Transactions of the American Fisheries Society 138:38–51, 2009

DOI: 10.1577/T07-154.1

[Article]

Temporal Variation in Trout Populations: Implications for Monitoring and Trend Detection

DANIEL C. DAUWALTER*[1] AND FRANK J. RAHEL

Department of Zoology and Physiology, University of Wyoming, Laramie, Wyoming 82071, USA

KENNETH G. GEROW

Department of Statistics, University of Wyoming, Laramie, Wyoming 82071, USA

Abstract.—We summarized the temporal variation in populations of inland trout *Salmo*, *Salvelinus*, and *Oncorhynchus* spp. from streams in North America and determined the statistical power to detect trends over time. The coefficients of variation in abundance averaged 49% (SD = 27%; range = 15–108%) over time for all ages of trout. Temporal variation was lower when more age-classes were monitored, but whether abundance or biomass was more variable differed among populations. Detecting population trends was difficult when using the traditional $\alpha = 0.05$ criterion. For example, detecting a 5% annual decline with good power ($1 - \beta \geq 0.80$) would require about 20 years if only one site were monitored. Even when α was relaxed to 0.20, 15 years were required to detect a 5% annual decline when the variation was average. Using a network of sites improved the ability to detect changes: a 5% annual decline at $\alpha = 0.05$ could be detected in 10 years when 30 sites were monitored. For high-value populations, it may require relaxing α to ensure that declines are detected, even if this increases the risk of claiming change when none has occurred and thus undertaking unnecessary management action. For example, a 5% annual decline could be detected with good power ($\geq$0.80) in 8 years when a network of 30 sites is monitored at $\alpha = 0.20$. Thus, biologists should monitor the least-variable component of a population, monitor a network of sites, and increase α for species of concern to ensure that real population trends are detected. Estimates of trend parameters (and their uncertainty) should be considered in addition to whether or not a statistical test for trend is significant. A pilot study or existing data can help estimate the variation that is typical of the population(s) to be monitored, determine whether trends can be reliably detected, and identify how much risk needs to be incurred to detect trends.

Fisheries biologists often implement monitoring programs to detect trends in fish populations and habitat conditions (Firman and Jacobs 2001; Larsen et al. 2004; Wagner et al. 2007). Monitoring can be conducted at a single location to examine local populations or at multiple locations to assess regional trends (Larsen et al. 2001). For example, Lyons et al. (1996) monitored one site on each of several Wisconsin rivers to evaluate the effect of a minimum length limit on the abundance and size structure of smallmouth bass *Micropterus dolomieu* in each river. The Oregon Department of Fish and Wildlife monitors stream habitat, spawning salmon, and juvenile salmon at a network of sites to make inferences regarding regional trends in stream habitat and salmon populations (Urquhart and Kincaid 1999; Firman and Jacobs 2001).

The temporal variation in fish population abundance is higher than that in many plant and animal populations that represent a variety of life history strategies (Gibbs et al. 1998). Natural population variation, sampling error, and sampling variation determine the amount of temporal variation observed. Natural variation results from environmental and demographic stochasticity. Although natural variation cannot be controlled, efforts should be made to reduce sampling error and sampling variation (Sulkava et al. 2007). Sampling error results from having to estimate the number or biomass of fish in a stream reach with methods, such as electrofishing, that are not 100% efficient (Link and Nichols 1994). Sampling error can be reduced by using a more efficient sampling gear, sampling more intensively, or using a more precise abundance estimator (Seber 1982; Riley and Fausch 1992; Bailey 2005). Sampling variation is caused by sampling a population at a different time each year or, for populations that are at a different point in an annual cycle when they are sampled (such as spawning, the timing of which can change from year to year), even by sampling at the same time each year. Sampling variation can be reduced by shortening the time window during which populations are sampled each year or by scheduling annual sampling to match an annual population cycle (Larsen et al. 2001).

Temporal variation that occurs even when habitat

---

* Corresponding author: ddauwalter@tu.org

[1] Present address: Trout Unlimited, 910 Main Street, Suite 342, Boise, Idaho 83702, USA.

Received July 20, 2007; accepted August 25, 2008

remains unchanged can limit the usefulness of habitat models for predicting fish abundance or biomass (Platts and Nelson 1988) and can mask the effects of land management activities on trout populations (House 1995). Natural variation in trout abundance may also prohibit detection of population declines before they reach harmful or irreversible levels (Ham and Pearsons 2000).

Although temporal variation can limit the statistical power to detect population trends, it is only one factor that influences power (Gerow 2007). Statistical power ($1 - \beta$, where β is type II error) also depends on sample size, the rate of change, and the error rate with which false changes are detected (α, known as the type I error rate; Gerrodette 1987; Peterman 1990). When a single site is monitored, sample size is the number of visits to that site across years. When multiple sites are monitored, sample size has two dimensions: the number of sites monitored and the number of revisits to those sites across years. Although larger sample sizes increase the statistical power to detect trends, fisheries managers typically face logistic and fiscal constraints in how many sites can be sampled. Type I and II error rates are chosen by managers according to the risks they are willing to accept while monitoring (Eberhardt 1978). For example, managers might choose to live with an increased type I error rate if it is critical to detect early declines in species of conservation concern (Gryska et al. 1997).

Other factors also affect the statistical power to detect population trends, though to a lesser extent. For example, there is typically more power to detect decreasing trends than increasing ones when other factors remain constant (Gerrodette 1987; Gerow 2007). Declines have been defined as the trend most often of interest for species conservation (Gibbs et al. 1998), but documenting increases in the abundance of invasive trout, for example, may also be of interest (Peterson et al. 2004).

We used published estimates of the annual abundance and biomass for North American stream-resident trout populations to evaluate population variability over time and estimate the power to detect population trends. Specifically, our objectives were to quantify the variation in abundance and biomass over time in trout populations, using the coefficient of variation in abundance or biomass; determine how that variation influences detection of population trends over time; and discuss the options managers and researchers have when designing a monitoring program. To meet these objectives, we used data on trout populations from eight studies representing 22 streams (Appendix). These studies ranged geographically from Oregon to Pennsylvania and had from 3 to 21 consecutive years of population data for brook trout *Salvelinus fontinalis*, brown trout *Salmo trutta*, bull trout *Salvelinus confluentus*, cutthroat trout *Oncorhynchus clarkii*, or rainbow trout *O. mykiss*. Three of the 22 streams had 3 years of data and the rest had 4 or more years of data.

Methods

Population Variability

For each stream we computed the temporal variation in abundance and biomass over time for all age-classes and trout species (including all ages and species combined) at each stream site. Variation was characterized as the coefficient of variation [CV, defined as (SD/mean) × 100] of abundance or biomass estimates among years. The CV is commonly used to summarize temporal variation in animal populations (Grossman et al. 1990; Gaston and McArdle 1994; Gibbs et al. 1998). We removed any variation due to trend only when the authors of a study suggested that there was a trend in their data. When the authors suggested there was a trend, we used the root mean square error from a regression of abundance versus year as the variance when computing SD. We did not test for trend in each population because of the low power to detect it in most data sets, and arbitrarily removing variation when no trend was present might remove variation that is real. Therefore, we consider our estimates of variation to be conservative.

