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Evaluation of a Regional Monitoring Program's Statistical Power to Detect Temporal Trends in Forest Health Indicators

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Abstract Forests are socioeconomically and ecologically important ecosystems that are exposed to a variety of natural and anthropogenic stressors. As such, monitoring forest condition and detecting temporal changes therein remain critical to sound public and private forestland management. The National Parks Service's Vital Signs monitoring program collects information on many forest health indicators, including species richness, cover by exotics, browse pressure, and forest regeneration. We applied a mixed-model approach to partition variability in data for 30 forest health indicators collected from several national parks in the eastern United States. We then used the estimated variance components in a simulation model to evaluate trend detection capabilities for each indicator. We investigated the extent to which the following factors affected ability to detect trends: (a) sample design: using simple panel versus connected panel design, (b) effect size: increasing trend magnitude, (c) sample size: varying the number of plots sampled each year, and (d) stratified sampling: post-stratifying plots into vegetation domains. Statistical power varied among indicators; however, indicators that measured the proportion of a total yielded higher power when compared to indicators that measured absolute or average values. In addition, the total variability for an indicator appeared to influence power to detect temporal trends more than how total variance was partitioned among spatial and temporal sources. Based on these analyses and the monitoring objectives of the Vital Signs program, the current sampling design is likely overly intensive for detecting a 5 % trend·year^{-1} for all indicators and is appropriate for detecting a 1 % trend·year^{-1} in most indicators.

Keywords Monitoring · Trend detection · Sampling design · Forest health indicators · Variance components

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Introduction

Understanding both the current condition of forest resources and how forests are changing over time is critical to sound public and private forestland management. Both ecological and anthropogenic forces shape the forests of the eastern United States. Ecological factors (e.g., geology, topography, soil nutrient availability, weather, and disturbance patterns) and anthropogenic stressors (e.g., harvest and land-use conversion) can act independently or in

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concert to directly influence the structure, composition, and dynamics of forest vegetation. For instance, exotic plant and animal species, climate change, white-tailed deer (*Odocoileus virginianus*), and altered disturbance regimes are complex factors that are important determinants of the current condition and structure of forests. These factors are also likely to influence how forest condition and structure will change over time in the eastern US.

The introduction and spread of invasive exotic plant and animal species has had profound impacts on eastern forests, including the near elimination of some important tree species (Pimentel et al. 2006). In the past decade, invasive insects, such as hemlock wooly adelgid (*Adelges tsugae*), emerald ash borer (*Agrilus planipennis*), gypsy moth (*Lymantria dispar*), and beech scale insect (*Cryptococcus fagisuga*), have caused wide-spread mortality or serious damage to many forests in the eastern US (Steinman 2004). Invasive exotic plant species also impact eastern forests through competition with native plant species, resulting in changes to the vegetation structure over space and time. Invasive plants can disrupt ecosystem-level processes by altering resource utilization, trophic structures, and disturbance regimes. These disruptions may result in altered fire regimes, nutrient cycling, or soil development (Vitousek 1990; Pimentel et al. 2000; Mack 2003).

In addition to invasive species, global climate change may further affect the composition and dynamics of eastern forests (Woodall et al. 2010). Chronic forest stress and mortality risk for some species may increase in coming decades due to warmer temperatures, more frequent heat waves, and more frequent or longer term regional drought conditions (Allen et al. 2010). Although increases in tree biomass are expected for some species due to increases in carbon dioxide concentrations (Norby et al. 2002), trees may also become more susceptible to insect pests and disease (Logan et al. 2003). Furthermore, some invasive plants may have a competitive advantage in a changing climate if they are more effective than native plants at adjusting their physiology (e.g., flowering times) to changing climatic conditions (Willis et al. 2010).

Changes in land use and land management over the previous decades have led to expanded native white-tailed deer (*Odocoileus virginianus*) populations (Latham et al. 2005). The effects of selective browsing by deer on forest ecosystems include shifted species composition toward browse-resilient species, competitive exclusion of native species, regional biotic homogenization, and reduced survival of tree seedlings and saplings, among others (Russell et al. 2001; Horsley et al. 2003; Rooney et al. 2004; Kirschbaum and Anacker 2005; Latham et al. 2005). In particular, browse pressure from deer has reduced the abundance, growth, and/or fecundity of many native plant species in the lily (Liliaceae), arum (Araceae), and orchid (Orchidaceae) families (Anderson 1994; Augustine and Frelich 1998; Ruhren and Handel 2003; Kirschbaum and Anacker 2005). Conversely, the spread of plant species less palatable to deer [e.g., hay-scented fern (*Dennsteadtia punctilobula*) and striped maple (*Acer pensylvanicum*)] can interfere with regeneration of desirable tree species and herbaceous species diversity (Latham et al. 2005).

Because these aforementioned stressors (and others, e.g., acid deposition), natural processes, and land management activities shape the temporal dynamics of eastern forested ecosystems, it is important for natural resource managers to understand the current condition of forest resources and how the forests are changing over time. To address this monitoring need, the National Park Service (NPS) began a long-term forest health monitoring program in 2007 (Perles et al. 2014) in nine national parks in the Appalachian Mountains, referred to as the Eastern Rivers and Mountains Network (ERMN). Long-term monitoring of forest vegetation and soils was identified as a high priority for the ERMN, because plant species diversity and functional plant communities are natural resources critical to the parks. Forest communities serve as a base for other trophic components and also serve as an integrated measure of terrestrial ecosystem health by expressing information about climate, soils, and disturbance. This monitoring effort is a component of the ERMN vital signs monitoring program (Marshall and Piekielek 2007) and part of the nationwide NPS inventory and monitoring program (Fancy et al. 2009).

The ERMN includes nine parks in New York, New Jersey, Pennsylvania, and West Virginia (Fig. 1), which together encompass nearly 91,000 ha of land area and over 965 km of streams and rivers within the parks' authorized boundaries. The network includes four smaller parks in central and southwestern Pennsylvania that have a primarily cultural or historical focus. These cultural parks are Allegheny Portage Railroad National Historic Site (NHS), Johnstown Flood National Memorial (NMem), Fort Necessity National Battlefield (NB), and Friendship Hill NHS. The remaining five larger parks preserve segments of large rivers and generally extend to the ridgetops surrounding the river section. These river parks are Upper Delaware Scenic and Recreational River (SRR), Delaware Water Gap National Recreation Area (NRA), New River Gorge National River (NR), Gauley River NRA, and Bluestone National Scenic River (NSR).

