USING MULT-SPECTRAL LANDSAT IMAGERY TO EXAMINE FOREST HEALTH TRENDS AT FORT BENNING, GEORGIA

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Assessing vegetation health attributes like canopy density or live crown ratio and ecological processes such as growth or succession ultimately requires direct measures of plant communities. However, on-the-ground sampling is labor and time intensive, effectively limiting the amount of forest that can be evaluated. Radiometric data collected with a variety of sensors from satellite platforms provide a partial solution to this challenge. Because plant function via photosynthesis is directly tied to electromagnetic energy, vegetation function has been successfully related to radiometric data (Lawley and others In press). Various indices have been developed to interpret vegetative functions or conditions including basal area, species composition, moisture stress, and damage from insects or disease (Liew and others 2008; Bannari and others 1995). The normalized difference vegetation index (NDVI), based on reflectance in the red (R) and near infrared (NIR) bands of the electromagnetic spectrum (NDVI = (NIR - R) / (NIR + R); range:-1 to 1), has been shown to be highly correlated with photosynthetic capacity, net primary productivity, leaf area index, and evapotranspiration. Further, time-series of NDVI have proven useful for evaluating such functions as canopy growth rates, and phenological events like the onset of spring (Pettorelli 2013).

Landsat TM data is one of the most useful types of radiometric data for interpreting vegetation. It has a moderate spatial resolution (30 m), high temporal resolution (images acquired every 16 days), and a long-term data archive from 1982 through present. The NDVI is readily calculated from Landsat TM data, adding to the desirability of these data for ecological applications. Finally, Landsat data are available at no charge, in part, ensuring their wide use in research and increasing the comparability among studies.

We conducted this study at Fort Benning, Georgia, where the upland landscape is managed to create an open pine forest that both meets military training needs and supports management of sensitive wildlife species. Management includes frequent prescribed burning to promote herbaceous groundcover and to control hardwood mid-story development, and thinning to achieve and maintain desired pine basal area. As early as 2005 Fort Benning forest managers voiced concerns about unexpected mortality in older loblolly pines. It was unclear if this phenomenon was novel, or if it was typical of historic patterns. To answer that question, in part, we proposed to investigate historic patterns of forest productivity using Landsat TM data. Here, we describe our approach to evaluating trends in pine forest productivity on the Fort Benning landscape. This project was conducted in partnership with the U.S. Forest Service Remote Sensing Applications Center (RSAC).

We used NDVI calculated from Landsat TM data as a general indicator of forest productivity, assuming that "greener" (higher NDVI, more productive) canopies are healthier than low productivity forests on similar sites. We used the USGS Earth Explorer website archive for identifying and downloading suitable scenes. We selected Landsat 5 scenes except in 2012 and 2013 when Landsat 7 scenes were the only ones available. With few exceptions we were able to identify scenes taken during leaf-off (December-March) and with minimal cloud cover. We downloaded Level 1 Product Generation System L1T Standard Terrain Correction ortho-corrected scenes. These were processed to Top-of-Atmosphere (Chandler and others 2009) and surface reflectance (Chavez 1988, Zhu and Woodcock 2012) using scripts developed by RSAC personnel and run within the Python and ERDAS Imagine software. The conversion from raw digital numbers to surface reflectance was done to minimize atmospheric effects (Song and others 2001). Two scenes were needed to cover the study area; they were joined within ERDAS. To calculate NDVI we used an RSAC-developed script that rescaled the index to integers between 0 and 200. Finally, we used the ARCINFO raster tool to extract values from each NDVI image for each of the 88 sample plots in which we had assessed pine canopy health following U.S. Forest Service Forest Health Monitoring protocols. Using these plots for which we have direct

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canopy health measures allowed us to relate spectral data to actual forest health conditions (results not reported here).

We examined the general trend in NDVI from 1984 to 2013 (fig. 1). Based on simple linear regression, the mean performance of all plots through time was negative (fig. 1).Though the trend in NDVI was negative (slope = -0.4241) the relationship was weak (r^2= 0.1052).