Power to Detect Trends

Trend model.—We determined the statistical power to detect trends in abundance and biomass at single sites and across a monitoring network of sites. We used an exponential growth model in which the change in the population is proportional to the abundance (or biomass) during the previous time period (Gerrodette 1987), that is,

$$N_t = N_1(1 - r)^{t-1}$$

where N_t is the abundance at time t, N_1 is the initial abundance, and r is the rate of change. This model has the slope parameter (Gerrodette 1987)

$$\beta = \log_e(1 + r),$$

which is estimated by using least-squares regression,

$$\log_e(N_t) = \alpha + \beta t + \varepsilon,$$

where the errors are identically and independently distributed. The antilog of the slope estimate represents the fraction of the population at time t that is present at time $t + 1$. This $\log_e$-linear model is biologically more realistic than an additive model and stabilizes error variances (Thompson et al. 1998). We restricted our

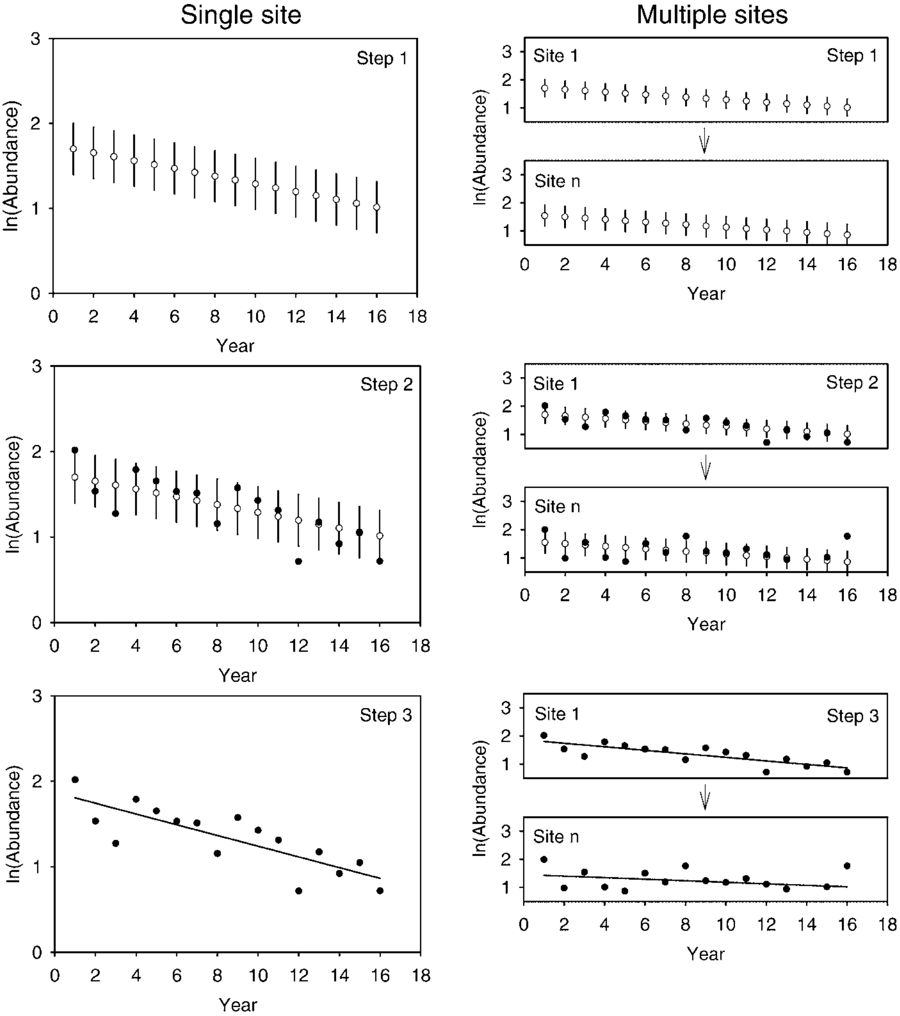

FIGURE 1.—Steps in simulating the statistical power of a monitoring program to detect trends in trout abundance at a single site or a network of multiple sites. In step 1, a declining trend was projected onto an initial abundance estimate for a site for the projected time frame of monitoring. For each year, open circles represent the mean abundance and lines represent one standard deviation. In step 2, random variation was added to the abundance estimate for each year (closed circles) by using a random deviate from a normal distribution with the mean equal to the projected abundance and the standard deviation approximated for the initial abundance estimate. In step 3, the slope of the least-squares regression line was estimated for each site. For single sites, we determined whether the slope was different from zero. For multiple sites, we determined whether the arithmetic mean slope among sites was different from zero. We repeated each step 1,000 times; the proportion of times a slope was different from zero represents the statistical power and assesses how often known trends are detected amid simulated variation. The figure was adapted from Gibbs (1998).

analysis to linear trends (on a $\log_e$ scale) because such trends will be present if there is a monotonic increase or decrease in the population (Urquhart and Kincaid 1999).

Simulating statistical power.—We estimated statistical power for both a single site and a network of sites using Monte Carlo simulation (Figure 1; Manly 1997; Gibbs 2000), as recommended by Link and Hatfield (1990). A deterministic trend was projected onto an initial abundance (or biomass) estimate over a specified time period for a site, after which random variation was added to each estimate per time period. Trends were then estimated by using linear least-squares regression (Draper and Smith 1966). For a single site, we determined whether the slope was different from zero (H_0: $\hat{b} = 0$) using a t-test (Zar 1999). For multiple sites, we again used a t-test (Zar 1999) to determine whether the arithmetic mean slope across sites was different from zero (H_0: $\hat{b} = 0$). This process was simulated 1,000 times, and the proportion of times the known trends were detected amid simulated variation was the estimate of power.

Population trends at a single site.—We used the Web-based version 7.0 of Program Monitor (based on version 6.2; Gibbs 1995), to estimate the power to detect population trends at a single site sampled every year. Program Monitor simulates statistical power as outlined above. We calculated the power to detect 2.5% and 5% annual declines over time periods of 5–25 years for a range of CVs that are realistic for the temporal variation in either abundance or biomass. We tested whether there was a significant declining trend—the trend most often of interest (Gibbs et al. 1998)—for each of 1,000 simulations. We repeated the analysis, using type I error rates of 0.05, 0.10, and 0.20.

We also determined our ability to detect trends in populations of different trout species that were known to be changing at a single site. Waters (1999) monitored trout populations in Valley Creek, Minnesota, over a period of 21 years from 1965 to 1986. Brook trout were always present. Rainbow trout became a significant member of the trout assemblage in 1971, as did brown trout in 1973. During the study, brook trout abundance and biomass decreased, whereas the abundance and biomass of brown trout increased. Rainbow trout abundance and biomass showed no consistent change. Given the observed population variability during the study, we wanted to know at what point a monitoring program would have detected changes in the abundance or biomass of each species. We estimated whether a statistically significant trend was evident in each trout population and for all trout species combined for increasing periods of time. This equated to time periods of 3–22 years for brook trout, 3–16 years for rainbow trout, and 3–14 years for brown trout. For each time period, we determined whether the estimated change in each population as estimated by the slope parameter was significantly different from zero, based on $\alpha = 0.10$.

Population trends at a network of sites.—We estimated the statistical power to detect trends in trout populations across a monitoring network of sites on the Medicine Bow National Forest, Wyoming. The managers at the forest are required to monitor all trout species (brook trout, brown trout, and rainbow trout) collectively as an indicator of the effects of forest management on aquatic ecosystems. A monitoring protocol has been developed that specifies an “always revisit” design (Urquhart and Kincaid 1999), where the same 30 sites are sampled every other year (2-year sampling interval) for up to 30 years (Eaglin et al. 2007). During each sampling period the biomass of all trout at each site is estimated within a 150-m reach by using depletion removal methods (Zippin 1958). We used Monte Carlo simulations within SAS version 9.1 (Statistical Analysis System, Inc., Cary, North Carolina) to estimate statistical power as described above. Estimates of biomass for the initial time period were simulated for the 30 sites using a $\log_e$ normal distribution ($\log_e$ normal mean = 79.3 kg/ha, SD = 2.9 kg/ha); this spatial distribution of biomass was based on trout population data (brook trout, brown trout, and rainbow trout combined) collected from streams on the Medicine Bow National Forest. Temporal variation for a site was determined from a $\log_e$ normal distribution of CVs defined on the basis of data from our literature search ($\log_e$ normal mean CV = 54%, SD = 2.1%). Power to detect trends was determined for different combinations of sites (2–30 sites) and years (5–30 years) for 2.5% and 5% annual declines at $\alpha = 0.05$, 0.10, and 0.20. Each combination of sites and years was simulated 1,000 times.

