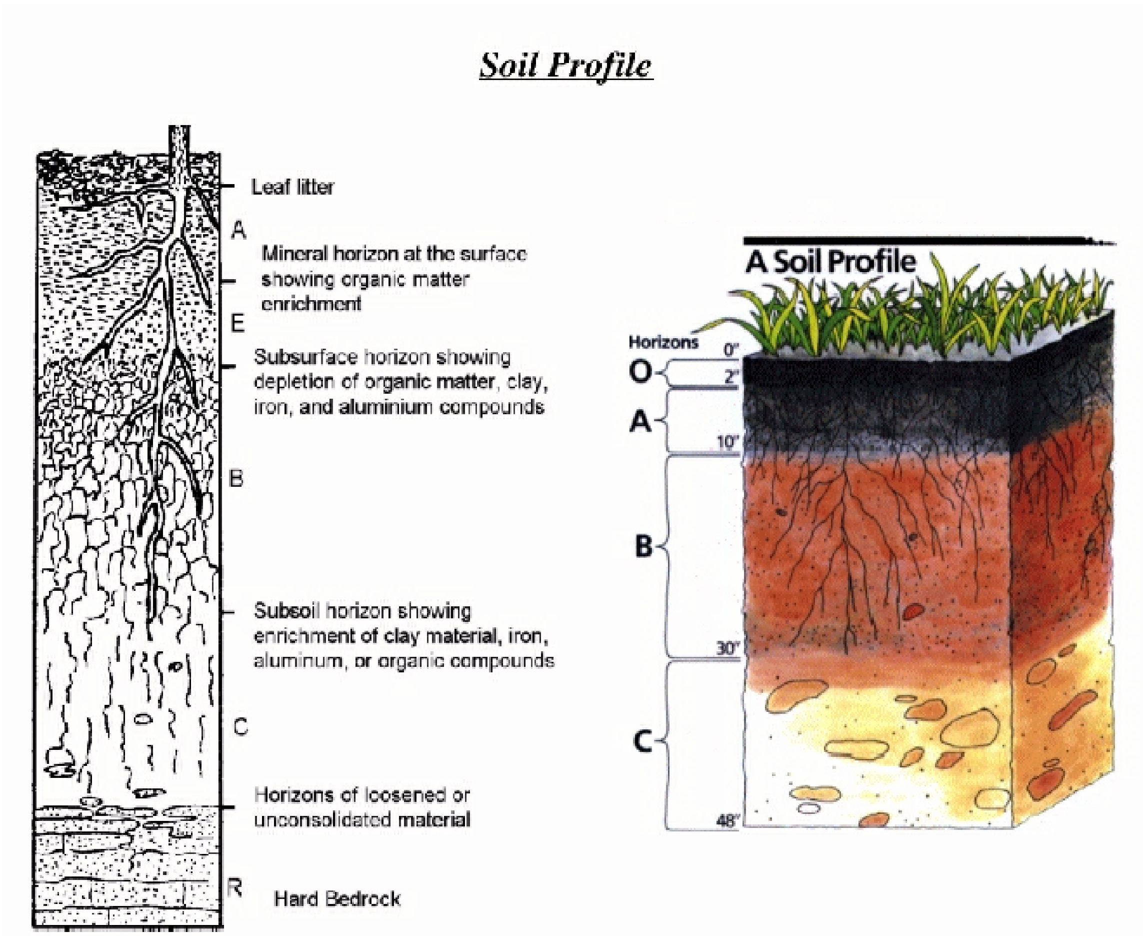

Figure 4-2. Illustrations of typical soil horizons. Left illustration accessed at www.cals.arizona.edu , right illustration accessed at www.mo15.nrcs.usda.gov .

Response to Stress. **W**ith increased land use, the inputs of organic matter and other particulates that increase or maintain the depth of the "A" horizon are reduced, and removal of organic matter and soil colloids are increased. The result is a net decrease in the soil "A" horizon with increased land use. Figure 4-3A and 4-3B shows the depth of the soil "A" horizon for five separate land management categories. The soils that received more traffic, e.g. MilTrF, MilWhF and WldD, have significantly smaller "A" horizon depth.

Relationships and feedback to other identified measured indicators. The reduction in the depth of the "A" horizon is a result of the loss of carbon inputs. The related indicators are:

- Canopy cover
- Understory cover
- Plant diversity

The loss of canopy cover and/or understory cover also causes a loss of SOM and its constituents (C and N), and a loss of bacterial biomass and activity per unit area.

Soil Chemical Indicators: Soil Organic Matter, C and N

Definition and background. Soil organic matter (SOM) is defined as the sum of all natural and thermally altered biologically derived organic material found in the soil or on the soil surface, irrespective of its source, whether it is living or dead, and independent of its stage of decomposition, but excluding the aboveground portion of plants (Baldock

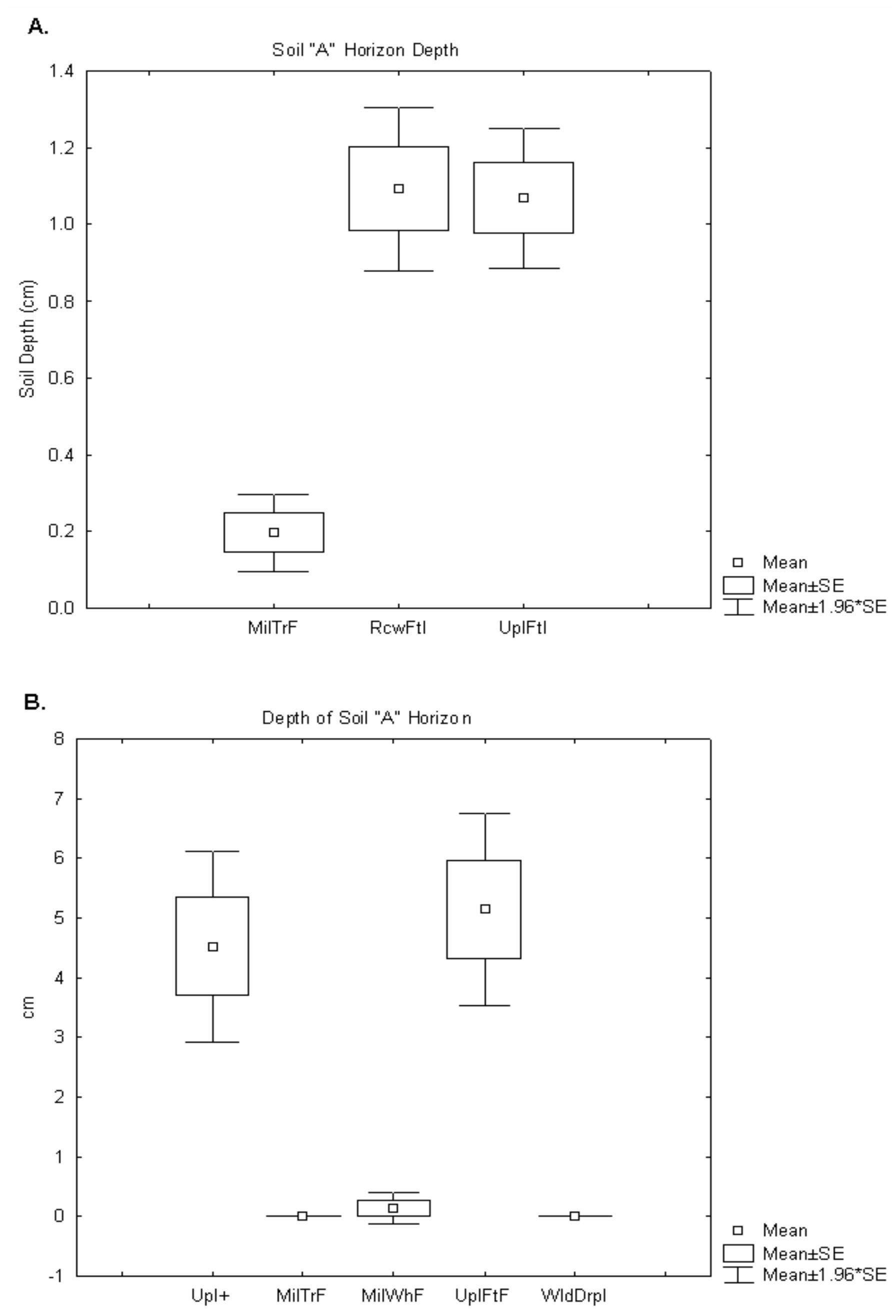

Figure 4-3. Two independent measures of the depth of the soil "A" horizon. Confidence level for mean: 95%. Upl+ = upland forest untrafficked, MilTrF = frequent military tracked vehicles, MilWhF = frequent military wheeled vehicles, UplFtF = upland forest frequent foot traffic, and WldDrpI = wildlife openings infrequent dropzone.

and Nelson, 2000). Soil organic matter has been found to contain approximately 50 to 58% carbon, 34 to 49% oxygen, 3.3 to 4.8% hydrogen and 3.7 to 4.1% nitrogen (Sparks, 1995). Sulfur(s) and phosphorus are also minor constituents of SOM, but SOM is the soil fraction where these elements are principally located (Essington, 2004). The amounts of SOM in the "A" horizons of mineral soils can range from 0.5 to 5% by weight, and it contains up to 90% of the total soil N.

Baldock and Nelson (2000) have identified several properties and functions of SOM:

- Reservoir of metabolic energy: SOM provides the physiological energy to drive system processes.
- Source of macronutrients: Mineralization of SOM impacts the amount of plant-available N, P, and S.
- Ecosystem resilience: The amount of SOM-associated nutrients can act as a buffer for natural or anthropogenic disturbances in the soil system.
- Stimulation and inhibition of enzyme activities and plant and microbial growth: Soil enzyme activity can be stimulated or inhibited by the presence of soil organic material.
- Stabilization of soil structure: The structure of the "A" horizon is most strongly influenced by biological factors, and soil aggregates are usually held together by SOM-mineral complexes.
- Water retention: SOM can hold up to 20 times its mass in water, and impacts soil structure and pore geometry.

- Low solubility: Protects soil carbon from leaching out of the soil profile.
- Color: The dark color of SOM can effect soil thermal properties.
- Cation exchange capacity: SOM is highly reactive, which enhances the retention of cations and micronutrients.
- Buffering capacity and pH effects: In alkaline and slightly acidic soils, SOM can act as a buffer and maintain acceptable pH conditions.
- Chelation of metals: SOM can form stable complexes with metals and trace elements and reduce the loss of micronutrients. SOM can also reduce the toxicity of metals and enhance the availability of P.
- Interactions with xenobiotics: SOM can enhance the biodegradability and persistence of many pollutants in the soil.