The ERMN Vegetation and Soil Monitoring Program (Perles et al. 2014) provides information regarding the condition of the parks' vegetation and how this condition is changing through time. In order to be effective, the monitoring program must be able to detect changes in the parks' vegetation within a reasonable period of time, with a reasonable level of statistical confidence. Power analysis is

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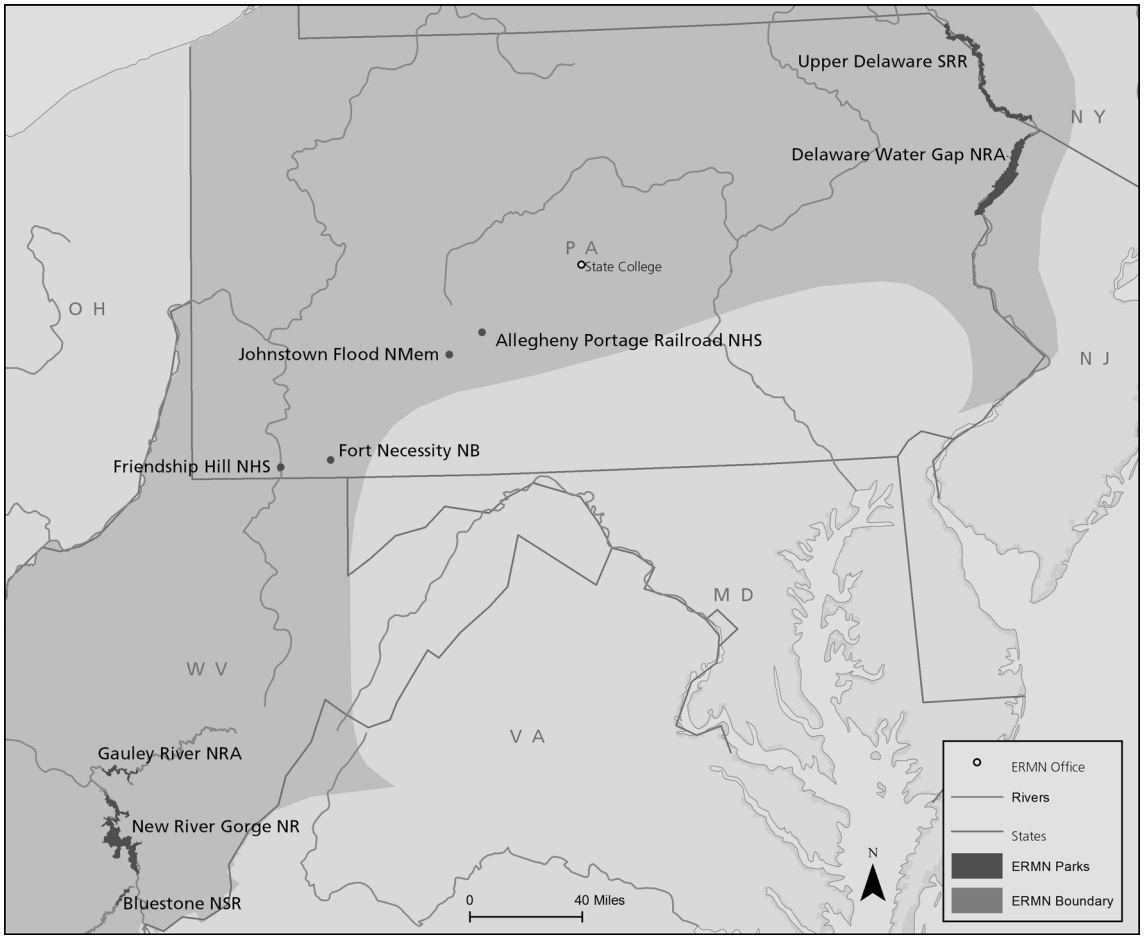

Fig. 1 Location of Eastern Rivers and Mountains Network (ERMN) parks

a useful tool for evaluating the performance of ecological monitoring programs (Peterman 1990; Fairweather 1991; Hatch 2003), and, in particular, for investigating how specific variance components affect the power to detect trends for a given sampling design (Urquhart et al. 1998).

Statistical power is the probability of rejecting the null hypothesis when it is, in fact, false (i.e., detecting a trend when a trend is present). Several factors influence the ability to detect change over time, including sample size, the probability of a type-I error (α), the probability of a type-II error (β), trend magnitude, and variance. Type-I error, or "false change," refers to falsely detecting a trend when no trend is present. Type-II error, or "missed change," refers to wrongly concluding that no trend is present when, in fact, there is a trend. Statistical power is defined as $1 - \beta$. Commonly used values of α and β range from 0.01 to 0.2 (Gibbs et al. 1998). The vegetation and soil monitoring protocol (Perles et al. 2014) suggested that this monitoring program should ideally be able to detect a 20 percent change in key indicators over five or ten years (i.e., two or three plot revisits, see below), with an α of 0.1 and a power of 0.80. Specifically, this program is interested in detecting monotonic increases or decreases in key indicators (Perles et al. 2014).

One approach to evaluating the statistical power of different sampling designs to detect trends in forest vegetation is to use estimated variance components within a simulation framework (e.g., Wagner et al. 2007). A component of variance approach has been advocated to quantify variability in ecological data when evaluating temporal trends and monitoring ecological systems (Urquhart et al. 1998; Larsen et al. 2001; Kincaid et al. 2004), largely, because the structure of variance, not just total variance, can influence trend detection capabilities (Wagner et al. 2007). Under this framework, total variance is partitioned into five components, including:

(a) spatial variation (site-to-site);
(b) coherent temporal variation (year-to-year) affecting all sites in a similar manner;
(c) ephemeral temporal variation (i.e., a site x year interaction) corresponding to independent yearly variation at each site;

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(d) trend variation corresponding to site-specific deviations from any long-term average trend; and
(e) residual variation which includes observer error and other unexplained sources of variation.

Power analysis is not only a useful tool for investigating the effectiveness of different sampling designs and the relative power of different indicators, but it can also be used to elucidate how specific variance components affect the power to detect trends for a given sampling design. This is important, because depending on the structure of the variance, power to detect trends may be increased by altering the sampling design.

The objectives of this study were to use a variance components approach on data collected from the ERMN vegetation monitoring program to (1) assess 30 key indicators of forest structure, function, or dynamics with respect to trend detection capabilities, and (2) investigate the extent to which the following conditions affected the ability to detect temporal trends in forest indicators:

(a) using a simple panel versus a connected panel design (defined below);
(b) increasing the trend magnitude effect size (from 1 to 10 % change in a forest indicator·year^{-1});
(c) varying sample size in relation to park size (ranging from 3 to 25 plots·year^{-1}); and
(d) post-stratifying sampling plots into vegetation domains (xeric and mesic).

In addition, we anticipated that our ability to estimate coherent temporal variability would be limited, because the time series for estimating variance components was relatively short (i.e., 4–5 years); therefore, we also investigated the effects of increasing the coherent temporal variation from 0 to 10 % of total variation on the power to detect trends. We elected to evaluate the effects of coherent temporal variation separately because manipulation of sampling design will not reduce the influence of this source of variation on the power to detect trends.