Results

Population Variability

Individual trout populations exhibited a wide range of temporal variation in abundance and biomass (Table 1). Coefficients of variation in abundance averaged 49% (SD = 27%) for all ages and trout species, and ranged from 15% for all ages of brook trout in Lawrence Creek, Wisconsin, to 108% for all ages of rainbow trout in Tabor Creek, Nevada. The coefficients of variation in biomass averaged 46% (SD = 25%), being lowest for all ages of brook trout in Lawrence Creek, Wisconsin (CV = 12%) and highest for all ages of brook trout in Otter Creek, Utah (CV = 125%). There was considerably less variation in abundance when multiple age-classes were monitored together than when only a single age-class was monitored (Figure 2, top panel). Abundance was more variable than biomass for bull trout, whereas biomass varied more in brook trout (Figure 2, middle and bottom panels). Each species, however, showed considerable variability among populations as to whether abundance or biomass was more variable (Table 1).

Power to Detect Trends

Single sites.—The power to detect a decline in abundance or biomass at a single site increased the longer a population was monitored or as the CV in abundance or biomass decreased (Figure 3). In general, however, there was low power to detect changes amid variation typical of trout populations unless a site was monitored for a long period of time. For example, detecting a 5% annual decline with a power of at least 0.80 would require about 20 years of data with a CV of

TABLE 1.—Coefficients of variation (CVs) for the abundance and biomass of trout species over time. Data for all species combined are presented when more than one species was reported per stream.

Species	Stream (years of data)	Age(s)	CV		Source
			Abundance	Biomass	
Brook trout	Bear Valley Creek, Idaho (5)	All	17	45	Platts and Nelson (1988)
	Colorado Creek, Colorado (8)	1	48		Gowan and Fausch (1996)
		≥1	28		
		≥2	28		
	Frenchman Creek, Idaho (8)	All	18	43	Platts and Nelson (1988)
	Horton Creek, Idaho (7)	All	48	81	Platts and Nelson (1988)
	Jack Creek, Colorado (7)	1	72		Gowan and Fausch (1996)
		≥1	25		
		≥2	32		
	Johnson Creek, Idaho (9)	All	34	28	Platts and Nelson (1988)
	Lawrence Creek, Wisconsin (11)	0	24	24	Hunt (1974)
		1	24	22	
		≥1	22	18	
		2	56	51	
		3	72	66	
		≥4	87	77	
		All	15	12	
	North Fork Poudre River, Colorado (8)	1	80		Gowan and Fausch (1996)
		≥1	23		
		≥2	24		
	Otter Creek, Utah[a] (3)	All	52	125	Platts and Nelson (1988)
	South St. Vrain Creek, Colorado (8)	1	61		Gowan and Fausch (1996)
		≥1	36		
		≥2	46		
	Valley Creek, Minnesota (21)	All	82[b]	52[b]	Waters (1999)
	Walton Creek, Colorado (7)	1	41		Gowan and Fausch (1996)
		≥1	22		
		≥2	26		
Brown trout	Little Beaver Creek, Colorado (8)	1	82		Gowan and Fausch (1996)
		≥1	23		
		≥2	15		
	Otter Creek, Utah[a] (5)	All	75	57	Platts and Nelson (1988)
	South St. Vrain Creek, Colorado (8)	1	49		Gowan and Fausch (1996)
		≥1	18		
		≥2	17		
	Spruce Creek, Pennsylvania (19)	1	35		Carline (2006)
		≥1	23		
		≥2	30		
	Valley Creek, Minnesota (21)	All	39[b]	19[b]	Waters (1999)
Bull trout	Bear Valley Creek, Idaho (5)	All	85	23	Platts and Nelson (1988)
	South Fork Salmon River, Idaho (11)	All	79	39	Platts and Nelson (1988)
	Yakima River tributaries, Washington (3)	All[c]	87		Ham and Pearsons (2000)
Cutthroat trout	Chimney Creek, Nevada (4)	All	61	45	Platts and Nelson (1988)
	Dead Horse Canyon Creek, Oregon (11)	0	47		House (1995)
		1	27		
		≥1	27		
		≥2	40		
		All	24		
	Gance Creek, Nevada (8)	All	75	53	Platts and Nelson (1988)
	Upper Big Creek, Utah (3)	All	64	29	Platts and Nelson (1988)
	Yakima River tributaries, Washington (9)	All[c]	65		Ham and Pearsons (2000)
Rainbow trout	Bear Valley Creek, Idaho (5)	All	81	39	Platts and Nelson (1988)
	Coweeta Creek, North Carolina, site 1 (4)	0	80		Freeman et al. (1988)
		All	78		
	Ball Creek, North Carolina, site 2 (4)	0	67		Freeman et al. (1988)
		All	56		
	Ball Creek, North Carolina, site 3 (4)	0	61		Freeman et al. (1988)
		All	29		
	Johnson Creek, Idaho (9)	All	97	37	Platts and Nelson (1988)
	Otter Creek, Utah[a] (5)	All	72	51	Platts and Nelson (1988)
	South St. Vrain Creek, Colorado (8)	1	71		Gowan and Fausch (1996)
		≥1	25		
		≥2	31		
	Tabor Creek, Nevada[a] (6)	All	108	55	Platts and Nelson (1988)
	Upper Big Creek, Utah[a] (3)	All	70	68	Platts and Nelson (1988)
	Valley Creek, Minnesota (21)	All	54	56	Waters (1999)
	Yakima River tributaries, Washington (9)	All[c]	29		Ham and Pearsons (2000)

TABLE 1.—Continued.

			CV		
Species	Stream (years of data)	Age(s)	Abundance	Biomass	Source
	Yakima River main stem, Washington (8)	All[c]	26		Ham and Pearsons (2000)
All	Bear Valley Creek, Idaho (5)	All	27	37	Platts and Nelson (1988)
	Johnson Creek, Idaho (9)	All	35	36	Platts and Nelson (1988)
	Otter Creek, Utah[a] (5)	All	69	50	Platts and Nelson (1988)
	South St. Vrain Creek, Colorado (8)	1	36		Gowan and Fausch (1996)
		≥ 1	15		
		≥ 2	23		
	Upper Big Creek, Utah[a] (3)	All	36	16	Platts and Nelson (1988)
	Valley Creek, Minnesota (21)	All	40	19[b]	Waters (1999)
Mean		All or ≥ 1	49	46	

[a] Supplemental stockings.

[b] Trend removed; variance used in the CV calculated as the root mean square error from the regression of abundance or biomass on year (Gibbs et al. 1998).

[c] Age-groups not reported; all age-groups were assumed.

50% at $\alpha = 0.05$ (Figure 3A). Even when α was relaxed to 0.20, detecting a 5% annual decline would still require 15 years of monitoring with a CV of 50% (Figure 3E). To detect a lower rate of annual decline (e.g., 2.5% versus 5%) at the same level of power would require even longer time periods for a given α level (Figure 3B, D, F).