Response to Stress. On a stable landscape, the amount of SOM (C and N) in the soil is a function of the balance between the rate of deposition of plant residues and the rate of utilization of the C and N by soil microbes. Other factors influencing the amount of SOM in the soil are erosion and leaching, which increase with more intensive land use. Figure 4-4 shows the percent organic carbon for three different military land uses as measured at Fort Benning, Georgia. The most intensive land use (MilTrF) contained the least amount of organic soil carbon, while the infrequently trafficked wetland soil (WetFtI) contained approximately 13 times more organic soil carbon. The soil nitrogen content (Figure 4-5) mirrors that of the carbon, with the highest level occurring in the lightly trafficked wetland soil and the lowest in the heavily trafficked soil. There is an

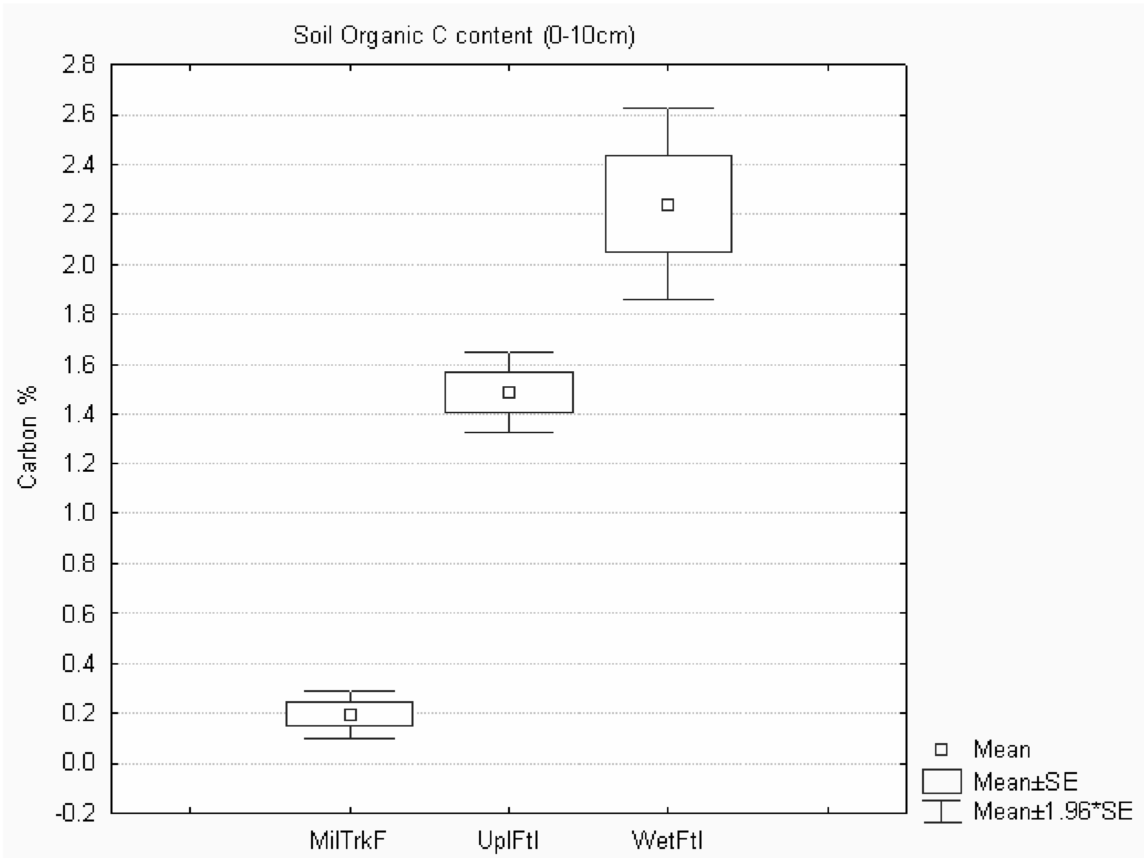

Figure 4-4. Percent soil organic carbon in the 0 to 10 cm horizon. Confidence level for mean: 95%. MilTrkF = frequent military tracked vehicles, UplFtI = upland forest infrequent foot traffic, WetFtI = wetland infrequent foot traffic.

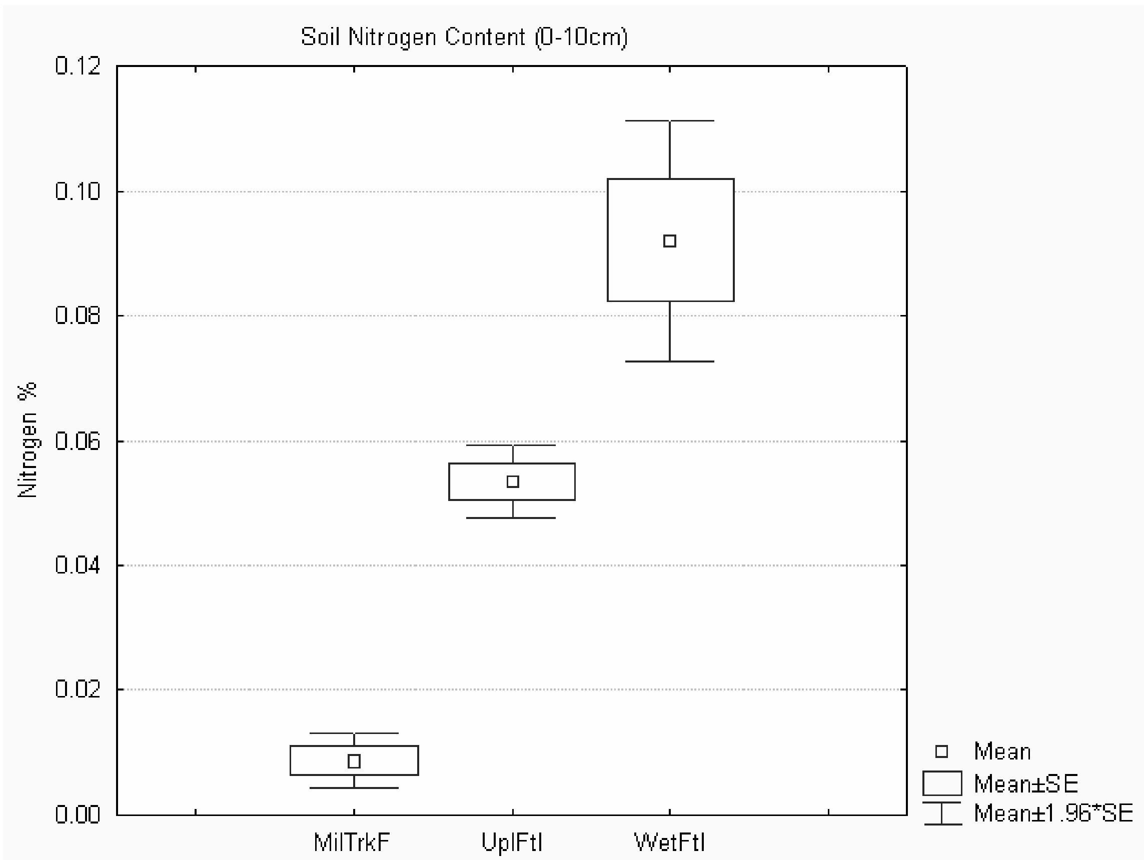

Figure 4-5. Percent soil nitrogen in the 0 to 10 cm horizon. Confidence level for mean: 95%. MilTrkF = frequent military tracked vehicles, UplFtI = upland forest infrequent foot traffic, WetFtI = wetland infrequent foot traffic.

overall loss of SOM carbon and nitrogen in response to stress (military traffic) in the system under study.

Relationships and feedback to other identified measured indicators. The relationships of soil organic matter to the other measured indicators are essentially the same as those of the soil "A" horizon. SOM is related to the amount and diversity of canopy and understory cover, activity and composition of the microbial community and the soil forming factors.

Soil Microbial & Biochemical Indicators; Microbial Community Composition, Respiration, N Mineralization Rate and Beta-Glucosidase Activity

Definition and background. The soil microbial biomass is the total amount of living microorganisms in the soil and contains mesofauna (e.g., nematodes), microfauna (e.g., protozoa) and microbes (e.g., bacteria, archea, fungi, and algae) (Essington, 2004). As reviewed in chapter two of this work, soil microbial biomass can react quickly to conditions of nutrients, moisture, temperature.

Response to Stress. In general, there is a decrease in microbial biomass with traffic disturbances at Fort Benning (Peacock et al., 2001a). Community composition is also impacted due to disturbance. For example, in areas where there is plenty of organic soil carbon, there appears to a healthy population of Gram-negative bacteria, but with more disturbed soils there is an increase in Actinomycetes (Peacock et al., 2001a). Soil microbial activity is also impacted by disturbance. Microbial activity as measured by β-glucosidase production is depressed in soils that are highly disturbed (Prenger, personal communication) as are N mineralization rates (Garten and Ashwood, 2004a, 2004b) (Figure 4-6).

Relationships and feedback to other identified measured indicators. The soil microbial community is intimately associated with the properties of SOM and its associated inputs (plant diversity, overstory and understory cover) and is the focal point through which many chemical transformations must pass. As such, soil microbes are the facilitators of the in-ground portion of the carbon and nitrogen cycles. Soil microbes are responsible for nitrogen mineralization and denitrification as well as the transformation of carbon into CO_2 and soil humic fractions.

Floristic & Vegetative Indicators; Canopy & Understory Cover, Plant Life Form and Legumes

Definition and background. Canopy cover measures the amount of cover over a plot (e.g., trees in a forest). Understory cover is defined as the percentage of an area's understory vegetation under one meter in height. Plant life form measures the amount of understory cover in an area (plot level) by the Raunkiaer (1934) life form system and the forms can be divided into Phanerophytes (trees and shrubs), Therophytes (annuals), Chamaephytes (plants with their buds slightly above the ground) and Chamaephytes or Hemicryptophytes (plants with dormant buds at ground level). Legumes (Leguminosae) are plants from the bean or pea family, containing about 18,000 species and 650 genera. Legumes are a significant component of most terrestrial ecosystems, for many Legumes

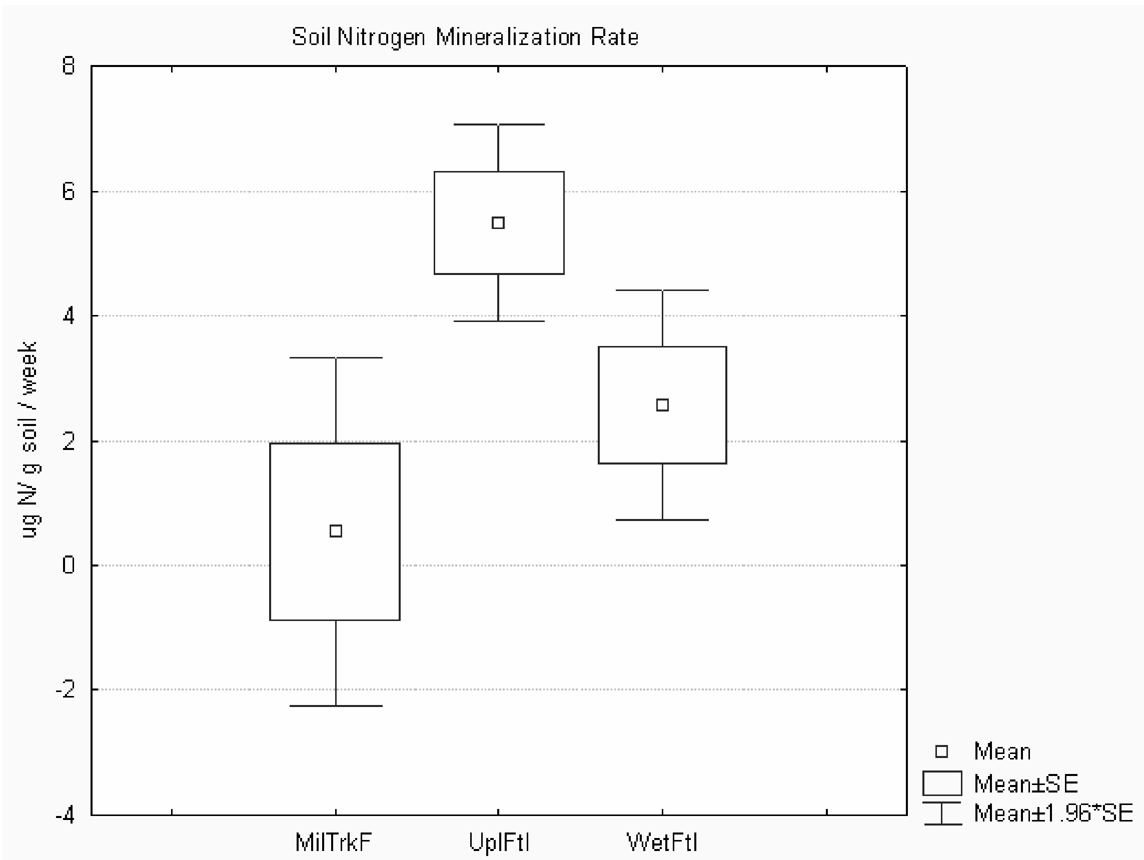

Figure 4-6. Soil nitrogen mineralization rate. Confidence level for mean: 95%. MilTrkF = frequent military tracked vehicles, UplFtI = upland forest infrequent foot traffic, and WetFtI = wetland infrequent foot traffic.

are nitrogen fixers through a symbiotic process with *Rhizobium* bacteria (Hickey and King, 1997). Canopy cover is indicative of changes in ecosystem processes over decades, and understory vegetation cover and plant life form or family indicators measure changes over years to decades.