Methods

Although a brief overview of vegetation and soil monitoring methods is provided here, a detailed rationale of sampling design and methods, in addition to data collection standard operating procedures, is provided in the vegetation and soil monitoring protocol (Perles et al. 2014). The protocol was based on the US Forest Service (USFS) Forest Inventory and Analysis (FIA) program (United States Department of Agriculture, Forest Service 2007) and the vegetation monitoring protocols of four other NPS Inventory and Monitoring programs in the eastern United States (Sanders et al. 2008; Comiskey et al. 2009; Schmit et al. 2009; Tierney et al. 2009).

Sampling Design

Vegetation was monitored at permanent plots (i.e., fixed sites) within each park. Between 2007 and 2011, in eight ERMN parks, 360 total plots were established, with the number of plots per park ranging from 12 to 102, proportional to the size of the park. This sample size was determined based on the experiences of other NPS networks that had implemented vegetation monitoring programs and by ERMN budgetary and logistical constraints.

To select monitoring locations, a regular grid of potential plot locations was overlain on a map of the park. Sampling locations were selected from the regular grid using a generalized random-tessellation stratified (GRTS) design (McDonald 2004; Stevens and Olsen 2004) in order to produce a randomly selected, spatially balanced sample of flexible size (Stevens and Olsen 2004). Plots were sampled on a 4-year simple panel design, in which one panel containing one-fourth of a park's total plots was sampled each year. On the fifth year, the vegetation in the first panel of plots was resampled. An alternative design we evaluated was a connected panel design in which some plots are visited every year (i.e., the common panel) in addition to the plots that were revisited once every fifth year. In theory, this "connectivity" through time can provide increased power in some cases and increase the ability to estimate ephemeral variability (i.e., site-by-year variance) by having among-year site revisits (Urquhart et al. 1998; Urquhart and Kincaid 1999). However, in practice, this design increased monitoring costs and could expose plots to additional sampling impacts (e.g., vegetation trampling). In the ERMN parks, a connected panel design was preliminarily implemented to better allow for the estimation of the ephemeral temporal variance component. This design entailed revisiting 5–14 plots that were established in 2007 and 2008 among three of the large parks as part of a common panel. In addition, each year, three plots from the panel were resampled within a few weeks of the original sampling as a quality control measure.

Field Methods

At each plot, the ERMN monitored a suite of forest health indicators using several embedded sampling units. Tree, stand, and plot measurements were collected within fixed area 15-m radius circular plots. Tree regeneration and shrub measurements were collected on four 2-m radius circular microplots embedded within each plot. Coarse woody debris data were collected using line intersect sampling along six 15-m transects. Understory plant

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Table 1 Forest health indicators evaluated for trend detection capabilities and used for evaluating the National Parks Service's Eastern Rivers and Mountains Network monitoring program's statistical power to detect temporal trends. Indicators marked with a "C" are count data; all other indicators are non-count data

Indicator	Calculation of indicator for each plot	Years of data used
Groundstory diversity		
Total quadrat species richness (C)	Count of all vascular species present among 12 quadrats	2008–2011
Walk around species richness (C)	Count of all vascular species observed during time-constrained search of entire plot (does not include any species observed in quadrats)	2008–2011
Total groundstory species richness (C)	Sum of total quadrat species richness and walk around species richness	2008–2011
Floristic quality index	Index (Chamberlain and Ingram 2012) incorporating the ecological conservatism of plant species observed in quadrats and total quadrat species richness	2008–2011
Number of key invasive exotic species present (C)	Count of invasive exotic species observed (Perles et al. 2014) among all sampling sub-units within the plot	2007–2011
Average proportion of total species richness in native species	For each quadrat calculated: [Native Species Richness]/[Total Species Richness]; then averaged across 12 quadrats	2007–2011
Average proportion of total species richness in non-native species	For each quadrat calculated: [Non-native species richness]/[Total species richness]; then averaged across 12 quadrats	2007–2011
Average proportion of total species richness in invasive exotic species	For each quadrat calculated: [Invasive exotic species richness]/[Total species richness]; then averaged across 12 quadrats	2007–2011
Average proportion of total cover in native species	For each quadrat calculated: [Sum of native species cover]/[Sum of all species cover]; then averaged across 12 quadrats	2007–2011
Average proportion of total cover in non-native species	For each quadrat calculated: [Sum of non-native species cover]/[Sum of all species cover]; then averaged across 12 quadrats	2007–2011
Average proportion of total cover in invasive exotic species	For each quadrat calculated: [Sum of invasive exotic species cover]/[Sum of all species cover]; then averaged across 12 quadrats	2008–2011
Total cover of invasive exotic species	Sum of midpoint values from cover class data for all invasive exotic species (Perles et al. 2014) among 12 quadrats	2008–2011
Average cover of invasive exotic species	Sum of midpoint values from cover class data for all invasive exotic species (Perles et al. 2014) within a quadrat, then averaged across 12 quadrats	2008–2011
Total cover of rhizomatous ferns	Sum of midpoint values from cover class data for all fern species among 12 quadrats	2007–2010
Browse indicators		
Total number of individuals of all browse-indicator species (C)	Count of all individuals of browse-indicator species (Perles et al. 2014) among 12 quadrats	2007–2011
Total number of Canada mayflower individuals (C)	Count of Canada mayflower individuals among 12 quadrats	2007–2011
Average height of tallest jack-in-the-pulpit[a]	Height of tallest jack-in-the-pulpit plant averaged across all quadrats ($n \leq 12$) within plot that contained jack-in-the-pulpit	2007–2010
Tree regeneration and shrubs		
Average stocking index	Index of tree seedling abundance and height (McWilliams et al. 2005) calculated for each microplot, then averaged across four microplots	2007–2010
Total seedling species richness (C)	Count of tree species present as seedlings among four microplots	2007–2011
Total sapling basal area	Sum of sapling basal area among four microplots	2007–2010
Total sapling density (C)	Sum of sapling counts among four microplots, converted to per hectare density	2007–2011
Total seedling density (C)	Sum of seedling counts among four microplots, converted to per hectare density	2007–2011
Total number of shrub stems (C)	Sum of all shrub stem counts among four microplots	2007–2011
Total shrub cover	Sum of midpoint values from cover class data for all shrub species among four microplots	2007–2010
Total shrub species richness (C)	Count of shrub species present among four microplots	2007–2011
Coarse woody debris		
Average coarse woody debris volume	Huber's formula (Marshall et al. 2000) used to estimate volume per transect, then calculated average volume from six transects	2007–2010

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Table 1 continued

Indicator	Calculation of indicator for each plot	Years of data used
Trees		
Live tree basal area	Sum of live tree basal area within plot	2007–2010
Live tree density (C)	Number of live trees in plot converted to per hectare density	2007–2011
Snag basal area	Sum of standing dead tree basal area within plot	2007–2010
Snag density (C)	Number of standing dead trees in plot converted to per hectare density	2007–2011

[a] Data were used only from plots that contained jack-in-the-pulpit in the 1-m^2 quadrats

composition and diversity data were monitored using twelve 1-m^2 quadrats set along the six transects. The number, height, and reproductive status of specific herbaceous species sensitive to deer browse are also recorded from the quadrats. For complete description of data collection methods, see Perles et al. (2014).