The analysis of trout populations in Valley Creek further illustrates how population variability influences the length of time needed to detect trends. Trends were more precisely estimated (i.e., confidence intervals decreased) with the passage of time for all species because more years of data were available to estimate trend, but it took longer to detect the decline in the more variable brook trout population (CV abundance = 82%) than to detect the increase in the less variable brown trout population (CV abundance = 39%; Figure 4). It would have taken 16 years (from 1965 to 1981) to detect the decline in brook trout abundance and 14 years (from 1965 to 1979) to detect the decline in biomass based on the point at which the confidence interval for the slope did not include zero. However, the increases in brown trout abundance and biomass were detectable after a minimum of 3 years of data were available to estimate the precision of percent annual change in the population. Interestingly, an increase in biomass of brook trout would have been found after the first 5 years of monitoring preceding the long-term population decline. Rainbow trout abundance and biomass also would have shown an increase from 1971 to 1976, but there was no trend across the complete period of monitoring. Collectively monitoring all trout together would have shown no trend in abundance but would have detected a 10% annual increase in biomass (i.e., slope = 0.1; Figure 4).

Network of sites.—The ability to detect declines in trout populations across a network of sites in Medicine Bow National Forest increased with the number of sites being monitored and with the length of time that sites were monitored (Figure 5). The time needed to detect a 5.0% annual decline with good power (≥ 0.80) at $\alpha = 0.05$ decreased from greater than 30 years when only two sites were monitored, to 17 years when 10 sites were monitored, to 10 years when 30 sites were monitored (Figure 5A). To detect a smaller decline required a longer time period. For example, 19 years were required to detect a 2.5% annual decline, whereas only 10 years were required to detect a 5.0% annual decline with a power of 0.80 when monitoring 30 sites at $\alpha = 0.05$ (Figure 5B versus Figure 5A). For most combinations of α and percent decline, adding up to 10 sites quickly improved statistical power to detect trends, but monitoring more than 25 sites resulted in only small increases in power. Interestingly, increasing α improved the ability to detect a decline. For example, the time needed to detect a 2.5% decline with a power of 0.80 when monitoring 30 sites was 19 years for $\alpha = 0.05$ but only 14 years for $\alpha = 0.20$ (Figure 5B versus 5F).

Discussion

Fluctuations in the abundance or biomass of trout over time are a management concern because they can mask population changes due to habitat degradation, habitat manipulations, or changes in management actions such as harvest regulations (Platts and Nelson 1988; Milner et al. 1993). We found that the CVs in abundance for North American inland trout populations averaged 49% and ranged from 15% to 108%. Population trends can be detected at a single site but

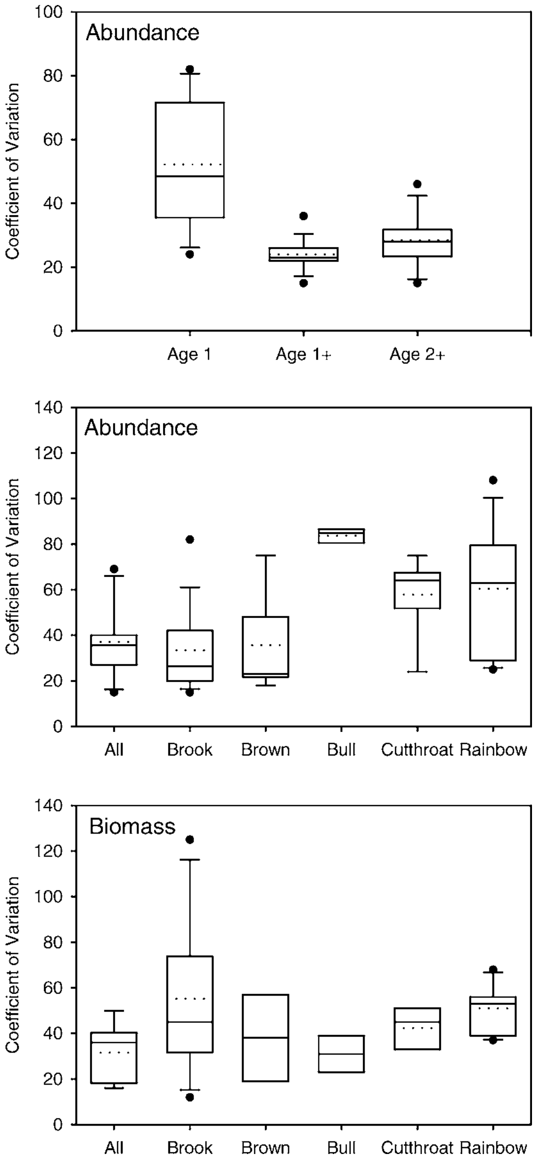

FIGURE 2.—Box plots of the coefficients of variation (CVs) in trout abundance or biomass among ages and species. The CVs for different ages were computed by using the abundance of all trout species combined (top panel). Age 1+ refers to age 1 and older; age 2+ refers to age 2 and older. The CVs for different species were computed for all ages combined for both abundance (middle panel) and biomass (bottom panel). In each panel, the solid line represents the median, the dotted line the mean, the box dimensions the 25th and 75th percentiles, the whiskers the 10th and 90th percentiles, and the dots outliers.

only after 10 years and only at very low levels of population variation. In most cases, managers will want to detect changes in less than 10 years (Marsh and Trenham 2008). To do so, managers should design their monitoring program to maximize the statistical power to detect trends at acceptable levels of risk in making a type I error.

One way to maximize power is to monitor the population characteristic that is least variable. For example, the variability in abundance was lowest when many age-classes were monitored as opposed to one or a few age-classes. Monitoring more age-classes dampens annual differences in reproductive success and recruitment because one age-class is a smaller fraction of all individuals being monitored. Variable recruitment may result in compensatory survival of other age-classes due to food or space limitation. Cattanéo et al. (2002) found that the density of age-1 brown trout in French streams was influenced by competition among age-0 brown trout the previous year. These intraspecific interactions can cause populations to self-thin (Dunham and Vinyard 1997) and lead to the overall abundance's being more stable than those of individual age-classes. The relative variation between abundance and biomass can differ among populations and species, and managers can monitor the parameter that is less variable. However, monitoring objectives will dictate the characteristic of a population to be monitored. For example, monitoring the effects of a fishing regulation often requires monitoring only the abundance of harvestable-sized individuals.

The data we assembled did not allow us to determine whether including age-0 fish would increase or decrease the variability in abundance or biomass over time. However, biologists often exclude age-0 fish from population analyses because their abundance can be highly variable as a result of variation in spawning success and high mortality rates and because of the difficulty in sampling them (Yant et al. 1984; Thompson and Rahel 1996).