Plants have been used as indicator organisms since the beginning of modern ecological monitoring (Hall and Grinnell, 1919). Plant communities and biomass provide a ready measure of differentiation between many land uses and do not require any special tools for analysis besides the knowledge of the person making identifications. Plant communities respond to temperature, moisture, soil condition, disturbances and several other ecological variables.

Response to stress. Dale et al. (2002) reported at Fort Benning that canopy and understory cover decreases with increased training activities (Figure 4-7). Neither measure of plant cover discriminated the extremes of training intensity. In order to achieve a higher resolution between treatments, a plant life-form measure was used. Cryptophytes were the most abundant of all categories studied, except in lightly-trafficked areas (Figure 4-8A). Phanerophytes (Figure 4-8B) were the most abundant in light training areas while Therophytes (Figure 4-8C) were least abundant in lighter training areas. Chamaephytes were least numerous in moderately trafficked sites and sites undergoing remediation (Figure 4-9A). Heavily tracked sites did not support Chamaephytes or Hemicryptophytes (Figure 4-9B). Legumes were most abundant in low traffic areas (Figure 4-10) and were sensitive to disturbance.

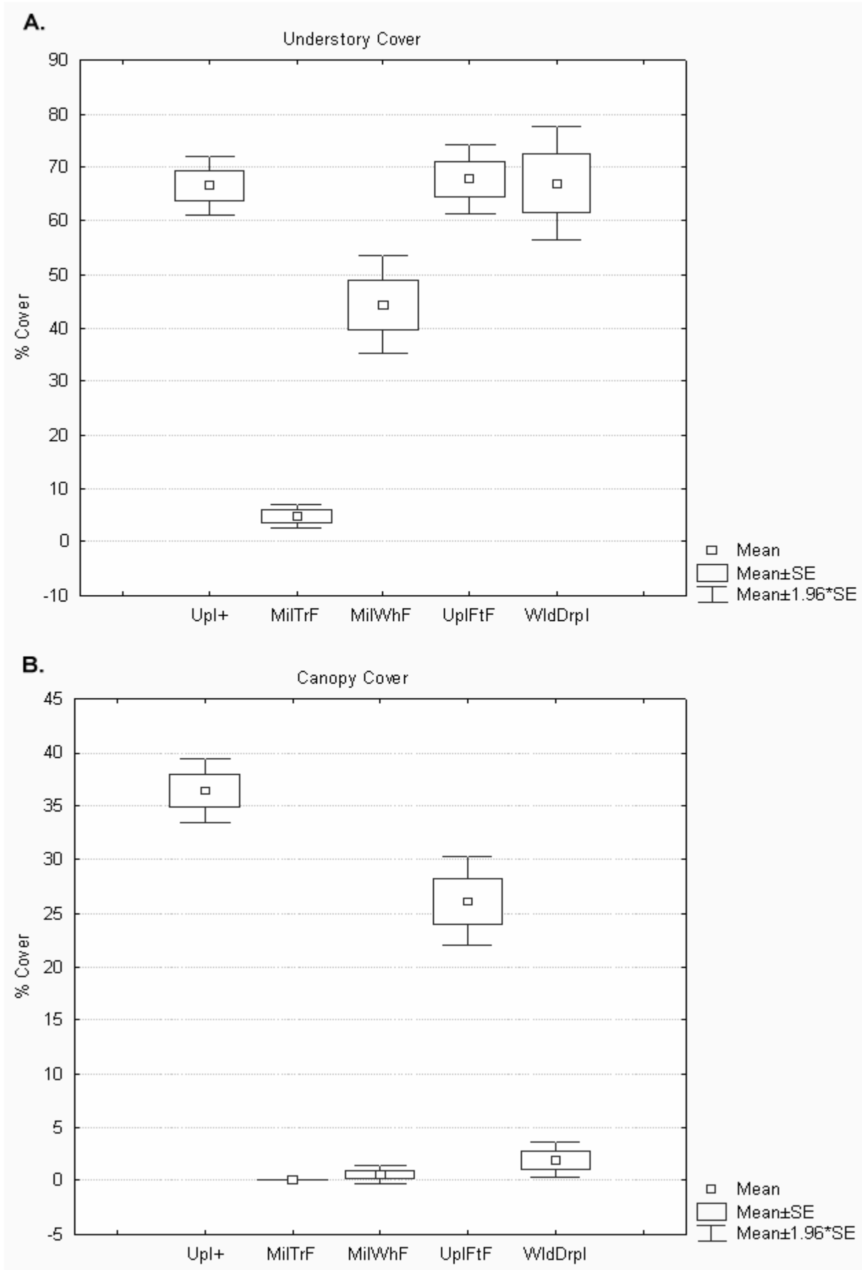

Figure 4-7. A. Understory cover and B. Canopy cover. Confidence level for mean: 95%. Upl+ = upland forest untrafficed, MilTrF = frequent military tracked vehicles, MilWhF = frequent military wheeled vehicles, UplFtF = upland forest frequent foot traffic, and WldDrpI = wildlife openings infrequent dropzoneFigure

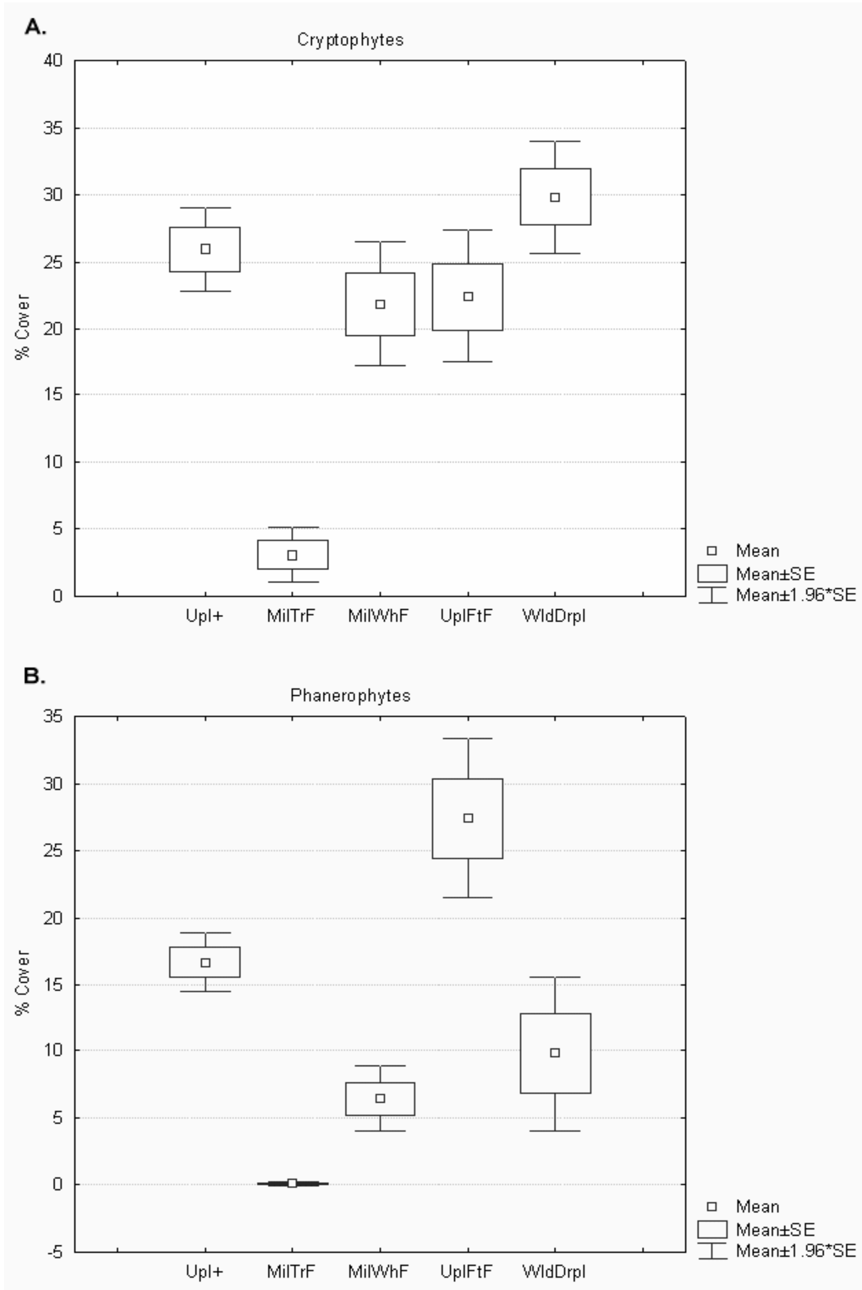

Figure 4-8. Distribution of plants by life form. A. Cryptophytes and B. Phanerophytes. Confidence level for mean: 95%. Upl+ = upland forest untrafficed, MilTrF = frequent military tracked vehicles, MilWhF = frequent military wheeled vehicles, UplFtF = upland forest frequent foot traffic, and WldDrpI = wildlife openings infrequent dropzone.

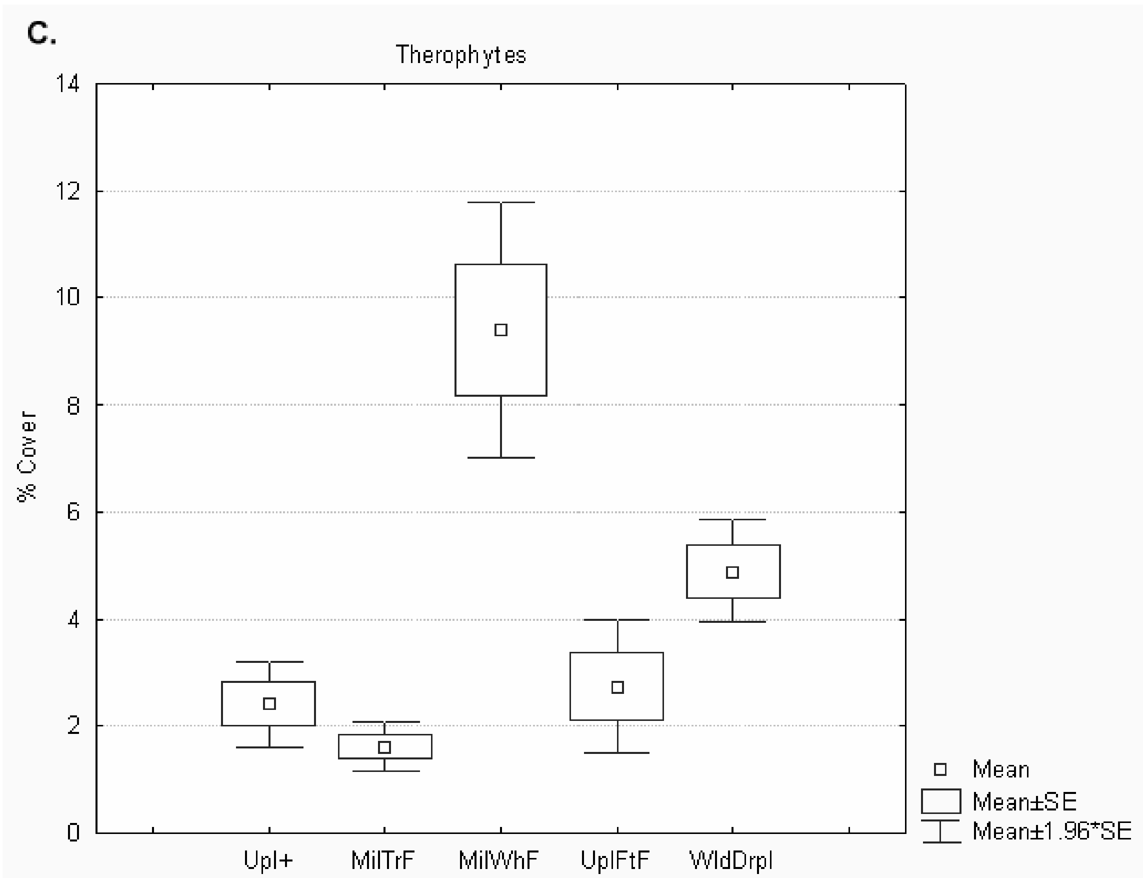

Figure 4-8 Continued. C, Percent cover for Therophytes in five Land-Management-Categories. Confidence level for mean: 95%. Upl+ = upland forest untrafficed, MilTrF = frequent military tracked vehicles, MilWhF = frequent military wheeled vehicles, UplFtF = upland forest frequent foot traffic, and WldDrpI = wildlife openings infrequent dropzone.