Statistical Analysis

Thirty indicators characterizing forest structure, function, and dynamics were included in this study (Table 1). Either 4 or 5 years of data were available at the time of analysis. For instance, some data from 2007 were not included due to differences in data collection procedures during the first year of sampling.

Because data collection protocols generated both discrete count (e.g., the number of individuals) and continuous non-count (e.g., live tree basal area) data, two separate statistical models, that assumed different error distributions, were used. For the non-count data (Table 1), a linear mixed model, that assumed Gaussian errors, was used to estimate variance components for 17 forest indicators, similar to the approach suggested by Piepho and Ogutu (2002). The mixed model used for the analyses was

$$y_{ijk} = \mu + a_i + \text{year}_j(\lambda + t_i) + b_j + c_{ij} + e_{ijk}, \quad (1)$$

where y_{ijk} is the log$_e$-transformed forest indicator from the kth sample for plot i in year j, and μ and λ are the intercept and slope fixed effects (i.e., the population-average intercept and trend), respectively. The a_i is a random effect for plot i, representing plot-to-plot (spatial) variability, independent, and identically distributed (iid) as $N\left(\sigma_a^2\right)$; b_j is a random effect for the jth year (coherent temporal variability), iid as $N\left(0, \sigma_b^2\right)$; t_i is a random effect for the trend for plot i, iid as $N\left(0, \sigma_t^2\right)$; c_{ij} is the plot × year interaction (ephemeral temporal variability), iid as $N\left(0, \sigma_c^2\right)$; e_{ijk} is the unexplained error (residual error), independent as $N\left(0, \sigma_e^2\right)$. The year covariate (*year*) is the jth year minus the mean year (i.e., grand-mean centered) used in the analysis. This standardization of year was performed to provide numerical stability.

For the 13 indicators summarized as count data (Table 1), a negative binomial mixed model was used to estimate temporal and spatial variances (Irwin et al. 2013). Thus, we assume that $Y_{ijk} \sim NB(\mu_{ijk}, \kappa)$ where $Y_{ijk}$is the kth sample of each indicator at plot i in year j, $\mu_{ijk}$is the expected value for that sample, plot, and year, and κ is the scaling parameter of negative binomial distribution. We employ a log-link function such that the log$_e$ of the expected value would be a linear function of the predictors:

$$\eta_{ijk} = v + a_i + \text{year}_j(\lambda + t_i) + b_j + c_{ij}, \quad (2)$$

where η_{ijk} is the log$_e$ of the expected value of each indicator from the kth sample at plot i in year j, v is the fixed intercept, and λ is the fixed slope for temporal trends using year as the covariate (i.e., the predictor variable as described above). The random effect terms a_i (plot-to-plot effects), t_i (plot-specific trend effects), b_j (coherent temporal effects), and c_{ij} (ephemeral temporal effects) are, as described above, independent and identically distributed (iid) as $N\left(0, \sigma_x^2\right)$; where $\left(\sigma_x^2\right)$ is the unique variance parameter for each random effect. Unlike Eq. 1, the negative binomial does not have an additive residual error term. Thus, to produce a value comparable to the scale of the other variance component terms and to what is estimated when lognormal error is assumed in simple linear regression, we calculated a quantity to represent the average of the squared CV for the observational error variance in the negative binomial context following methods outlined in Irwin et al. (2013).

All parameter estimation was conducted using the Random Effects module of AD Model Builder (ADMB), statistical programming software for fitting nonlinear models (http://admb-project.org; Fournier et al. 2012). Additional details on the variance-component framework

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and these estimation procedures can be found in Wagner et al. (2007) and Irwin et al. (2013).

Preliminary models estimating components of variance (described above) used data from eight ERMN parks and indicated that spatial variability was the largest source of variance. For subsequent simulation analyses (described below), we used data only from Delaware Water Gap NRA for estimating variance components, because, (a) a main goal of ERMN monitoring is to provide park-specific information, (b) using data from one park reduced the spatial variability, and (c) Delaware Water Gap NRA was the only single park that contained revisited plots from the common panel as well as within-year quality control revisits necessary to calculate all of the components of variance. However, one set of simulations (i.e., coarse woody debris volume from xeric forests) used data from all xeric plots in New River Gorge NR, Gauley River NRA, and Bluestone NSR instead of Delaware Water Gap NRA data (see effect of post-stratification into vegetation Domains below).

Next, we used a simulation approach to examine the statistical power to detect temporal trends in 30 forest indicators. Simulations followed the approach outlined in Wagner et al. (2007) and Wagner et al. (2009). Briefly, 250 simulations were performed for each indicator and sampling scenario. During each simulation, a 30-year-time series of a vegetation indicator was simulated for 500 plots (the number of potential plots available to be sampled in Delaware Water Gap NRA under the current ERMN sampling plan) using the estimated spatial and temporal components of variation. A population-average temporal trend (λ) was then specified (e.g., an increase of 1 % of the forest indicator·year^{-1}); however, each individual plot could deviate from this population-average trend, with the deviation dependent on the magnitude of the trend variance component (t_i). Linear trends were investigated and appropriate, because we wanted to link the overall management question (i.e., detecting the presence of a monotonic change) to the monitoring objective (Wagner et al. 2013). Each year, the simulated vegetation data were sampled from the population of plots using one of the available panel designs. The number of sampled plots ranged from 3 to 25. Plots were sampled either with a simple 4-year panel design in which a specified number of plots were sampled in each panel, or with a connected 4-year panel design in which one-fifth of the plots were sampled every year in the common panel (see Fig. 2 in Urquhart et al. 1998 for a schematic illustrating sampling designs). During each simulation, every 3 years of the sampling process, models outlined in Eqs. 1 or 2 were used to test the null hypothesis that $\hat{\lambda} = 0$, and the test statistic was calculated and compared to a critical value (with $\alpha = 0.05$). Because the data generated depict a situation in which we know the null hypothesis is false (i.e., a trend of pre-specified magnitude was incorporated into the data), power was estimated as the percentage of trials (i.e., of 250 simulations) that rejected the null hypothesis.