Another way to increase the statistical power to detect trends is by increasing the number of monitoring sites. The increase in power observed by adding sites to a monitoring network was high when the initial number of sites was low, but the increase in power was small beyond about 25 sites. The positive relationship between sample size and power is well-known (Gerrodette 1987), but sites must be analyzed collectively (i.e., by determining the mean slope across sites) for this effect on power to be realized. A collective analysis also increases the scope for inference beyond the spatial location of the monitoring sites. Inference regarding trend is extendable to the sample frame (e.g., national forest) if the sample of monitoring sites was

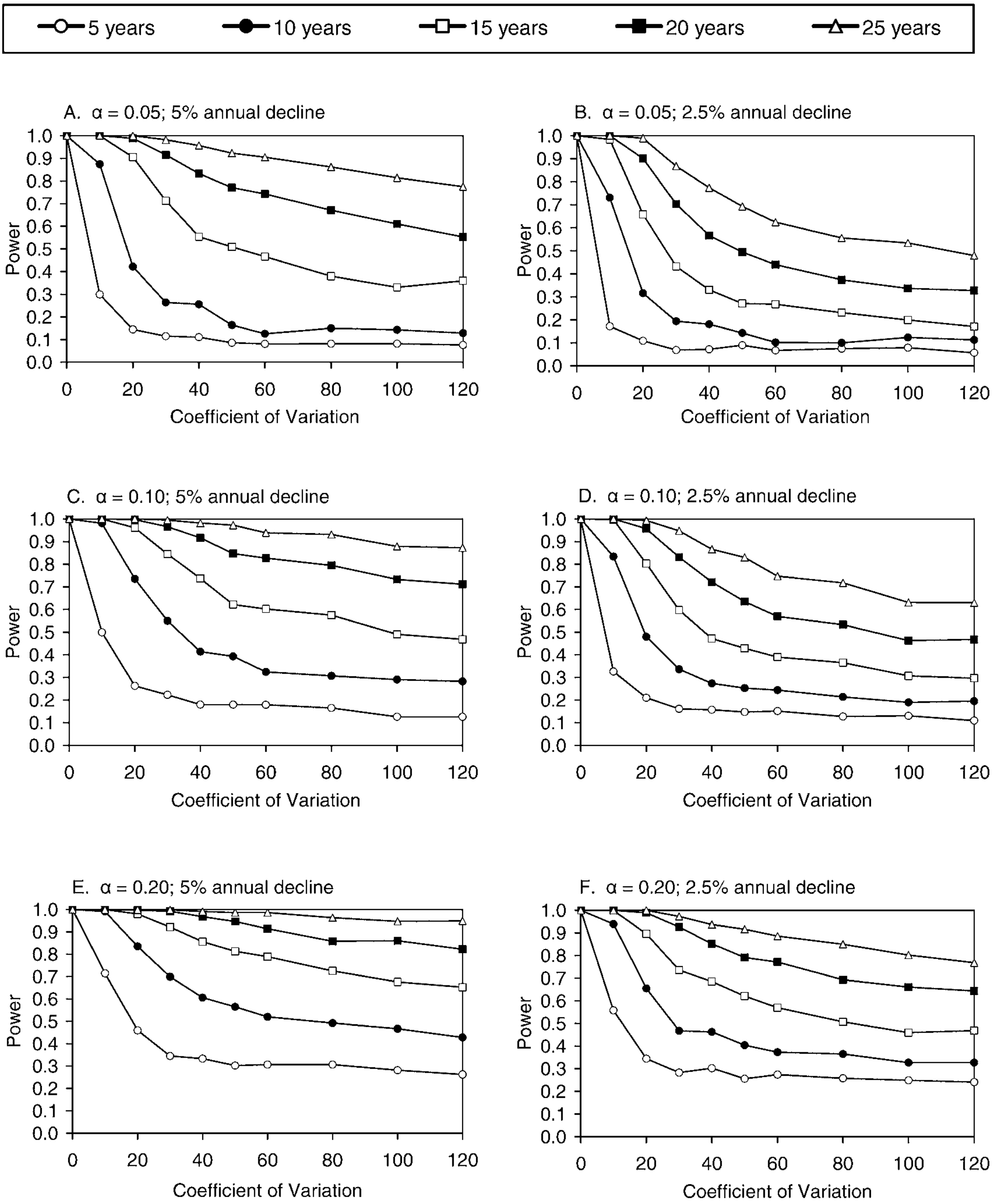

FIGURE 3.—Simulated power (1 – β) to detect annual declines of 2.5% and 5% in the abundance or biomass of a trout population after 5–25 years, given the temporal variation in the population parameter represented by the coefficient of variation and the type I error rate (α). The comparisons across rows show the effect of decreasing the magnitude of the annual decline from 5% to 2.5%; the comparisons down columns show the effect of increasing α from 0.05 to 0.10 and 0.20.

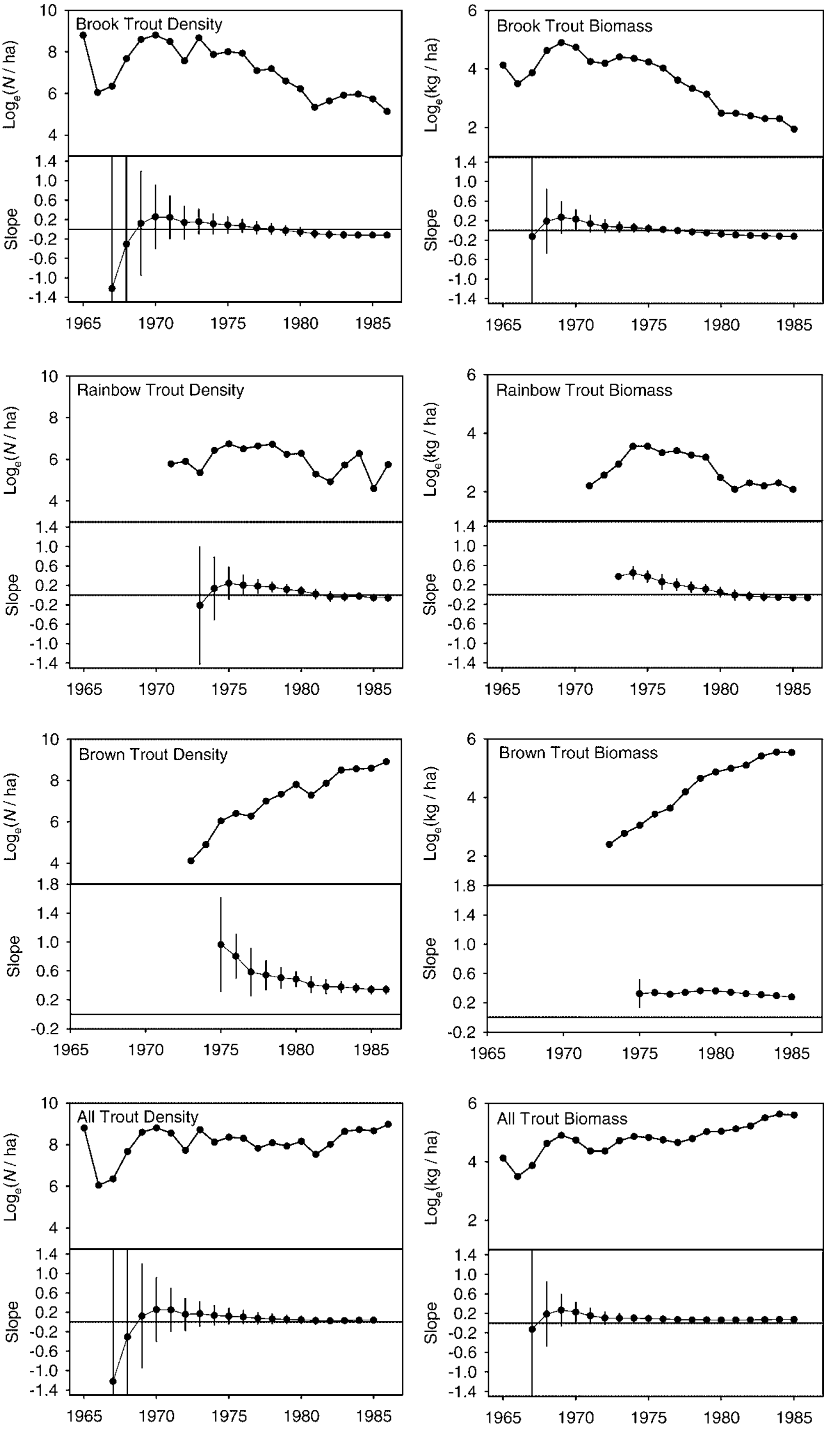

FIGURE 4.—Density or biomass of brook trout, rainbow trout, brown trout, and all trout in Valley Creek, Minnesota, from 1965 to 1986 (top halves of panels; data from Waters 1999) and slope estimates (with 90% error bars) from a regression of $\log_e$(density or biomass) on year for each year (bottom halves of panels). Each regression includes data from all prior years.