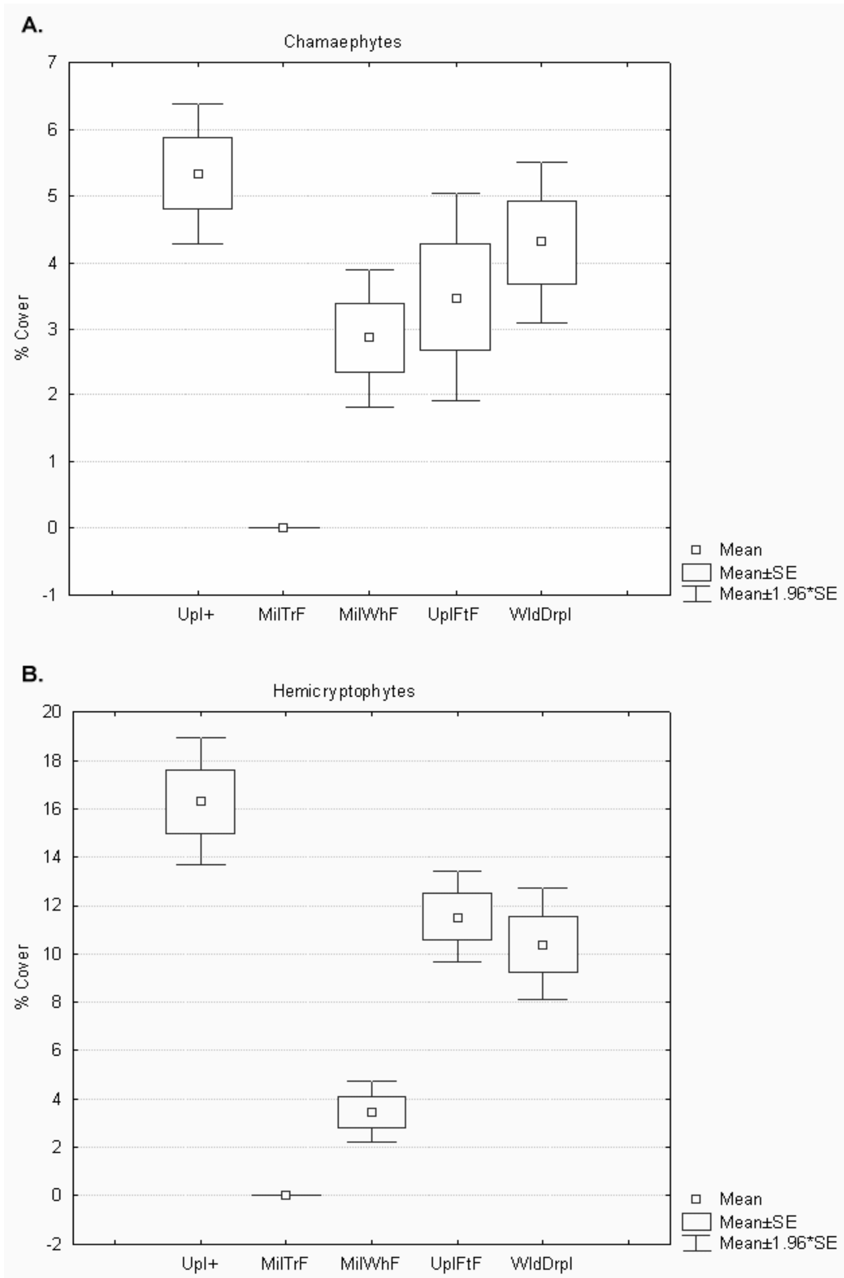

Figure 4-9. Cover of plants by life form. A. Chamaephytes. B. Hemicrytophytes. Percent cover in five Land-Management-Categories. Confidence level for mean: 95%. Upl+ = upland forest untrafficed, MilTrF = frequent military tracked vehicles, MilWhF = frequent military wheeled vehicles, UplFtF = upland forest frequent foot traffic, and WldDrpI = wildlife openings infrequent dropzone.

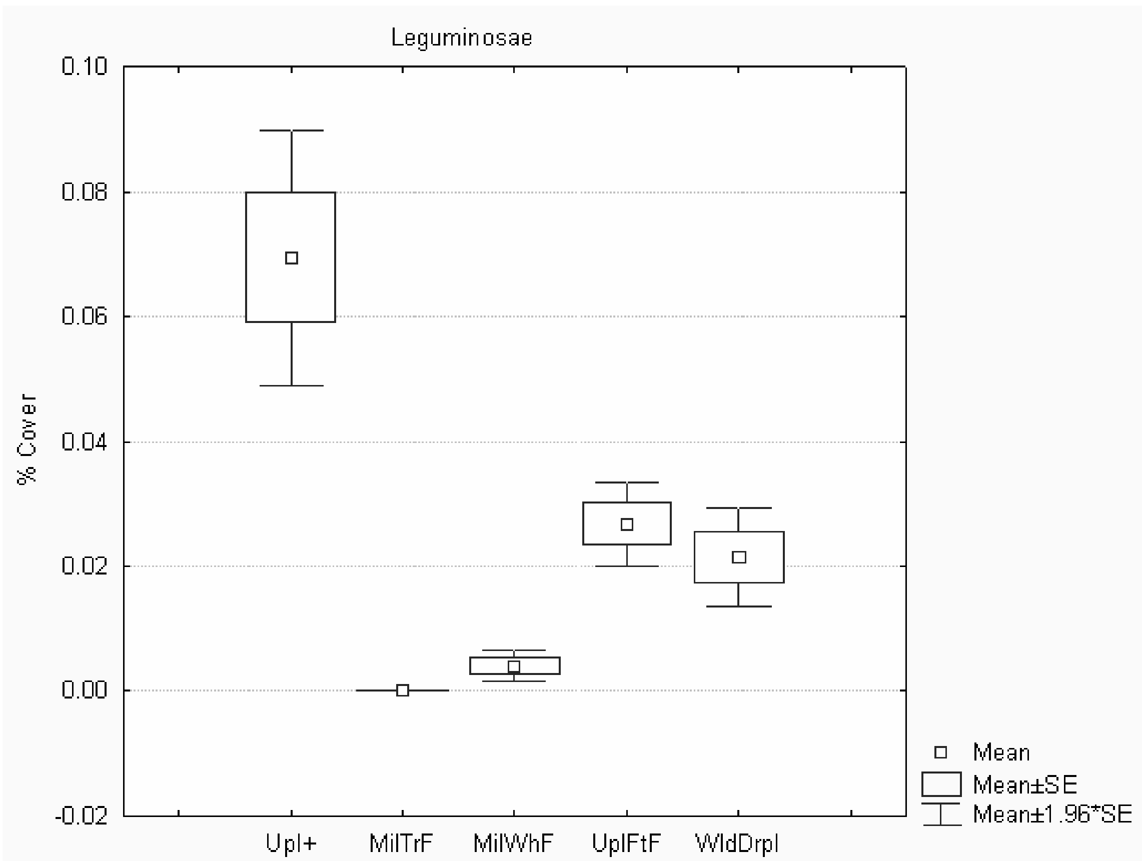

Figure 4-10. Legumes percent cover for five Land-Management-Categories. Confidence level for mean: 95%. Upl+ = upland forest untrafficed, MilTrF = frequent military tracked vehicles, MilWhF = frequent military wheeled vehicles, UplFtF = upland forest frequent foot traffic, and WldDrpI = wildlife openings infrequent dropzone.

Relationships and feedback to other identified measured indicators. Vegetation can influence soil organic C and N levels as a result of the amount, type, and biodegradability of plant residues returned to the soil. Soil N levels are also influenced by the uptake from plants. These effects are most profound in the "A" horizon since concentrations of organic C below this horizon are due mainly to pedogenic processes (Volkoff and Cerri, 1988). Plant material can be thought of as the parent material for soil organic C, and varies in composition and concentration across the landscape. Soil microbial biomass, composition and activity are also closely linked to the type and amount of plant residues and exudates (Zak et al., 2003).

Erosion Statement

Through the course of this study over 100 candidate ecological indicators measured by several research teams, were screened for relevance and possible use in an ecological monitoring program. The results of these analyses have also illustrated that other ecological indicators or processes that were not measured as a part of this work are critical to the sustainability of land for military training or other uses. Erosion plays a dominant role in the continuing health of this ecological system. According to Jawdy, (2003, and references therein) erosion degrades soil quality quickly because it affects the most productive portion of the soil, the surface layer. The organic rich surface layer is critical for plant growth because plant roots depend on its loose texture, high porosity, and nutrient richness. If this layer is removed the soil is less able to support plants, retain and cycle nutrients, filter pollutants, and regulate water flow. As a consequence, if the soil is eroded, it is lost and it does not matter what else is monitored, because there will be nothing but weathered rock. In this sense all of the indicators in this study are related to or affected by erosion.

Knowledge Mapping

The concept of knowledge is as old as human thought. In the *Theaetetus* (369 BC), Plato has Socrates pose the question, “What is knowledge?” There were three answers provided, the first being that knowledge is perception. The second answer was that knowledge is true belief, and the third answer was that knowledge is true belief with an account (logos). After a lengthy discussion all attempts to define knowledge failed, and the story ends when Socrates leaves to face his accusers in the courtroom.

For our purposes, knowledge or knowledge management can be viewed as turning data (raw material) into information (finished products) and from there into knowledge (actionable products) (Spiegler, 2000). In other words, data becomes information when it adds values in some way, and information becomes knowledge when it adds insight, abstractive value or better understanding: in this case an ecological system and the place of the measured indicators in that system. Knowledge can thus be gained by visualization techniques.

Figure 4-11 maps the selected indicators in relation to the carbon and nitrogen cycle in a functioning ecosystem. Wail et al. (1999) and Garten and Ashwood (2004b) have suggested that the biogeochemical cycles of C and N connect all of the biotic and abiotic components of an ecosystem to one another in a holistic fashion. Figure 4-11 was intended to illustrate to land managers and those who may not be familiar with geochemical cycles how the different indicator types correspond to these critical soil