Results

Partitioning of Variance Using Mixed Models

We attempted to fit mixed models and estimate variance components for all 30 forest indicators. For the non-count data, all models ran to convergence. The fixed slope, total variance, and percent of total variance in different variance components are shown in Table 2. The fixed slope provides an estimate of the yearly change occurring for each indicator over the 4–5-year sampling period. For most indicators, the vast majority of the total variance was spatial. Total variance for total cover of rhizomatous ferns, average cover of invasive exotic species, and total cover of invasive exotic species was notably higher than for the other indicators.

For the count data, the estimation procedure ran to completion for all of the indicators except for total number of Canada mayflower individuals. However, convergence warnings were produced for the majority of the indicators (Table 2), suggesting that the model was not generating reliable estimates for all parameters. Inspection of the resulting parameter estimates suggested that the model was likely having trouble estimating several of the temporal variance parameters (Table 2), likely due to the relatively short (4 or 5 years) nature of the time series and because incorporating spatial effects into the model appeared to allow for close approximation of the observed data. The high percent of the total variance contained in derived residual variance term in these cases does not necessarily refer to observer error while collecting field measurement. It refers to all of the remaining unexplained variation, which includes some temporal variation that could not be estimated separately by the model. As such, power simulations were run only for the four count indicators which did not produce convergence warnings during model estimation (Table 2).

Power to Detect Trends in Forest Health Indicators

Overall, the simulations indicate that the current sampling design for the ERMN Forest and Soil Monitoring Program (Perles et al. 2014) will likely yield greater than 80 % power to detect a 1 % trend·year^{-1} in most forest health indicators within two to three sampling cycles

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Table 2 Percent of total variance in each of five variance components, total variance, and fixed slope estimated by mixed models for 30 forest health indicators

	Mean (±SD) units	Percent spatial	Percent coherent temporal	Percent ephemeral temporal	Percent trend	Percent residual	Total variance	Slope	Slope standard error
Non-count indicators									
Average height of tallest jack-in-the-pulpit	17.5 (±7.1) cm	73.82	3.11	3.43	13.76	5.88	0.1645	0.1243	0.0558
Average proportion of total species richness in native species	0.82 (±0.17)	87.48	2.19	4.83	0.00	5.51	0.0119	0.0044	0.0068
Average proportion of total cover in non-native species	0.17 (±0.23)	91.11	0.64	3.00	5.19	0.05	0.0366	0.0051	0.0081
Average proportion of total cover in native species	0.79 (±0.24)	91.16	0.00	3.88	1.11	3.85	0.0262	0.0028	0.0060
Floristic quality index	22.8 (±5.4)	91.89	1.07	0.24	0.00	6.80	0.0810	0.0018	0.0167
Average coarse woody debris volume	18.5 (±18.5) $m^3 \cdot hectare^{-1}$	93.18	0.00	1.02	4.74	1.05	1.6528	0.0703	0.0616
Total sapling basal area	0.10 (±0.14) $m^2 \cdot hectare^{-1}$	94.34	0.00	0.00	5.24	0.42	0.0135	−0.0031	0.0044
Average proportion of total species richness in non-native species	0.12 (±0.15)	95.43	0.14	3.28	0.98	0.17	0.0175	0.0040	0.0045
Total shrub cover	158.9 % (±170.5 %) [can exceed 100 %]	95.63	1.51	2.14	0.13	0.58	1.4449	0.1501	0.0853
Average stocking index	122 (±114)	95.64	0.00	0.63	2.82	0.91	1.7336	0.0619	0.0527
Snag basal area	2.1 (±2.5) $m^2 \cdot hectare^{-1}$	96.58	0.29	1.25	1.86	0.01	0.4706	0.0499	0.0329
Total cover of rhizomatous ferns	85.41 % (±149.9 %) [can exceed 100 %]	97.42	1.41	0.06	0.00	1.11	4.7291	−0.0312	0.1236
Average cover of invasive exotic species	17.0 % (±28.0 %) [can exceed 100 %]	98.21	0.00	0.53	0.00	1.27	3.0173	−0.1229	0.0463
Total cover of invasive exotic species	204.7 % (±336.5 %) [can exceed 100 %]	98.87	0.00	0.43	0.00	0.71	7.9293	−0.1223	0.0647
Average proportion of total cover in invasive exotic species	0.16 (±0.24)	99.09	0.00	0.10	0.79	0.02	0.0370	0.0013	0.0031
Average proportion of total species richness in invasive exotic species	0.11 (±0.15)	99.23	0.00	0.18	0.00	0.59	0.0171	0.0003	0.0022
Live tree basal area	24.2 (±11.8) $m^2 \cdot hectare^{-1}$	99.89	0.00	0.09	0.02	0.00	0.7860	0.0214	0.0091
Count indicators[a]									
Total shrub species richness	5.6 (±3.1) species	46.46	0.00	0.00	0.00	53.54	0.3798	0.1046	–
Total seedling species richness	7.8 (±3.9) species	51.76	0.00	0.00	0.00	48.24	0.3047	0.1001	–
Number of key invasive exotic species present	3.7 (±3.7) species	65.19	0.00	0.00	0.00	34.81	3.2671	0.0771	–
Snag density	52.0 (±58.3) $snags \cdot hectare^{-1}$	65.94	0.00	0.00	0.00	34.06	1.5185	0.0418	–
Total sapling density	835.0 (±1,455.4) $saplings \cdot hectare^{-1}$	66.54	0.00	0.00	0.00	33.46	3.1686	−0.0079	–
Walk around species richness	18.1 (±8.0) species	73.71	0.00	0.00	0.00	26.29	0.2432	−0.0947	0.0259

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Table 2 continued

	Mean (±SD) units	Percent spatial	Percent coherent temporal	Percent ephemeral temporal	Percent trend	Percent residual	Total variance	Slope	Slope standard error
Total number of individuals of all browse-indicator species	76.4 (±198.4) individual plants	81.81	0.00	0.00	0.00	18.19	11.5714	0.0080	–
Total quadrat species richness	30.3 (±15.6) species	85.81	0.00	0.00	0.00	14.19	0.2928	0.0058	–
Total groundstory species richness	48.3 (±20.5) species	88.39	0.00	0.00	0.00	11.61	0.2116	−0.0270	–
Live tree density	416.2 (196.0) trees·hectare^{-1}	89.01	0.00	0.00	0.00	10.99	0.4389	0.0074	0.0118
Total seedling density	23,141.0 (±26,217.9) seedlings·hectare^{-1}	92.46	1.71	0.77	2.21	2.86	1.8934	0.1705	0.0648
Total number of shrub stems	200.0 (±263.6) stems	94.75	0.79	0.11	0.20	4.15	3.5003	0.0754	0.0578

Indicators are sorted from the lowest to highest percent spatial variation

[a] Indicators in italics produced convergence warnings during the model estimation, and the model was unable to estimate slope standard deviation for these indicators