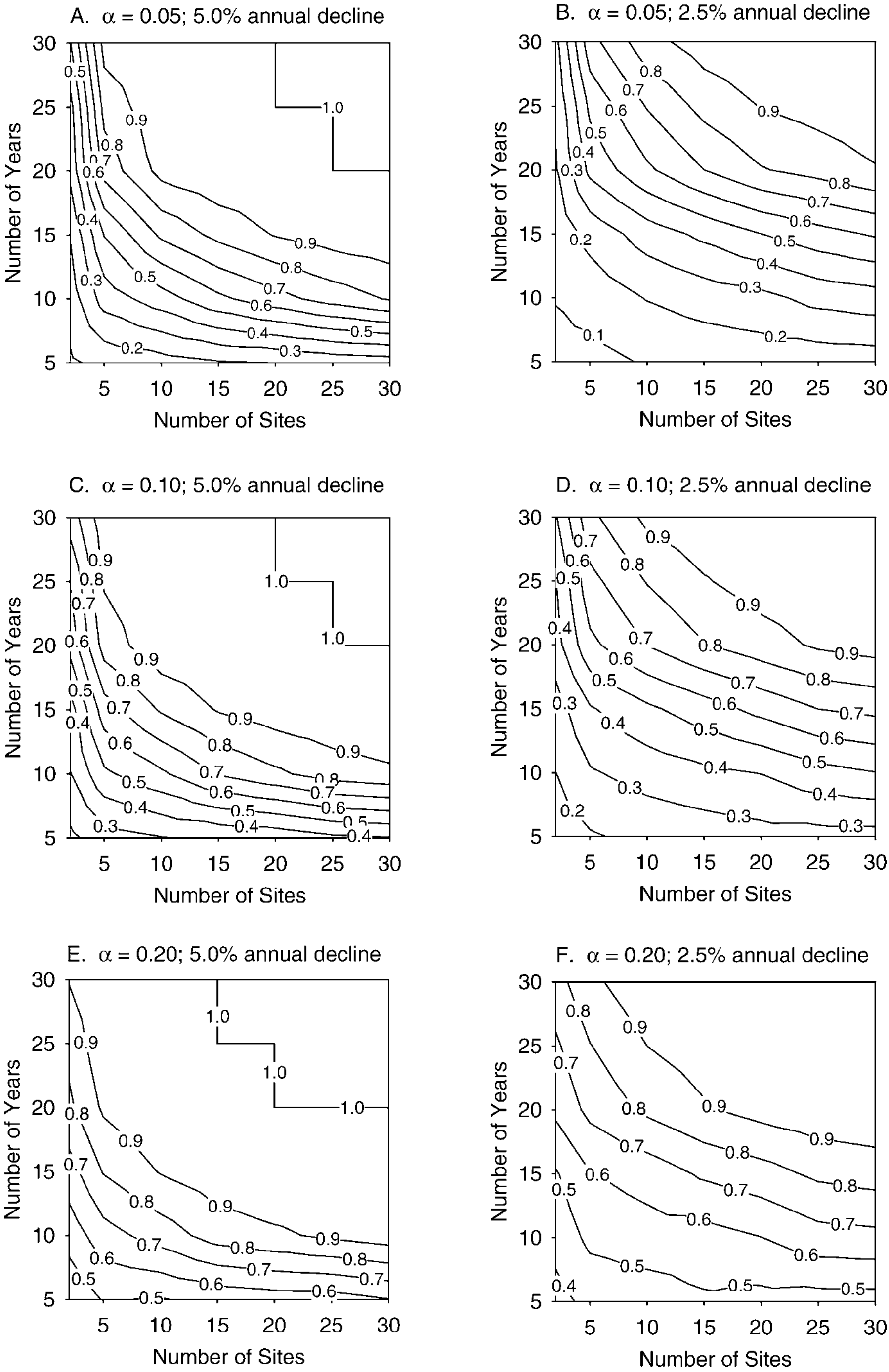

FIGURE 5.—Isopleths of simulated power (1 – β) to detect annual declines in the biomass of trout in streams of the Medicine Bow National Forest, Wyoming, when the number of sites and number of years monitored is varied. The mean temporal variation (CV) used in the simulations was 54%. The comparisons across rows show the effect of reducing the annual rate of decline from 5.0% to 2.5%; the comparisons down columns show the effect of increasing the type I error rate (α) from 0.05 to 0.10 and 0.20.

selected by an unbiased process such as random site selection. This practice is important because many land management agencies, such as the U.S. Forest Service, are required to monitor regionwide population trends to determine the impacts of land management and guide forest planning (U.S. Forest Service 2005; Vesely et al. 2006). The overall analysis can be broken down post hoc to determine where changes have occurred; post hoc analysis also can direct investigations to determine the cause(s) of change so that decisions can be made regarding appropriate management action. However, this can be successful only for monitoring designs that specify revisits to every site in the monitoring network. Designs that specify revisits have the highest statistical power to detect trends (Urquhart et al. 1998; Urquhart and Kincaid 1999; Quist et al. 2006).

A pilot study is important in designing a long-term monitoring plan (Noble et al. 2007). It can help determine the population parameter (abundance or biomass) to monitor and estimate the amount variation anticipated to be observed. These estimates of variation can be used to determine the sample sizes necessary to detect certain levels of change and to decide whether a monitoring program can detect target levels of change within a specific amount of time. However, pilot data will yield only estimates of variation (Sims et al. 2007). Carey and Keough (2002) found that pilot data can yield variance estimates that differ from estimates based on more comprehensive data by 50% or more and thus result in the design of monitoring programs with sample sizes that are insufficient. This uncertainty in the variance estimate can be used to determine the uncertainty associated with estimates of power (Taylor and Muller 1995).

We used a null-hypothesis-testing framework to evaluate the effect of temporal population variability on the power to detect trends. In addition to determining whether the null hypothesis of no trend is rejected, managers should consider the confidence interval around the trend estimate (Johnson 1999). For example, the null hypothesis might be rejected because the confidence interval around the trend estimate is small (indicating high power), but the trend might be biologically unimportant. In other cases, the null hypothesis may not be rejected because the confidence interval is large and includes zero; this indicates low power, but performing a post hoc power analysis is problematic (Hoenig and Heisey 2001). Here, the confidence interval might barely contain zero. This indicates some chance of no trend, but there is also a good chance that the trend may be very large (positive or negative) and biologically important (Thompson et al. 1998). Proactive management could be implemented in this situation to slow or reverse the probable population decline just in case a large decline is imminent. Regardless, managers need to be cautious when confidence intervals are wide and the null hypothesis of no trend is not rejected because there may be large population trends even when the statistical power is insufficient to detect them (Johnson 1999; McBride 2002). This is why the trend parameter estimate, and its uncertainty, should be evaluated regardless of whether or not the statistical null hypothesis of no trend is rejected, as advocated by Johnson (1999).