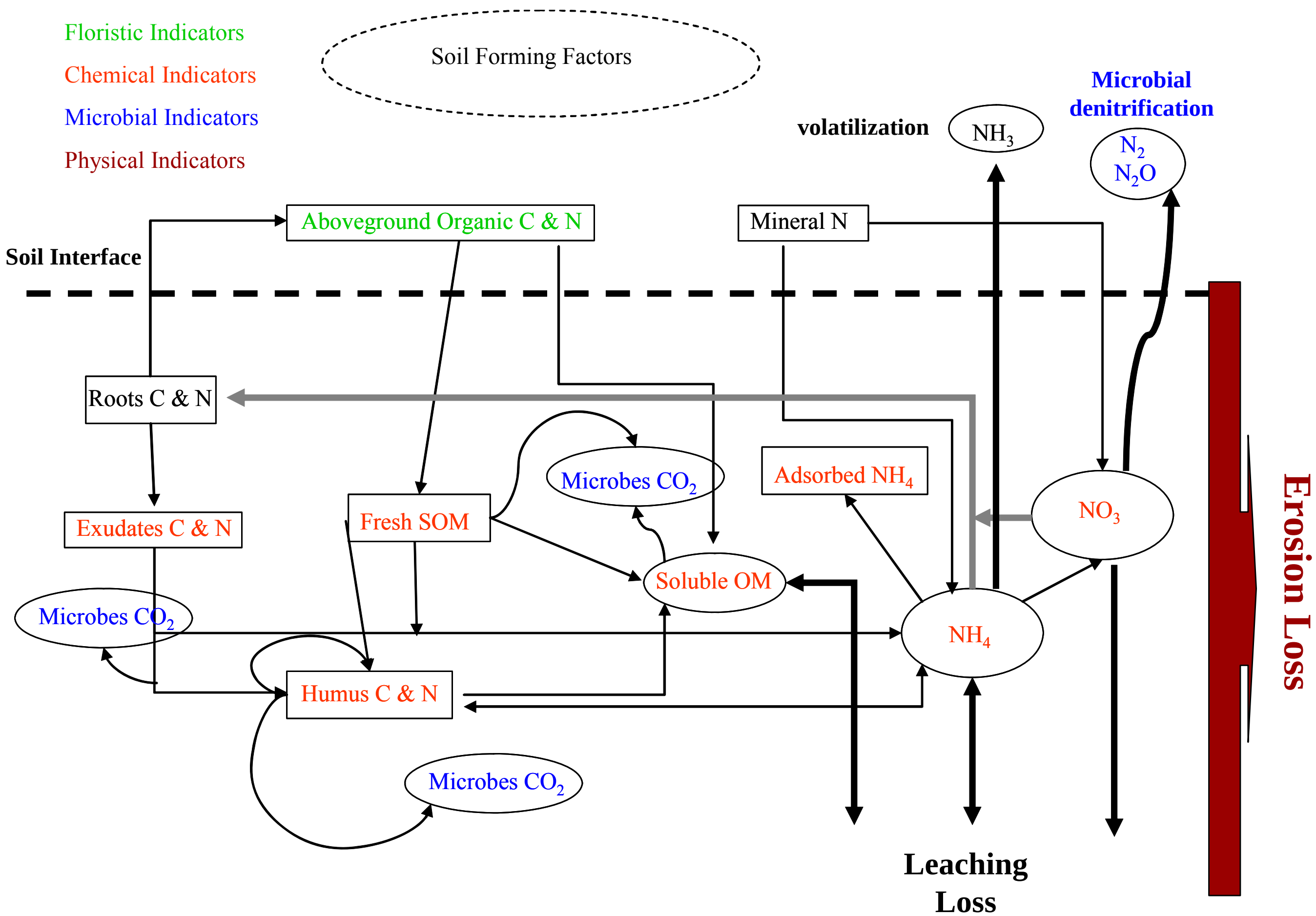

Figure 4-11. Map of how ecological indicators relate to carbon and nitrogen cycling.

sustaining processes. The illustration of the cycle shows the processes that transform CO_2 and N into organic matter and then return of the photosynthetically fixed C and N to mineral forms via biological mineralization. Using the color code allows the reader to relate given types of measured ecological indicators (plant, chemical, microbial or physical) to a specific ecosystem process, and further illustrates how those processes are related to and dependent upon other parts of the process. Understanding the system at a functional level provides a base of understanding for more complicated concepts such as modeling or sustainability paradigms.

Figure 4-12 adds to the base of knowledge from Figure 4-11 and presents a conceptual model of the soil horizon building process. This model illustrates the mass balance relationships within the ecological system. As long as inputs in the form of biomass to the soil are maintained, or exceed the outputs, the soil should remain stable and provide required services. However, if the inputs from the overlying plant community do not balance the losses from the soil system due to erosion and leaching, then soil quality will decline over time. Figure 4-12 also shows the relationship between military traffic and the soil building process. As traffic increases, plants are damaged or removed, and over time there is less addition of organic matter (as plant residue) to the soil. Increased traffic also causes soil compaction and erosion. Without some mitigating influence, the soil quality will eventually degrade. Figure 4-12 may seem elementary and redundant, but this is the level of understanding of someone who does not work with these systems and processes on a daily basis. In order for scientists to make sure the message is clear and understood, complicated concepts must be distilled to their essence.

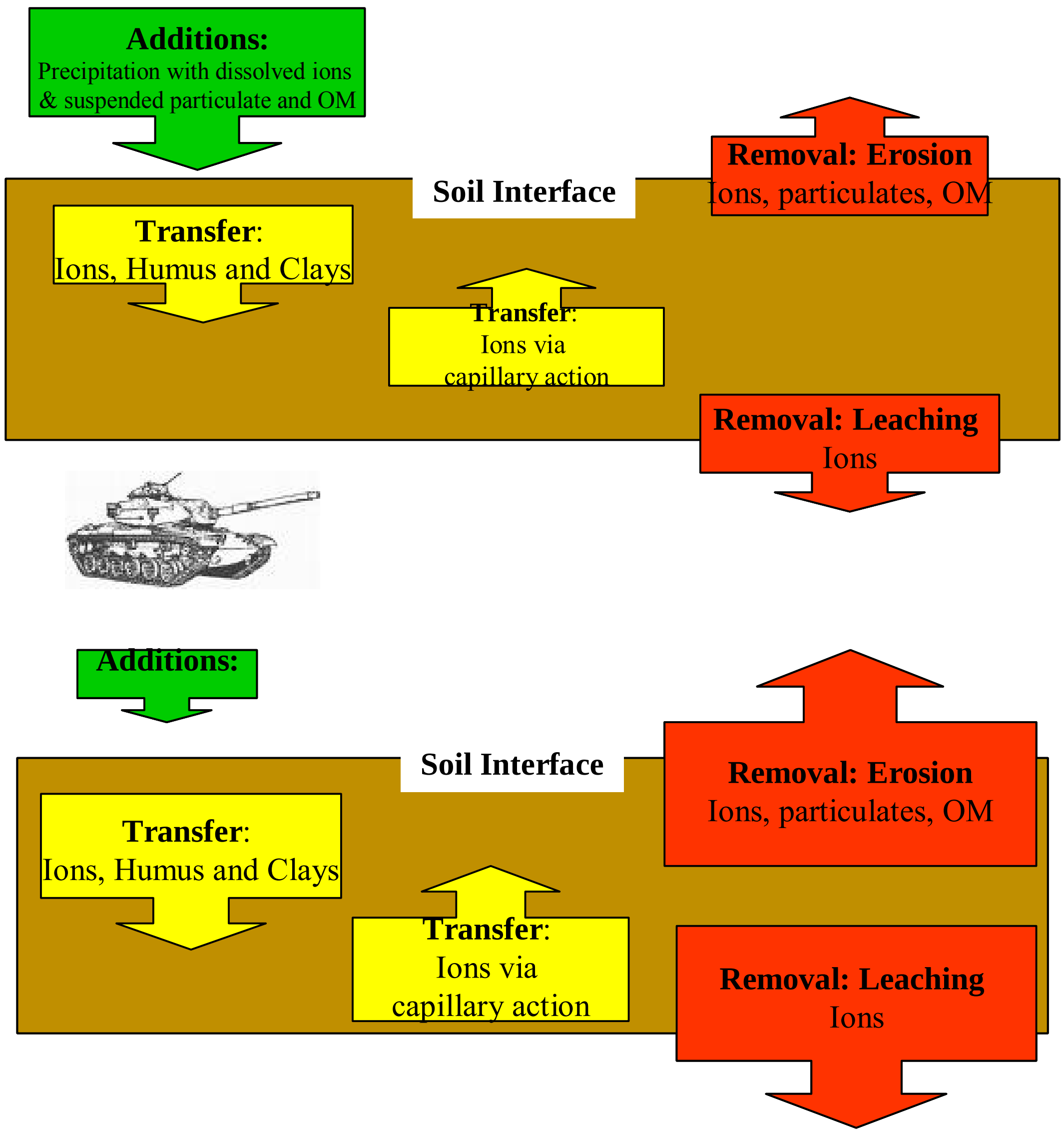

Figure 4-12. Conceptual model of the soil building process. Pane A shows a balanced soil system and Pane B shows the loss of organic matter and an increase in removal of soil and OM from the system due to traffic disturbance.

Figure 4-13 maps the relationships of the previously selected ecological indicators to the soil maintenance process. By displaying the indicators in this fashion, it is hoped that the knowledge of what the indicators represent to the functioning of the ecological system can be understood. For the practitioner, this knowledge should lead to actionable products or at the least a better understanding of what is being measured and how it relates to broader ecosystem dynamics. For the manager that may or may not be familiar with ecological function the figure illustrates the relationships between the given indicators and how they are dependent on each other.

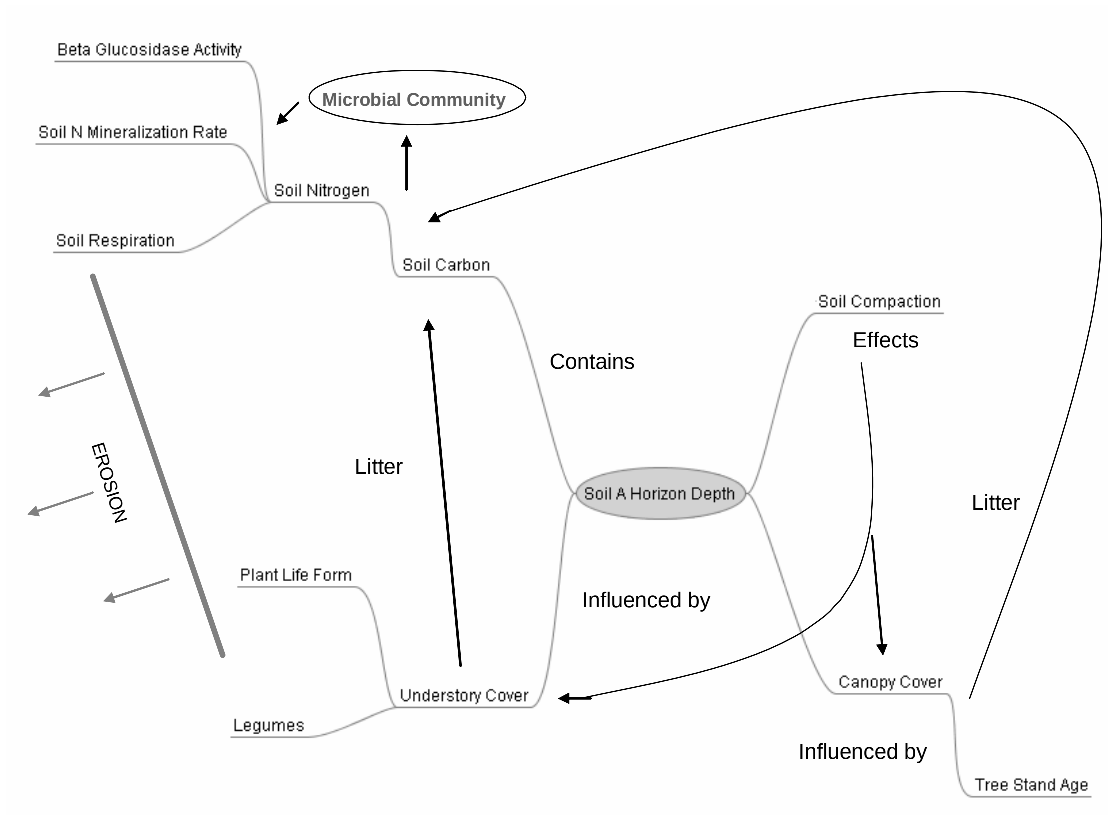

Figure 4-13. Knowledge map of the soil building process.

Chapter 5

Conclusions and Next Steps

The stated objectives of this work were:

1. To test the hypothesis that a suite of microbial ecological indicators would distinguish between the management (use) of military lands.
2. To develop a method for the integration of disparate or legacy ecological indicator data for the management of military lands.
3. To extract relevant facts from the preceding two objectives and develop a Knowledge Map/Conceptual Model that illustrates and explores the relationships between the ecological indicators and military training impacts.

In order to address the objectives the research was divided into three distinct phases. In Phase I, a series of field sites was selected that were representative of several different environmental impacts caused by military use, as well as reference control areas. Representative soil samples were taken from each of the selected sites. The soil was extracted and analyzed for phospholipid fatty acid (PLFA) content, which provided an index of the soil microbial community biomass, composition and metabolic status. The aim of the experiment was to discover if soil PLFA (the soil microbial community) could provide indicators to ultimately predict different types of military land use or degradation. Accurate, quantitative data representative of an entire microbial community allowed the application of discriminant and neural network models to authenticate differences across the environment and between treatments and was successful.