To better understand the variation among plots, we attempted to account for two components of the temporal trend: the NDVI level and slope. We first standardized NDVI values across all plots within each year, thereby assigning a standardized (z-transformed) NDVI score for each plot in each year. We calculated an average standardized NDVI score for each plot across all years. Then we calculated the slope of NDVI through time for each plot, and calculated a standardized slope score. Using both the mean standardized NDVI and standardized slope, we divided the plots into sixteen classes (table 1) defined by all combinations of four NDVI levels and four slope categories (strongly positive, flat, decreasing, and strongly decreasing). Levels were determined by natural breaks in the distributions of plots across the standardized NDVI and slope values, respectively.

Most sample plots were declining in greenness through time, consistent with the overall NDVI trend (fig. 1). The classification identified some plots that were both low NDVI but strongly increasing and high NDVI but strongly declining, combinations that were not intuitively easy to interpret. Based on an examination of a series of aerial photos, we determined that the former included relatively young fast-growing plantations and the latter occurred where management activities (e.g. fire, harvest) had reduced canopy cover abruptly.

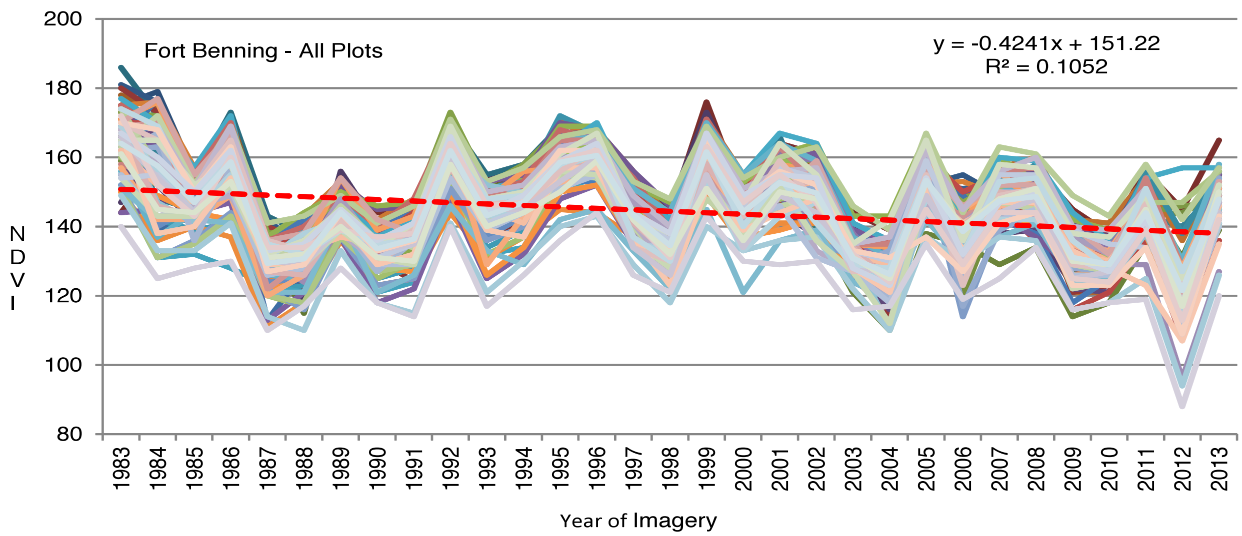

Figure 1—Trend analysis graph showing the NDVI values for each plot over the 30 year time series and the trend line (in red) which shows the slope of mean plot performance against year (linear regression).

Table 1—Distribution of 88 sample plots across trend classes defined by combining the NDVI standardized (z-transformed) within each year and averaged across all years with the magnitude of the slope of NDVI regressed on year

Class	Strong decline	Declining	Flat	Improving
Very healthy	5	12	0	1
Healthy	13	3	4	1
Unhealthy	5	13	1	1
Very unhealthy	5	15	6	3

Our results indicate the complexity of interpreting temporal trends in productivity on a managed landscape. Though overall trends appeared negative, management actions, especially those that cause abrupt changes in canopy cover, may influence trends. The use of Landsat based NDVI trends to interpret changes in forest health are complicated by image resolution that may not show isolated small patches of dying trees. At the very least, interpretations must be corroborated by other data, for example, information about stand management or natural disturbance.

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