Detecting initial declines in fish populations can be important in preventing large changes that may be irreversible. However, some studies have suggested that interannual variation in abundance of trout populations makes it difficult to detect small amounts of population change over short periods of time (Platts and Nelson 1988; Ham and Pearsons 2000). Our results support this conclusion, but they also suggest three strategies that managers can use to increase the chance of detecting changes in stream fish populations. As noted above, the first two options are to select the population parameter that is less variable (i.e., abundance versus biomass) and to monitor a network of sites. The third option is to relax α from the traditional value of 0.05. This latter approach could be especially important for monitoring species of great value to anglers or species of conservation concern. For instance, Gryska et al. (1997) recommended using an $\alpha = 0.20$ and $\beta = 0.10$ when monitoring the endangered Kendall Warm Springs dace *Rhinichthys osculus thermalis* in Wyoming. In these cases, the consequences of falsely claiming a population is declining when it is not (i.e., a type I error) are less important than failure to detect a real decline in the population (a type II error) because taking management action when it is not needed may be less problematic than not taking action when it is needed (Gibbs et al. 1998). It also might be less expensive to reverse a population decline in the early stages than after a severe decline. Thus, we deem it important to consider the trend parameter estimate (and its uncertainty) in addition to whether the statistical null hypothesis of no trend is rejected. Many trout populations are of conservation concern (Benke 1992), and monitoring programs for these populations should consider incorporating both a network of sites and relaxed α levels to ensure that population changes are detected early enough to allow appropriate management responses.

Acknowledgments

This project was funded by U.S. Forest Service. S. LeGates, N. Cook, G. Hayward, and three anonymous reviewers provided helpful comments on the manuscript.

References

Bailey, P. E. 2005. Seining effort needed to detect changes in relative abundance of common littoral zone fishes in Wyoming reservoirs. Journal of Freshwater Ecology 20:65–69.

Benke, R. J. 1992. Native trout of western North America. American Fisheries Society Monograph 6, Bethesda, Maryland.

Carey, J. M., and M. J. Keough. 2002. The variability of estimates of variance and its effect on power analysis in monitoring design. Environmental Monitoring and Assessment 74:225–241.

Carline, R. F. 2006. Regulation of an unexploited brown trout population in Spruce Creek, Pennsylvania. Transactions of the American Fisheries Society 135:943–954.

Cattanéo, F., N. Lamouroux, P. Breil, and H. Capra. 2002. The influence of hydrological and biotic processes on brown trout (*Salmo trutta*) population dynamics. Canadian Journal of Fisheries and Aquatic Sciences 59:12–22.

Draper, N. R., and H. Smith. 1966. Applied regression analysis. Wiley, New York.

Dunham, J. B., and G. L. Vinyard. 1997. Relationships between body mass, population density, and the self-thinning rule in stream-living salmonids. Canadian Journal of Fisheries and Aquatic Sciences 54:1025–1030.

Eaglin, G. S., D. C. Dauwalter, F. J. Rahel, K. G. Gerow, and G. D. Hayward. 2007. Medicine Bow National Forest, USDA Forest Service, Region 2 trout MIS monitoring protocol. University of Wyoming, Report prepared in part for the Medicine Bow National Forest, Laramie.

Eberhardt, L. L. 1978. Appraising variability in population studies. Journal of Wildlife Management 42:207–238.

Firman, J. C., and S. E. Jacobs. 2001. A survey design for integrated monitoring of salmonids. Pages 242–252 *in* T. Nishida, P. J. Kailola, and C. E. Hollingworth, editors. Proceedings of the first international symposium on geographic information systems (GIS) in fishery science. Fishery GIS Research Group, Saitama, Japan.

Freeman, M. C., M. K. Crawford, J. C. Barrett, D. E. Facey, M. G. Flood, J. Hill, D. J. Stouder, and G. D. Grossman. 1988. Fish assemblage stability in a southern Appalachian stream. Canadian Journal of Fisheries and Aquatic Sciences 45:1949–1958.

Gaston, K. J., and B. H. McArdle. 1994. The temporal variability of animal abundances: measures, methods, and patterns. Philosophical Transactions of the Royal Society of London B 345:335–358.

Gerow, K. G. 2007. Power and sample size estimation techniques for fisheries management: assessment and a new computational tool. North American Journal of Fisheries Management 27:397–404.

Gerrodette, T. 1987. A power analysis for detecting trends. Ecology 68:1364–1372.

Gibbs, J. P. 1995. Monitor version 6.2 users manual. Exeter Software, Setauket, New York.

Gibbs, J. P. 2000. Monitoring populations. Pages 213–252 *in* L. Boitani and T. K. Fuller, editors. Research techniques in animal ecology. Columbia University Press, New York.

Gibbs, J. P., S. Droege, and P. Eagle. 1998. Monitoring populations of plants and animals. BioScience 48:935–940.

Gowan, C., and K. D. Fausch. 1996. Long-term demographic responses of trout populations to habitat manipulation in six Colorado streams. Ecological Applications 6:931–946.

Grossman, G. D., J. F. Dowd, and M. Crawford. 1990. Assemblage stability in stream fishes: a review. Environmental Management 14:661–671.

Gryska, A. D., W. A. Hubert, and K. G. Gerow. 1997. Use of power analysis in developing monitoring protocols for the endangered Kendall Warm Springs dace. North American Journal of Fisheries Management 17:1005–1009.

Ham, K. D., and T. N. Pearsons. 2000. Can reduced salmonid population abundance be detected in time to limit management impacts? Canadian Journal of Fisheries and Aquatic Sciences 57:17–24.

Hankin, D. G., and G. H. Reeves. 1988. Estimating total fish abundance and total habitat area in small streams based on visual estimation methods. Canadian Journal of Fisheries and Aquatic Sciences 45:834–844.

Hoenig, J. M., and D. M. Heisey. 2001. The abuse of power: the pervasive fallacy of power calculations for data analysis. American Statistician 55:19–24.

House, R. 1995. Temporal variation in abundance of an isolated population of cutthroat trout in western Oregon, 1981–1991. North American Journal of Fisheries Management 15:33–41.

Hunt, R. L. 1974. Annual production by brook trout in Lawrence Creek during eleven successive years. Wisconsin Department of Natural Resources, Technical Bulletin 82, Madison.

Johnson, D. H. 1999. The insignificance of statistical significance testing. Journal of Wildlife Management 63:763–772.

Larsen, D. P., P. R. Kaufmann, T. M. Kincaid, and N. S. Urquhart. 2004. Detecting persistent change in the habitat of salmon-bearing streams in the Pacific Northwest. Canadian Journal of Fisheries and Aquatic Sciences 61:283–291.

Larsen, D. P., T. M. Kincaid, S. E. Jacobs, and N. S. Urquhart. 2001. Designs for evaluating local and regional scale trends. BioScience 61:1069–1078.

Link, W. A., and J. S. Hatfield. 1990. Power calculations and model selection for trend analysis: a comment. Ecology 71:1217–1220.

Link, W. A., and J. D. Nichols. 1994. On the importance of sampling variance to investigations of temporal variation in animal population size. Oikos 69:539–544.

Lyons, J., P. D. Kanehl, and D. M. Day. 1996. Evaluation of a 356-mm minimum-length limit for smallmouth bass in Wisconsin streams. North American Journal of Fisheries Management 16:952–957.

Manly, B. F. J. 1997. Randomization, bootstrap, and Monte Carlo methods in biology, 2nd edition. Chapman and Hall, London.

Marsh, D. M., and P. C. Trenham. 2008. Current trends in plant and animal population monitoring. Conservation Biology 22:647–655.

McBride, G. B. 2002. Statistical methods helping and hindering environmental science and management. Journal of Agricultural, Biological, and Environmental Statistics 7:300–305.

McFadden, J. T. 1961. A population study of the brook trout, *Salvelinus fontinalis*. Wildlife Monographs 7.

Milner, N. J., R. J. Wyatt, and M. D. Scott. 1993. Variability in the distribution and abundance of stream salmonids, and the associated use of habitat models. Journal of Fish Biology 43(Supplement A):103–119.