In Phase II, ecological indicator data previously collected by the five SEMP research teams was compiled, integrated as far as possible, and then screened through a data mining approach that used variable selection techniques combined with a multiple models solution to elucidate which ecological indicators (predictors) were best able to discriminate between different military land uses. Soil physical and chemical variables that received high selection scores included soil "A" horizon depth, compaction, organic matter, organic layer N, NH_3, Total N, N mineralization rate, total carbon and % carbon. Soil microbiological indicators that received high selection scores included biomarkers for fungi, Gram-negative Eubacteria, soil microbial respiration and β-glucosidase activity. Plant family and life form indicators that received high selection scores were the family Leguminosae, possibly Rosaceae, and the plant life forms Therophyte, Cyptophyte, Hemicryptophyte and Chamaephyte. Understory cover, overstory cover and tree stand characteristics also scored well in the ability to discriminate between Land-Management Categories. The results and insights gained from this effort appear to be consistent with other work in ecological indicators.

In Phase III, the indicators that made it through the relevance screen were used as inputs in Knowledge Maps. The purpose of the effort was to validate the chosen indicators by the use of visualization, presentation, and modeling capabilities in order to gain a better understanding of ecosystem dynamics on military managed landscapes. This effort showed the relationship between the above-ground and below-ground systems and how they are related to and dependent upon the other. It is hoped that the information provided can aid in the education of land managers and also provide the tools necessary for them to accomplish the goal of sustainability.

Next Steps

If the military wants to maintain training areas in perpetuity, then it must develop guidelines that take into account the mass balance aspect of soil stability. Of all the ecological indicators measured for this work, soil organic matter content was perhaps the key most important in predicting amount and type of military land use. There were several measured forms of SOM used in this study (organic layer N, NH_3, Total N, N mineralization rate, total carbon and % carbon). Once these ecological indicators have been identified there is the question of what to do next. Concurrent with this project, Garten and Ashwood (2004a, 2004b) used simple models of soil C and N dynamics to predict recovery thresholds from degraded soils at Fort Benning. They surmised that although ecosystem rehabilitation could be less complex than restoration, especially if monocultures are used, that there are likely thresholds associated with soil quality that may be the root cause that determines the success of land rehabilitation. This concept is important for the military because it goes to the heart of sustainability. We have already established that SOM is important through not just the work included here, but from many other researchers.

Wail et al. (1999) proposed that biogeochemical cycles of C and N connect all of the abiotic and biotic components of ecological systems to one another in a holistic way. Garten and Ashwood authored a simple model of soil C and N dynamics to predict thresholds to soil recovery on degraded landscapes at Fort Benning, Georgia. There were four factors important to the development of thresholds to soil recovery: (1) initial amounts of aboveground biomass, (2) initial C stocks (i.e. soil quality), (3) relative recovery rates of biomass, and (4) soil sand content. In this work it was discovered that initial C stocks in the soil influenced the predicted patterns of landscape or ecological recovery. Calculations with the model also indicated that the reestablishment of vegetation on barren sites to a level of future desired condition is not possible with low initial soil carbon levels. The work of Garten and Ashwood demonstrate the practical utility of quantified ecological indicators such as SOM and what these indicators mean for sustainability.

This project has produced a suite of quantifiable ecological indicators for the management of land and mapped the interactions and relationships between them. This project has also illustrated and defined how the identified ecological indicators are involved in the processes which either build or degrade soil over time. By using the selected indicators within a mass balance framework, it is believed that land managers will be able to better manage land resources for sustainability.

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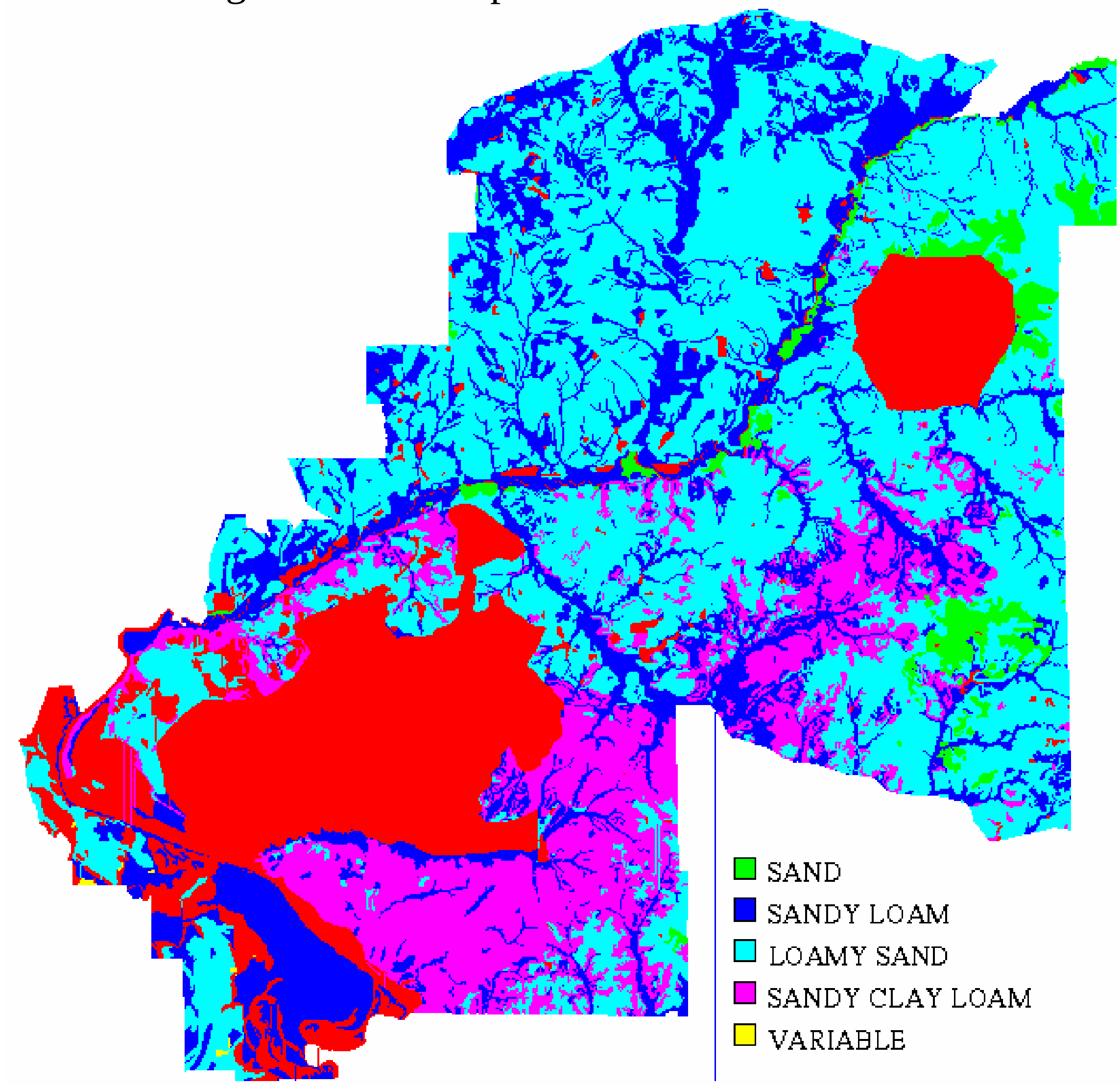
Appendix 1. Fort Benning, Georgia Soil Cover Map

Fort Benning Soil cover map



Appendix 2. Ecological Indicators

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
Prescott College	Ant Community Structure	The ground/litter ant community species composition and their relative abundances	Systematic clusters of pit-fall traps along perpendicular transects with a random orientation; pit-fall traps are 9 oz. plastic cups	abundances of all ant species	Ant community structure (relative population sizes and species composition)	Integrates the response of a very important animal community to ecosystem type, condition, and relative disturbance; very critical for our integrated ecological indicator set	It is a difficult and time consuming task to identify and count ants in the lab; typically over 100,000 ants are identified and counted; taxonomy is currently in a very dynamic state, making it very difficult to keep up with the "correct scientific nomenclature"; requires assistance from specific ant taxa specialists from all over the country; for optimal benefits as a stand-alone or integrated indicator requires specialized knowledge and experience in multivariate analyses
SREL	% Ground Cover Vegetation	% coverage of vegetation less than 1.4m high	This % cover was derived from a 6 meter line transect at 25 points in each 100 m and 100 m plot, and thus is not an ocular estimate based on a circular plot or square quadrat - The 'cover' would be any cover at a point along the transect (all species combined).	%	Plant colonization of an area	It acts as an integrated measurement for positive environmental properties enabling plant growth.	Can be canopy-dependent past a certain tree density, and dependent on understory tolerance, complicating broad across-site comparisons.
UF	Herbaceous Vegetation Cover	Aerial herbaceous vegetation cover	Estimated using foliar ocular observation in two independent m^2 quadrats within a 10 m x 10 m plot	%	Ground cover, primary production	Indicator of recent disturbance level and recovery	
ORNL1	Total Understory Cover	Percentage cover of all understory vegetation (<1 m in height)	Visual estimation within 5 m radius plots set along transects within training classifications	%	Response of total vegetation to various levels of training intensity	Total cover may differ in its ecological response to environmental disturbance	Dale et al. 2002 article in Ecological Indicators

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
Prescott College	Bare Ground	% of bare ground	Estimated from % bare ground in 0.58 m2 circular quadrats systematically-random located on 4 perpendicular transects with a random orientation	%	Lack of surface litter	A composite indicator for the direct loss of vegetation in all vegetation strata; a good stand-alone indicator; very critical for our integrated ecological indicator set	
ORNL1	Ground Cover (Bare)	% exposed soil	Visual estimation within 5 m radius plots set along transects within training classifications	%	Response of vegetation to various levels of training intensity	% bare ground may differ in response to environmental disturbance	Dale et al. 2002 article in Ecological Indicators
ORNL1	Ground Cover (Litter)	% cover of litter on ground surface	Visual estimation within 5m radius plots set along transects within training classifications	%	Response of vegetation to various levels of training intensity	% litter may differ in response to environmental disturbance	Dale et al. 2002 article in Ecological Indicators
UF	Herbaceous community Structure	Vegetation cover by species	Estimated using foliar ocular observation and species identification in 2- 1 m2 quadrats within a 10 m2 plot		Species composition of herbaceous community	Relative contribution of weedy, invasive species versus disturbance sensitive species gives indication of level of disturbance and time since disturbance	
ORNL1	Understory Cover by Family	% cover of understory plants by taxonomic family	Visual estimation by Braun-Blanquet cover category within 5m radius plots set along transects within training classifications	%	Response of vegetation to various levels of training intensity by family	Taxonomic families may differ in their ecological response to environmental disturbance	Dale et al. 2002 article in Ecological Indicators
ORNL1	Understory Cover by Life Form	% cover of understory plants by Raunkiaer life form	Visual estimation by Braun-Blanquet cover category within 5m radius plots set along transects within training classifications	%	Response of vegetation to various levels of training intensity by lifeforms	Raunkiaer lifeforms may differ in their ecological response to environmental disturbance	Dale et al. 2002 article in Ecological Indicators

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
ORNL1	Overstory Cover	Amount of canopy cover above plot	Average of four measures of canopy densiometer readings within each 5m radius plots set along transects within training classifications	%	Amount of clear sky viewable hemispherically above plot	Measure of photosynthetically active radiation for understory	Dale et al. 2002 article in Ecological Indicators
SREL	Tree Density	number of trees within study site in trees per ha	4 trees at each of 25 points in each 100meter x 100-meter stand were measured (diameter and distance to the point). Point quarter calculations were done to provide tree/ha estimates for each stand.	no./area	Density of trees	It is the density of trees in the stands and influences light for understory, litter amount and quality and many other stand characteristics.	
ORNL1	DBH of Trees Greater than 5 cm	Diameter at breast height of trees	DBH tape within 5 m radius plots set along transects within training classifications	m^2	Stand basal area	Inter-tree competition and shading	Dale et al. 2002 article in Ecological Indicators
ORNL1	Stand Age	Maximum stand age	Greatest of two perpendicular increment bores from the 4 largest trees near each transect within a training classifications	years	Age of oldest tree in transect	Time since last stand-clearing disturbance	Dale et al. 2002 article in Ecological Indicators
Prescott College	Soil A-Horizon Depth	Thickness of A-Horizon, depending on varying specific definitions, includes Oa layer, and may include Oe layer	Surface litter is brushed away and a small garden trowel is used to remove a soil plug, based on color change the A-Horizon thickness is measured with a stainless steel metric ruler		Soil integrity and erosion losses	Our research is developing the theme that soil integrity is a major indicator of ecosystem condition; a good stand-alone indicator; very critical for our integrated ecological indicator set	It is important for measurement reliability and consistency that a SINGLE investigator conduct all the readings. This indicator may be influenced by other soil properties (e.g., texture), forest community type, and physiography. Therefore, we are investigating this important aspect.