(10–15 years, Table 3) at the two largest ERMN parks. Power curves for these simulations are shown in the Supplementary Material (Supplementary Material 1; note that any irregularities in the power curves, as opposed to smooth lines, are a result of variability among simulation runs). For some indicators, such as average coarse woody debris volume, average stocking index, total shrub cover, total cover of invasive exotic species, and average cover of invasive species, the sampling design never attains 80 % power to detect a 1 % trend·year^{-1} even after 30 years. The total variance for these indicators was larger (> 1) than for the other non-count indicators. For average height on the tallest jack-in-the-pulpit and total cover of rhizomatous ferns, power to detect a 1 % trend·year^{-1} exceeded 80 % only after 15–20 years. Power curves for the count indicators indicate that the sampling design will likely yield greater than 80 % power to detect a 5 % trend·year^{-1} within one to two sampling cycles (5–10 years) but will not yield greater than 80 % power to detect a 1 % trend·year^{-1} until after three sampling cycles (>15 years) for three of the four indicators (Supplementary Material 1, Table 3). The sampling design is likely overly intensive for detecting a 5 % trend·year^{-1} in the two largest parks for nearly all of the key indicators, since the simulations showed nearly 100 % power for all indicators after 12 years (Table 3). In general, indicators that measure the proportion of the total species richness or total cover (e.g., average proportion of total quadrat plant cover in non-native species) yielded much higher power than indicators that measure absolute total cover or average cover. We propose that this is explained by the fact that using proportions reduces the variability in cover measurements caused by yearly weather patterns (e.g., temperature and precipitation) and different observers.

Effect of Sampling Design and Trend Magnitude

The simple panel and connected panel designs had similar power estimates for detecting temporal trends (Fig. 2). Within the first 5 years, the connected panel design initially exhibited slightly higher power than the simple panel design, but this advantage was not retained in subsequent years. This pattern was similar regardless of the magnitude of trend (1–10 %·year^{-1}) that was being imposed. As expected, the power curves in Fig. 2 illustrate that trends of higher magnitude can be detected with higher statistical power. Given these results, the added cost of implementing the connected panel is not justified, especially considering the potential for annual sampling to impact the vegetation (e.g., trampling). In addition, for some key field measurements such as tree diameter-at-breast-height (DBH), the average annual change (0.38 cm for DBH) is nearly equivalent to the average error in field measurement

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Table 3 Power of ERMN Vegetation Monitoring Program to detect trends in key forest health indicators after 6 and 12 years

Non-count indicators	Power to detect 1 %·year^{-1} trend after 6 years (%)	Power to detect 1 %·year^{-1} trend after 12 years (%)	Power to detect 5 %·year^{-1} trend after 6 years (%)	Power to detect 5 %·year^{-1} trend after 12 years (%)
Average coarse woody debris volume	46.4	57.6	88.7	100.0
Total cover of invasive exotic species	47.9	60.5	71.5	95.5
Total cover of rhizomatous ferns	52.3	63.4	75.2	99.2
Total shrub cover	53.5	67.7	88.7	100.0
Average cover of invasive exotic species	47.6	69.3	84.7	100.0
Average stocking index	57.8	71.8	90.4	100.0
Average height of tallest jack-in-the-pulpit	62.4	73.7	98.6	100.0
Snag basal area	65.2	85.5	100.0	100.0
Average proportion of total species richness in native species	81.2	87.4	100.0	100.0
Average proportion of total cover in non-native species	94.4	100.0	100.0	100.0
Average proportion of total cover in native species	98.1	100.0	100.0	100.0
Floristic quality index	93.5	100.0	100.0	100.0
Total sapling basal area	100.0	100.0	100.0	100.0
Average proportion of total species richness in non-native species	98.4	100.0	100.0	100.0
Average proportion of total cover in invasive exotic species	99.4	100.0	100.0	100.0
Average proportion of total species richness in invasive exotic species	100.0	100.0	100.0	100.0
Live tree basal area	100.0	100.0	100.0	100.0
Count indicators				
Walk around species richness	18.4	53.5	92.2	100.0
Live tree density	22.4	56.1	84.1	100.0
Total seedling density	26.5	54.6	74.1	95.3
Total number of shrub stems	50.3	65.5	53.1	80.3

(0.27 cm for DBH). For measurements such as DBH, yearly sampling would likely add unnecessary "noise" to the data since observer error is nearly equal to the average annual change.

Effect of Sample Size

The sampling effort varies among ERMN parks in relation to park size, ranging approximately from 3–25 plots·park^{-1}·year^{-1}. Using variance components estimated from Delaware Water Gap NRA data only, simulations were performed with sample sizes similar to those in four parks (i.e., Delaware Water Gap NRA with 25 plots·year^{-1}, Bluestone NSR with 10 plots·year^{-1}, Fort Necessity NB with 5 plots·year^{-1}, and Johnstown Flood NMem with 3 plots·year^{-1}). Simulations indicate that, even for the smallest parks, the current sampling design is adequate to detect a 5 % trend·year^{-1} in average coarse woody debris volume (Fig. 3) and 1 % trend·year^{-1} in live tree basal area (Fig. 4) within three sampling cycles. Power curves in Figs. 3 and 4 indicate that the sample size could be reduced by more than half and retain a similar level of power. These results could be interpreted to indicate that the sampling design is overly intense, and that a smaller number of plots could detect trends at an acceptable level for less time and cost investment. However, the larger parks contain diverse vegetation which could be analyzed separately, since different trends may be occurring in different vegetation types (see Effect of Post-Stratification into Vegetation Domains below).

Effect of Post-stratification into Vegetation Domains

In the larger ERMN parks (Delaware Water Gap NRA, New River Gorge NR, Gauley River NRA, and Bluestone NSR), the forests found on the upper slopes and ridgetops are very different than the forests growing on the lower slopes and valley bottoms. Xeric forests on higher

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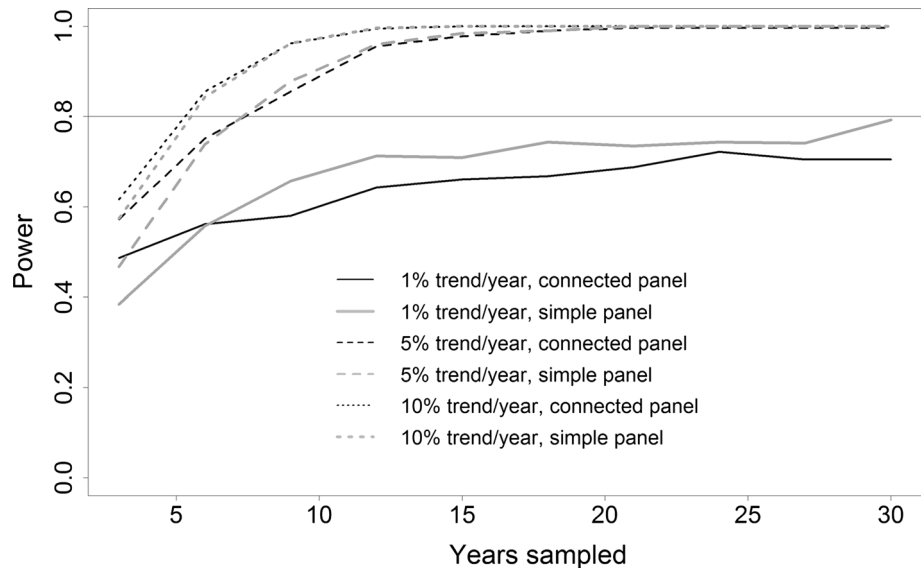