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
SREL	Soil A-Horizon Depth	Depth of soil A-horizon	12 random A-depth measurements in each 100 m x 100 m stand were recorded. Measurements were done in the field using a cm ruler and soil corer.	cm	Depth of A soil horizon	It is the development of soil A layer which is a cumulative indicator of soil development and quality over longer time periods	
UF	Soil A-Horizon Depth	Mineral horizon formed at the surface or below an O horizon and containing accumulated decomposed organic matter	By visual estimation of A horizon development using a 1 inch soil probe.	cm	Soil carbon and soil structural integrity	Indicates recent disturbance, erosion, mixing of soil horizons	Can be difficult to distinguish in very low carbon systems. There may be more than one A-horizon (i.e. buried A horizons)
ORNL1	Soil A-Horizon Depth	Thickness of A-Horizon	Soil probe used to obtain sample. Depth of A horizon measured in field with a ruler from bottom of surface litter layer (if present) to change in color indicating bottom of A horizon	cm	Amount of undisturbed soil	Quantitative measure of disturbance	Dale et al. 2002 article in Ecological Indicators
Prescott College	Soil Compaction	Self-explanatory	Lang Penetrometer, Lang Penetrometer, Inc.		Relative compaction of soil surface	Direct indicator of degree of vehicle activity, relative habitat disturbance, ecosystem relevance for biological activity and water infiltration; very critical for our integrated ecological indicator set	This indicator is influenced by other soil properties (e.g., texture), and possibly also forest community type, and physiography. Therefore, we are investigating this important aspect.
ORNL2	Soil Density	Grams of dry soil per cubic centimeter of soil	Determine the dry mass of a known volume of soil	g/cc	Soil compaction	High soil density inhibits root growth and the infiltration of water	

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
UF	Soil Respiration	Aerobic carbon mineralization	CO2 production determined in soil slurries incubated at standard temperature (30°C) by GC (Zibilske, 1994)	µg CO_2 / (g soil x hour)	Competence of soil microbiota to mineralize carbon; quality of soil carbon stocks	Undisturbed soil will have higher overall respiration than eroded soils, but may have lower ratio of CO2 production/unit total carbon	CO2 production is dependent on both the quantity and quality of soil carbon stores
UF	Soil Total Carbon	Total carbon content of soil	Total carbon; dry combustion method (Nelson and Sommers, 1996).	g C / kg dry soil	g C /kg dry soil	Carbon is an indicator of primary productivity inputs and soil structure, and is an important determinant of soil fertility.	
ORNL2	Soil Carbon Conc.	Grams of carbon per gram of dry soil	Measured by combustion of the soil sample (elemental analysis) in a LECO CN-2000	% dry mass	Soil carbon is related to organic matter	Organic matter imparts many favorable qualities to soil (nutrients, soil structure, water retention, etc.)	Our combustion methods (high temperature combustion) give total soil carbon (both organic and inorganic)
ORNL1	Soil Carbon Conc.	Grams of carbon per gram of dry soil	Measured by combustion of the soil sample (elemental analysis) in a LECO CN-2000	% dry mass	Soil carbon is related to organic matter	Organic matter imparts many favorable qualities to soil (nutrients, soil structure, water retention, etc.)	Our combustion methods (high temperature combustion) give total soil carbon (both organic and inorganic)
ORNL2	Carbon Conc. in MOM	Conc. of carbon in the silt and clay fractions from mineral soil samples	Mineral-associated organic matter is physically separated from mineral soil by wet sieving after soil dispersion and the dry MOM (silt and clay size fractions) is analyzed on an elemental analyzer for its carbon concentration	g C / sq.m.	Carbon associated with mineral-associated organic matter is generally considered to be more humified than POM-C	MOM-C has a longer mean residence time in the soil than POM-C and is a less favorable energy source for some soil microorganisms	Amounts of MOM-C are generally greater than POM-C

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
ORNL2	Soil Carbon Stocks	Grams of carbon per unit area of ground to a specified soil depth	Calculated as the product of soil density and soil carbon concentration	g C / sq.m.	Amounts of soil organic matter on an area basis	Organic matter imparts many favorable qualities to soil (nutrients, soil structure, water retention, etc.)	Soil carbon stocks depend on the depth over which the stock is calculated
ORNL1	Soil Carbon	Grams of carbon per unit area of ground to a specified soil depth	Calculated as the product of soil density and soil carbon concentration	mg C / sq. cm	Amounts of soil organic matter on an area basis	Organic matter imparts many favorable qualities to soil (nutrients, soil structure, water retention, etc.)	Soil carbon stocks depend on the depth over which the stock is calculated
ORNL2	Carbon Stock in POM	Mass of soil carbon found in particulate organic matter present in the mineral soil	Particulate organic matter is physically separated from mineral soil samples by wet sieving after soil dispersion and the dry POM (sand size fraction) is analyzed on an elemental analyzer for its carbon concentration; the stock is calculated as a product of POM amount and carbon concentration in POM	g C / sq. m	Carbon in particulate organic matter is generally free or released from soil macro-aggregates; it is thus considered to be more readily available as a carbon source for heterotrophic soil microorganisms that promote soil carbon mineralization	Amounts of particulate organic matter are generally regarded as a good indicator of soil quality (i.e., a readily available pool of labile soil carbon to support soil microorganisms)	This measurement is only done on mineral soil samples (not O-horizons)

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
ORNL2	Carbon Stock in MOM	Mass of soil carbon in mineral-associated organic matter from the mineral soil	Mineral-associated organic matter is physically separated from mineral soil by wet sieving after soil dispersion and the dry MOM (silt and clay size fractions) is analyzed on an elemental analyzer for its carbon concentration; the stock is calculated as a product of concentration and amount of mineral-associated organic matter	g C / sq. m	It is an amount rather than a concentration; carbon associated with mineral-associated organic matter is generally considered to be more humified than POM-C	MOM-C has a longer mean residence time in the soil than POM-C and is a less favorable energy source for some soil microorganisms	Should correlate with carbon concentration in mineral-associated organic matter
ORNL2	Fraction of Soil Carbon in POM	Fraction of total soil carbon (to a specified soil depth) in particulate organic matter	Calculated -- it is the amount of carbon in POM normalized by the total soil carbon stock	fraction of total soil carbon	Relative amounts of labile soil carbon pool in the mineral soil	Amounts of particulate organic matter are generally regarded as a good indicator of soil quality (i.e., a readily available pool of labile soil carbon to support soil microorganisms)	
ORNL2	Soil Nitrogen Conc.	Grams of nitrogen per gram of dry soil	Measured by combustion of the soil sample (elemental analysis) in a LECO CN-2000	% dry mass	The concentration of a critical plant nutrient in soil	Nitrogen is usually the single most important soil nutrient that constrains biomass production	Soil nitrogen generally declines with increasing soil depth
ORNL1	Soil Nitrogen Conc.	Grams of nitrogen per gram of dry soil	Measured by combustion of the soil sample (elemental analysis) in a LECO CN-2000	% dry mass	The concentration of a critical plant nutrient in soil	Nitrogen is usually the single most important soil nutrient that constrains biomass production	Soil nitrogen generally declines with increasing soil depth

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
ORNL2	Nitrogen Conc. in MOM	Concentration of nitrogen in the silt and clay fractions from mineral soil samples	Mineral-associated organic matter is physically separated from mineral soil by wet sieving after soil dispersion and the dry MOM (silt and clay size fractions) is analyzed on an elemental analyzer for its nitrogen concentration	% dry mass	A pool of soil nitrogen with a relatively long mean residence time	Under some conditions, MOM can be an important source of slow-release soil nitrogen	
ORNL2	Soil Nitrogen Stocks	Grams of nitrogen per unit area of ground to a specified soil depth	Calculated as the product of soil density and soil nitrogen concentration	g N / sq. m	The amount of soil nitrogen (total soil nitrogen)	N\itrogen is the single most important soil nutrient that constrains biomass production	Soil nitrogen stocks depend on the depth over which the stock is calculated
ORNL1	Soil Nitrogen	Grams of nitrogen per unit area of ground to a specified soil depth	Calculated as the product of soil density and soil nitrogen concentration	mg N / sq. cm	The amount of soil nitrogen (total soil nitrogen)	Nitrogen is the single most important soil nutrient that constrains biomass production	Soil nitrogen stocks depend on the depth over which the stock is calculated
ORNL2	Soil C:N Ratios	Ratio of soil carbon concentration to soil nitrogen concentration	Calculated from soil carbon and nitrogen concentration data	none (ratio)	The amount of soil carbon relative to nitrogen	High soil C:N ratios indicate that soil microbes are N limited rather than C limited and so N is immobilized during microbe growth; low soil C:N ratios indicate that soil microbes are more C liimited than N limited and so N is released (mineralized) during decomposition of soil organic matter	Soil C:N ratios generally decline with soil depth

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
Prescott College	Soil Nitrate	Soil concentration of nitrate and ammonium	Systematic-random collection of soil samples, composited, lab analysis		Absolute and relative amounts of nitrate and ammonium in the soil	Nitrogen has been identified as an important integrator of ecosystem condition, successional stage, and productivity; often the limiting macro-nutrient in terrestrial ecosystems; most critical for our integrated ecological indicator set	

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SREL	Soil Extractable N	Extractable mineral nitrogen in soil	A hammer corer (AMS, American Falls, ID) was used to extract two soil cores (15.2 cm deep by 5.1 cm diameter) beneath each organic layer sample at 4 random points in each 100m x 100m plot. The cores were stored at 5 oC until processing. In the laboratory, one of each pair was passed through a 6.3 mm sieve; roots were sorted and removed from the soil. A subsample of the sieved soil (ca. 10 g) was extracted using 2 M KCl (10 ml soln:1 g soil). The solution was shaken mechanically for two hours and allowed to clear overnight at 4 oC. The clear extract was pipetted off for NO3-N and NH4-N analysis using automated colorimetry (Alpkem FS3000) with a detection limit of 0.01 ppm.	µg/g soil	Extractable mineral nitrogen in the soil	It is the current level of extractable nitrogen for the soil.	
ORNL2	Extractable Soil Nitrate-N	Grams of nitrate-N that can be extracted from the mineral soil	Soils are extracted with 2 molar potassium chloride and nitrate-N is displaced from anion adsorption sites in the soil	µg N / g soil	A chemically available form of soil nitrogen that may indicate the availability of nitrate-N to plant roots	Soil nitrate is highly mobile and readily leached from the plant rhizosphere if it is not immobilized by soil microorganisms or taken up by plant roots	

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SREL	Soil Potential N	Defined as mineral nitrogen production in the laboratory. It is a potential estimate and the exact definition depends on the time interval and mineral nitrogen components used in the calculations.	See attached	µg/g soil	Potential mineral nitrogen in the soil based on laboratory incubations under favorable conditions	It is the potential nitrogen production for the soil and represents the production of nitrogen available from soil components under favorable conditions.	
ORNL2	Potential Net Soil Nitrogen Mineral-ization	Potential for transformation of organic soil nitrogen to inorganic soil nitrogen	Laboratory incubations over a specified period of time to determine the production of inorganic soil nitrogen during decomposition of organic matter	µg N / (g soil x wk)	The relative availability of soil nitrogen to plants and the net potential of the soil to produce inorganic soil nitrogen	Soil nitrogen mineralization is the primary process by which nitrogen is made available to plant roots	This is measurement is net production of nitrogen and may not reflect gross rates under field conditions
ORNL2	Potential Net Soil Nitrification	Potential for transformation of ammonium nitrogen to nitrate nitrogen in mineral soil samples	Laboratory incubations over a specified period of time to determine the production of nitrate during decomposition of organic matter	µg N / (g soil x wk)	The relative activity of nitrifiers in the soil	Nitrification produces nitrate from ammonium and nitrate is a highly mobile and leachable form of soil nitrogen	Nitrification is an aerobic process
ORNL2	Extractable Inorganic Soil Nitrogen	Grams of inorganic soil nitrogen that can be extracted from the mineral soil	Soils are extracted with 2 molar potassium chloride	µg N / g soil	Chemically available forms of soil nitrogen (a relative measure of soil nitrogen availability to plant roots)	Soil nitrogen is the primary nutrient limiting plant growth	This is the sum of extractable soil ammonium and extractable soil nitrate; most of the soil nitrogen is organically bound so extractable pools are usually very small relative to total soil nitrogen

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Prescott College	Soil Ammonium	Soil concentration of ammonium	Systematic-random collection of soil samples, composited, lab analysis		Absolute and relative amounts of nitrate and ammonium in the soil	Nitrogen has been identified as an important integrator of ecosystem condition, successional stage, and productivity; often the limiting macro-nutrient in terrestrial ecosystems; most critical for our integrated ecological indicator set	
ORNL2	Extractable Soil Ammonium-N	Grams of ammonium-N that can be extracted from the mineral soil	Soils are extracted with 2 molar potassium chloride and ammonium-N is displaced from cation adsorption sites on the soil	µg N / g soil	A chemically available form of soil nitrogen that may indicate the availability of ammonium-N to plant roots	Some plant roots preferentially absorb ammonium nitrogen	Ammonium-N is not very mobile in soils (because it is a cation)
Prescott College	Soil Organic Matter	Organic matter in the soil	Based on soil samples collected for nitrogen analysis; loss of weight on ignition		Absolute and relative amounts of organic matter and carbon in the soil	Soil carbon and organic content is directly linked to biological productivity and ecosystem condition; very critical for our integrated ecological indicator set	

Inst.	Indicator	Brief Description	How the Indicator Is Measured	Units	What It Measures	Why the Indicator Is Important	Notes, Clarifications, References, or Caveats
SREL	Soil Organic Layer Mass	Oven dry mass of pooled organic layers Oi, Oe and Oa.	From a destructive harvest of pooled organic layers in the field. A circular sampling guide of 495 cm2 was laid on the soil surface. Clippers were used to cut around the perimeter of the guide to the mineral soil surface. All organic layer sample was removed up to the mineral soil interface. Surface organic layer samples were collected at 8 random points in each study site.	g/m^2	Mass of organic layer on an aerial basis	It acts as an integrated measurement for litter input, decomposition, erosion and fire for a plot	Can be canopy-dependent and is also dependent on fire, quality of litter produced and other factors
ORNL2	O-Horizon Dry Mass	Grams of O-horizon per unit area	The O-horizon is removed from a known area of ground and its dry mass is determined	g dry mass / m^2	It can represent several different things but is basically a measure of the balance between litter inputs and litter decomposition	O-horizons promote water retention and help prevent erosion; O-horizons are an important source of nutrients for plant roots and they provide protection for decomposer organisms that help breakdown litter for the supply of plant nutrients	O-horizons can be partially or completely lost as a result of ground fires
SREL	Soil Organic Layer %N	% N composition of pooled organic layer samples	See organic layer mass. Physical sample ground in a Wiley mill then a subsample was ground in a Spex ball mill then analyzed for nitrogen using a CHN analyzer	%	Nitrogen content of organic layer	It acts as an integrated measurement for quality of litter inputs and the pool of nitrogen.	Can be canopy-dependent for both density and species.

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ORNL2	O-Horizon Nitrogen Stock	Grams of nitrogen present in the O-horizon per unit area of ground	Calculated as the product of O-horizon nitrogen concentration and O-horizon dry mass	g N / sq. m	An important nitrogen pool that is released to supply plant nutrients as the litter decomposes	Plant growth on sandy, nutrient poor soils is highly dependent on recycling of nitrogen through the O-horizon	Nitrogen can be lost from the system during ground fires that consume the O-horizon thus contributing to even greater nitrogen limitations on plant growth
ORNL2	O-Horizon Carbon Stock	Grams of carbon present in the O-horizon per unit area of ground	Calculated as the product of O-horizon carbon concentration and O-horizon dry mass	g C / sq. m	The amount of soil carbon in the O-horizon	It is directly correlated with the amount of surface organic matter which can be important in water retention and an important source of nutrients for plant growth and soil microorganisms	This pool can be lost from the system during ground fires or transformed to highly refractory forms of soil carbon (charcoal)
ORNL2	O-Horizon C:N Ratio	Ratio of O-horizon C concentration to O-horizon N concentration	Calculated from O-horizon C and N concentrations	none (ratio)	Generally believed to be a measure of litter quality; litter with a high C:N ratio undergoes slow initial rates of decomposition because N limits decomposer activity while litter with a low C:N ratio undergoes high initial rates of decomposition (i.e., decomposition and release of nutrients proceeds more quickly in litters with a low C:N ratio)	It can indicate the rate at which litter will decompose and the rate at which nutrients are released to the mineral soil	Although the literature is conflicting; litter C:N ratios are sometimes a good predictor of litter decomposition
Prescott College	Microbial Biomass Carbon			mg MBC/g soil	The amount of microbial carbon in the soil		

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ORNL1	Soil Microbes: Biomass	We are measuring the total amount of microbial biomass (as PLFA) in the soil.	Quantitative measure of the phospholipid fatty acid content of the soil is extracted, purified and anayzed by GC.	pmol/g dry soil	The viable PLFA content of the soil.	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems, they represent critical integrators of ecosystem structure and dynamics	Must be analyzed as part of a complete PLFA suite.
Prescott College	Bacteria Total Activity	We are measuring the total activity and functional diversity of the fungal and bacterial communities	Systematic-random soil samples are composited and taken to the lab where they are tested with BioLog and FungiLog protocols		Relative degree of bacteria and fungal activity to a wide range of nutrient substrates	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems they represent critical integrators of ecosystem structure and dynamics; most critical for our integrated ecological indicator set	Cannot readily use this indicator by itself without its integration with soil chemistry and physical environmental metrics
Prescott College	Bacteria Functional Diversity	We are measuring the total activity and functional diversity of the fungal and bacterial communities	Systematic-random soil samples are composited and taken to the lab where they are tested with BioLog and FungiLog protocols	substrate richness & utilization	Ability of soil bacteria to use carbon	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems they represent critical integrators of ecosystem structure and dynamics; most critical for our integrated ecological indicator set	Cannot readily use this indicator by itself without its integration with soil chemistry and physical environmental metrics

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Prescott College	Fungi Total Activity	We are measuring the total activity and functional diversity of the fungal and bacterial communities	Systematic-random soil samples are composited and taken to the lab where they are tested with BioLog and FungiLog protocols		Relative degree of bacteria and fungal activity to a wide range of nutrient substrates	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems they represent critical integrators of ecosystem structure and dynamics; most critical for our integrated ecological indicator set	Cannot readily use this indicator by itself without its integration with soil chemistry and physical environmental metrics
Prescott College	Fungi Functional Diversity	We are measuring the total activity and functional diversity of the fungal and bacterial communities	Systematic-random soil samples are composited and taken to the lab where they are tested with BioLog and FungiLog protocols	substrate richness & utilization	Ability of soil fungi to use carbon	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems they represent critical integrators of ecosystem structure and dynamics; most critical for our integrated ecological indicator set	Cannot readily use this indicator by itself without its integration with soil chemistry and physical environmental metrics
ORNL1	Soil Microbes Biomarkers for Microeukaryotes	We are measuring the biomass of the microeukaryotes like fungi etc.	Specific PLFA (polyunsaturates) which are indicative of microeukaryotes are extracted and analyzed	pmol/g dry soil	Amount of the group of PLFA in picomols	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems, they represent critical integrators of ecosystem structure and dynamics	Must be analyzed as part of a complete PLFA suite.
ORNL1	Soil Microbes Community Composition	Measuring distribution of different classes of microbes	Specific classes of PLFA are extracted and quantified.	mole %	Amount of the group of PLFA in picomols	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems, they represent critical integrators of ecosystem structure and dynamics	Must be analyzed as part of a complete PLFA suite.

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ORNL1	Soil Microbes Actinomycetes	Measures PLFA specifc of Actinomycetes	Specific class of PLFA (Mid-Chain Branched saturates) are extracted and quantified.	pmol/g dry soil	Amount of the group of PLFA in picomols	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems, they represent critical integrators of ecosystem structure and dynamics	Must be analyzed as part of a complete PLFA suite.
ORNL1	Soil Microbes Gram-Negative	Measures PLFA specific for Gram-negative eubacteria	Specific class of PLFA (Monounsaturates) is extracted, purified and analyzed.	pmol/g dry soil	Amount of the group of PLFA in picomols	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems, they represent critical integrators of ecosystem structure and dynamics	Must be analyzed as part of a complete PLFA suite.
ORNL1	Soil Microbes Gram-Positive Bacteria	Measures PLFA specific for Firmicutes	Specific class of PLFA (Terminally branched saturated) is extracted, purified and analyzed.	pmol/g dry soil	Amount of the group of PLFA in picomols	Because bacteria and fungi are involved in decomposition and nutrient cycling in all ecosystems, they represent critical integrators of ecosystem structure and dynamics	Must be analyzed as part of a complete PLFA suite.
UF	Beta-Glucosidase Activity	Activity of soil ectoenzyme involved in cellulose degradation	Measured in aqueous soil dilutions by production of methyl-umbelliferone from the artificial substrate MUF-glucoside (Sinsabaugh et al., 1997)	µmole / (g dry soil x hour)	Competence of soil to degrade cellulose; microbiological activity.	An indicator of microbial nutrient cycling	Varies seasonally due to temperature, moisture, carbon inputs from leaf fall, etc.

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Prescott College	Nutrient Leakage: Nitrate	The measurement of leachate ions ½ m below soil surface	Water collected from field lysimeters; ion concentrations measured in lab		Anions and cations that are being leached from top soil	Direct measure of the loss or "leakage" of major and minor nutrients from soils; very critical for our integrated ecological indicator set	Particularly useful in combination with other indicators; for most informative results this indicator requires the use of an independent site-specific specialized calibration technique developed by a team member
Prescott College	Nutrient Leakage: Ammonium	The measurement of leachate ions ½ m below soil surface	Water collected from field lysimeters; ion concentrations measured in lab		Anions and cations that are being leached from top soil	Direct measure of the loss or "leakage" of major and minor nutrients from soils; very critical for our integrated ecological indicator set	Particularly useful in combination with other indicators; for most informative results this indicator requires the use of an independent site-specific specialized calibration technique developed by a team member
Prescott College	Nutrient Leakage: Phosphate	The measurement of leachate ions ½ m below soil surface	Water collected from field lysimeters; ion concentrations measured in lab		Anions and cations that are being leached from top soil	Direct measure of the loss or "leakage" of major and minor nutrients from soils; very critical for our integrated ecological indicator set	Particularly useful in combination with other indicators; for most informative results this indicator requires the use of an independent site-specific specialized calibration technique developed by a team member
Prescott College	Nutrient Leakage: Sulfate	The measurement of leachate ions ½ m below soil surface	Water collected from field lysimeters; ion concentrations measured in lab		Anions and cations that are being leached from top soil	Direct measure of the loss or "leakage" of major and minor nutrients from soils; very critical for our integrated ecological indicator set	Particularly useful in combination with other indicators; for most informative results this indicator requires the use of an independent site-specific specialized calibration technique developed by a team member

Vita

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