Fig. 2 Power to detect trends in coarse woody debris volume using two sampling designs

topographic positions are dominated by oaks (*Quercus* spp.) and hickories (*Carya* spp.), often with ericaceous shrubs (e.g., blueberries, mountain laurel) in the understory. In the West Virginia parks, forests in lower topographic positions are often lush mixed mesophytic vegetation dominated by sugar maple, yellow buckeye (*Aesculus flava*), and American basswood (*Tilia americana*), with a wide diversity of herbaceous and graminoid plants in the understory. In Delaware Water Gap NRA, mesic forests are highly variable, due to the varied land-use history in the river valley. It is possible that different trends in the key indicators are occurring in the different forest types. Plots were classified as either mesic or xeric based on the plots' location on park-specific vegetation maps (Perles et al. 2006a, Perles et al. 2006b, Perles et al. 2006c; Perles et al. 2007a, Perles et al. 2007b; Vanderhorst et al. 2007, 2008, 2010) and the species observed in the monitoring plots.

Simulations using data from all four large parks indicate that power remains similar when plots are post-stratified by vegetation type, despite the corresponding reduction in sample size by half. For these simulations, the full sample (25 plots·year^{-1}) used the variance components estimated from all Delaware Water Gap NRA plots, the mesic simulations used variance components from only mesic Delaware Water Gap NRA plots and simulated half the sample (13 plots·year^{-1}), and the xeric simulation used variance components from only xeric plots in New River Gorge NR, Gauley River NRA, and Bluestone NSR and simulated half the sample (13 plots·year^{-1}).

Effect of Coherent Temporal Variation

For many of the key indicators, the coherent temporal variation was estimated to be zero or very small (Table 2). The true value is likely greater than zero; however, we were unable to find any published values for coherent temporal variation in forest monitoring data. Therefore, we ran several simulations increasing (1–10 %) the proportion of the total variance allocated to coherent temporal variation (Fig. 5). The power to detect a 1 % trend·year^{-1} was unaffected by the amount of coherent temporal variation we evaluated. We suspect that increasing the coherent temporal variance had little effect on power, because a very large proportion of the total variance is spatial, which we can reduce the influence of by simply sampling more plots. However, the power to detect a 5 % trend·year^{-1} decreases with the increasing coherent temporal variation. If the true value of coherent temporal variation was larger than the small values used in the simulations for many of the key indicators, then actual power will be lower than reported in Table 3 and Supplementary Material 1.

Discussion

The simulations described herein provide an evaluation of a regional forest monitoring program's statistical power to detect temporal trends, as applied in the Delaware Water Gap NRA, in 21 key forest health indicators. Compared to monitoring programs focused on other taxa, such as insects or amphibians, monitoring programs focused on terrestrial plants generate data with lower variability and higher power to detect temporal trends (Gibbs et al. 1998).

Given the ERMN's Vegetation and Soil Monitoring Program's primary objective, the sampling design is likely overly intensive for detecting a 5 % trend per year for all of the indicators, is appropriate for detecting a 1 % trend per year in most indicators, and is insufficient for detecting a 1 % trend per year for a few indicators. For this particular

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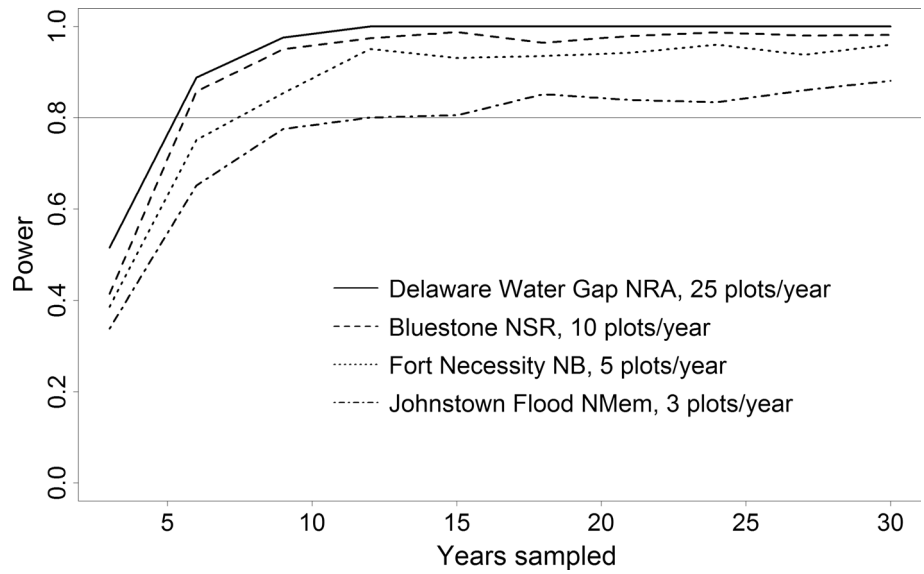

Fig. 3 Power to detect a 5 % trend per year in average coarse woody debris volume as simulated using different sample sizes for different parks

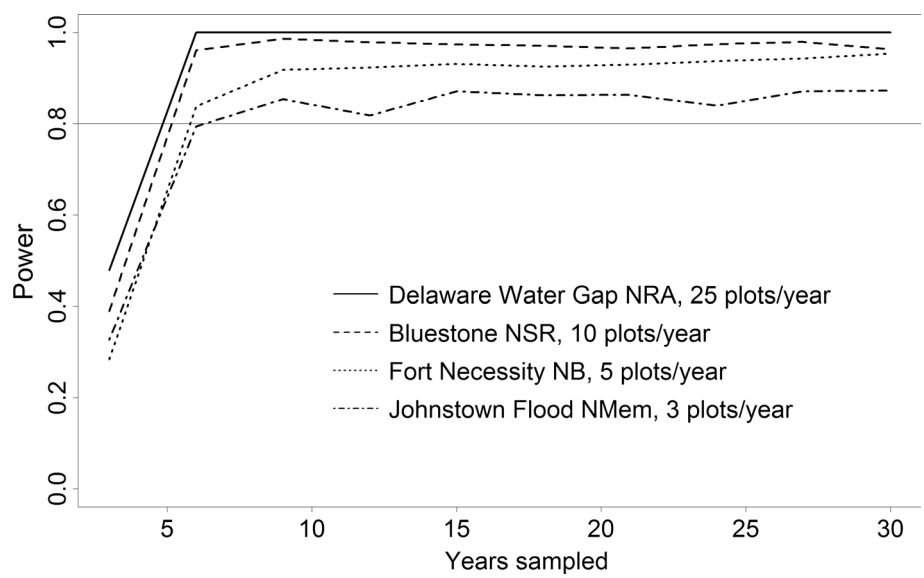

Fig. 4 Power to detect 1 % trend per year in live tree basal area as simulated using different sample sizes for different parks

monitoring program, it was decided a priori that the ability to detect a linear trend when it was, in fact, present with a high level of confidence was important in order to identify changes in forest structure relatively early on in the progression of change. Our analysis suggests that this is possible for many indicators given the present sample size, type-I error rate, the underlying variance structure, and the statistical models use to assess trends. For those indicators with what we define as low power (<0.80), they can be re-evaluated in terms of their importance to retain within the monitoring program, or the type-I error rate could be increased if managers decide that failing to detect a real trend is deemed more important than detecting a false trend. In addition, although more difficult logistically to implement, we could use what we have learned about how total variance is partitioned for these "low power" indicators and modify the sampling design in such a way to reduce certain sources of variation. In our case, the primary source of variation for "low power" indicators was spatial variability. Therefore, additional sites could be added or a spatial stratification scheme could be implemented (e.g., develop a landscape-based classification scheme that groups similar plots and then look for trend within those vegetation classes).

These power estimates were "best case scenarios," since the estimates of coherent temporal variation and estimates of trend variation were likely underestimated based on only 4–5 years of data. If the true value of coherent temporal variation is much larger than the values used in the simulations (resulting in a lower proportion of the total variation

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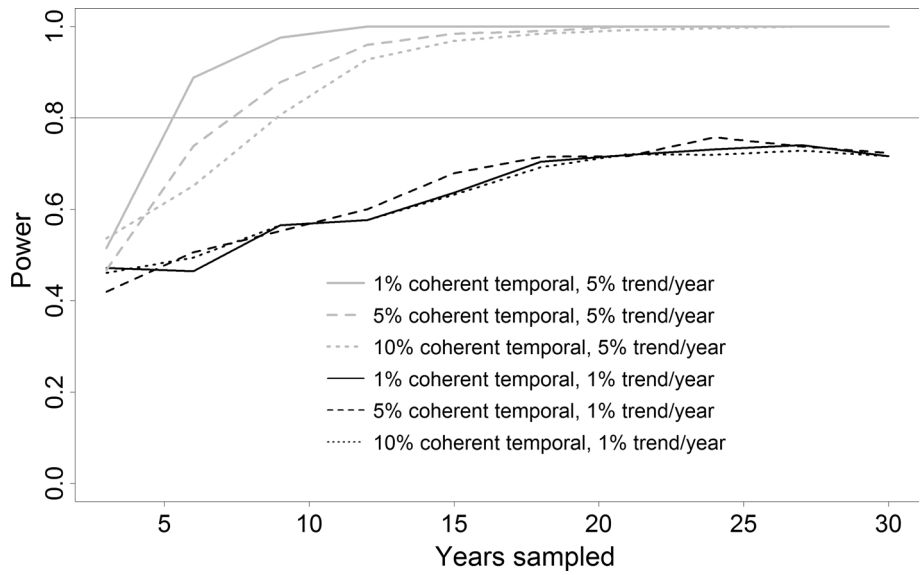

Fig. 5 Power to detect 1 and 5 % trend per year in coarse woody debris volume with coherent temporal variance set at 1, 5, and 10 % of the total variance

being spatial), then actual power would be expected to be lower than reported here. A larger dataset spanning more years (e.g., in 2016 after all plots have been sampled twice) would improve estimability of components of variance and thus power estimates. Although the power curves reported here are potentially overly optimistic, they suggest that the current sampling design is meeting the program's objectives of detecting a 20 % change in key parameters over five or ten years (Perles et al. 2014).

An important caveat is that most power simulations presented here are based on variance components calculated from data collected only in one park (Delaware Water Gap NRA), primarily because the sampling design employed in that park provided the kinds of data necessary to calculate all of the components of variance. From a broad perspective (i.e., comparing ERMN forests to forests nationwide), Delaware Water Gap NRA forests are relatively similar to forests in the other ERMN parks. However, there are important differences among park forests that are influenced by geology, topography, land-use history, distribution of forest pests, etc. These park-specific differences may influence the power of the sampling design in ways not captured by this analysis.

In addition, it is important to view the results of the power analyses within the context of the management objective, which was to detect linear (monotonic) change in forest indicators over time. Although it was appropriate in this case to evaluate the power to detect linear trends, because it linked the value-based management objective to the statistically based monitoring objective (Wagner et al. 2013), it may not adequately represent the ability to detect nonlinear changes, such as abrupt shifts in forest conditions. In fact, it has been proposed that rapid changes in system state, including forest ecosystems, may occur if thresholds are exceeded (Peters et al. 2004). This is of particular concern in the face of a changing climate where temperature or moisture thresholds may be exceeded for forest ecosystems (Burkett et al. 2005). As such, if the objective of a forest monitoring program is to detect nonlinear changes or abrupt shifts in system state over time, the results of this power analysis may not be particularly relevant, and new analyses should be performed based on specific monitoring objectives. Even so, partitioning variance into its component sources, as was done here, may be a useful tool to consider when attempting to quantify system responses to large perturbation, even if management objectives are not focused on linear trend detection.

For the metrics examined here, total variance appeared more influential in determining power than the structure of the variance components. Similarly, Stow et al. (1998) found total variance to be one of the primary factors affecting the ability to detect trends. Indicators that measure the proportion of a total (i.e., species richness or percent cover) yielded much higher power than indicators that measure absolute or average values, since using the proportion reduces the variability in cover measurements caused by yearly weather patterns and different observers.

The analyses also indicated that the connected panel design does not provide substantial additional power over the simple panel design but would likely incur additional sampling cost. Similarly, Urquhart et al. (1993) found that a connected panel design had the greatest benefit to trend detection within the first four years of sampling with negligible benefit after eight years.

These results provided crucial guidance for the ERMN and other regional forest monitoring programs by identifying the sensitivity of key forest indicators to temporal trend detection. These analyses also offered essential

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information on the time required to detect temporal trends in important forest indicators. Both sets of information are critical to the development and successful implementation of long-term regional monitoring programs.

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