Noble, R. L., D. J. Austen, and M. A. Pegg. 2007. Fisheries management study design considerations. Pages 31–49 *in* C. S. Guy and M. L. Brown, editors. Analysis and interpretation of freshwater fisheries data. American Fisheries Society, Bethesda, Maryland.

Otis, D. L., K. P. Burnham, G. C. White, and D. R. Anderson. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs 62.

Peterman, R. M. 1990. Statistical power analysis can improve fisheries research and management. Canadian Journal of Fisheries and Aquatic Sciences 47:2–15.

Peterson, D. P., K. D. Fausch, and G. C. White. 2004. Population ecology of an invasion: effects of brook trout on native cutthroat trout. Ecological Applications 14:754–772.

Platts, W. S., and R. L. Nelson. 1988. Fluctuations in trout populations and their implications for land-use evaluation. North American Journal of Fisheries Management 8:333–345.

Quist, M. C., K. G. Gerow, M. R. Bower, and W. A. Hubert. 2006. Random versus fixed-site sampling when monitoring relative abundance of fishes in headwater streams of the upper Colorado River basin. North American Journal of Fisheries Management 26:1011–1019.

Ricker, W. E. 1975. Computation and interpretation of biological statistics of fish populations. Fisheries Research Board of Canada Bulletin 191.

Riley, S. C., and K. D. Fausch. 1992. Underestimation of trout population size by maximum-likelihood removal estimates in streams. North American Journal of Fisheries Management 12:768–776.

Seber, G. A. F. 1982. The estimation of animal abundance and related parameters, 2nd edition. Charles Griffith, London.

Seber, G. A. F., and E. D. Le Cren. 1967. Estimating population parameters from catches large relative to the population. Journal of Animal Ecology 36:631–643.

Sims, M., D. A. Elston, M. P. Harris, and S. Wanless. 2007. Incorporating variance uncertainty into a power analysis of monitoring designs. Journal of Agricultural, Biological, and Environmental Statistics 12:236–249.

Sulkava, M., S. Luyssaert, P. Rautio, I. A. Janssens J. Hollmen. 2007. Modeling the effects of varying data quality on trend detection in environmental monitoring. Ecological Informatics 2:167–176.

Taylor, D. J., and K. E. Muller. 1995. Computing confidence bounds for power and sample size of the general linear univariate model. American Statistician 49:43–47.

Thompson, P. D., and F. J. Rahel. 1996. Evaluation of depletion-removal electrofishing of brook trout in small Rocky Mountain streams. North American Journal of Fisheries Management 16:332–339.

Thompson, W. L., G. C. White, and C. Gowan. 1998. Monitoring vertebrate populations. Academic Press, San Diego, California.

Urquhart, N. S., and T. M. Kincaid. 1999. Designs for detecting trend from repeated surveys of ecological resources. Journal of Agricultural, Biological, and Environmental Statistics 4:404–414.

Urquhart, N. S., S. G. Paulsen, and D. P. Larsen. 1998. Monitoring for policy-relevant regional trends over time. Ecological Applications 8:246–257.

U.S. Forest Service. 2005. Black Hills National Forest land and resource management plan: phase II amendment. U.S. Forest Service, Custer, South Dakota. Available: http://www.fs.fed.us/r2/blackhills/projects/planning/index.shtml. (August 2008).

Van Deventer, J. S., and W. S. Platts. 1983. Sampling and estimating fish populations from streams. Transactions of the North American Wildlife and Natural Resources Conference 48:349–354.

Van Deventer, J. S., and W. S. Platts. 1985. A computer software system for entering, managing, and analyzing fish capture data from streams. U.S Forest Service Research Note INT-352.

Vesely, D., B. C. McComb, C. D. Vojta, L. H. Suring J. Halaj, R. S. Holthausen, B. Zuckerberg, and P. M. Manley. 2006. Development of protocols to inventory or monitor wildlife, fish, or rare plants. U.S. Forest Service General Technical Report WO-72. Available: http://www.fs.fed.us/biology/wildecology/. (June 2008).

Wagner, T., J. R. Bence, M. T. Bremigan, D. B. Hayes, and M. J. Wilberg. 2007. Regional trends in fish mean length at age: components of variance and the statistical power to detect trends. Canadian Journal of Fisheries and Aquatic Sciences 64:968–978.

Waters, T. F. 1999. Long-term trout production dynamics in Valley Creek, Minnesota. Transactions of the American Fisheries Society 128:1151–1162.

White, G. C., D. R. Anderson, K. P. Burnham, and D. L. Otis. 1982. Capture–recapture and removal methods for sampling closed populations. Los Alamos National Laboratory, LA-8787-NERP, Los Alamos, New Mexico.

Yant, P. R., J. R. Karr, and P. L. Angermeier. 1984. Stochasticity in stream fish communities: an alternative interpretation. American Naturalist 124:573–582.

Zar, J. H. 1999. Biostatistical analysis, 4th edition. Prentice Hall, Upper Saddle River, New Jersey.

Zippin, C. 1958. The removal method of population estimation. Journal of Wildlife Management 22:82–90.

Appendix: Underlying Data Sources

We used data from the following eight studies to summarize the temporal variation in trout populations and determine the statistical power with which population trends could be detected.

Hunt (1974).—Hunt (1974) monitored all ages of a brook trout population in a 5.4-km segment of Lawrence Creek, Wisconsin, annually for 11 years, from 1960 to 1970. Abundance and biomass were estimated by using electrofishing and a mark–recapture estimator (McFadden 1961; Hunt 1974). Trout sampling was conducted in both April and September; we used the data from September because that time frame was comparable to that of the other studies, in which sampling was done in summer and early fall.

Platts and Nelson (1988).—Platts and Nelson (1988) monitored trout populations in the Intermountain West at 10 randomly selected sites on 10 streams that were subjectively chosen to represent a wide range of environmental conditions and fish assemblages. Each site was 549 m in length (except for one that was 488 m and another that was 732 m), and was monitored annually about August 1 for 3–11 years from 1975 to 1985. In 1975 and 1976, only two electrofishing passes were made at each stream; four passes were made at all sites each year thereafter. The abundance and biomass of all size-classes of trout were estimated by using a maximum likelihood removal estimator (Van Deventer and Platts 1983, 1985). The species collected were brook trout, brown trout, bull trout, cutthroat trout, and rainbow trout. Brook trout, brown trout, and rainbow trout were supplementally stocked in some streams.

Freeman et al. (1988).—Freeman et al. (1988) monitored the fish assemblage in Coweeta Creek, North Carolina, multiple times annually from 1984 to 1987. Monitoring took place at three permanent sites, each 30 m in length. Sites were sampled by electrofishing, and population sizes were estimated by using a generalized removal estimator (White et al. 1982). All ages of rainbow trout data from May, June, or July were used.

House (1995).—House (1995) monitored all ages of coastal cutthroat trout *O. c. clarkii* in 1,846 m of Dead Horse Canyon Creek, Oregon, for 11 years, from 1981 to 1991. Trout were sampled from late August to early September annually. Five 30.5-m segments were sampled by electrofishing, and abundance was estimated by using a two-pass removal estimator (Seber and Le Cren 1967). The abundances in the five segments were extrapolated to the study reach (Hankin and Reeves 1988).

Gowan and Fausch (1996).—Gowan and Fausch (1996) monitored age-1 and older trout in six streams in northern Colorado to evaluate the effects of stream habitat manipulations. Sites were selected to reflect stream sites typically chosen for manipulation. Each site was 500 m in length, one-half of which was treated with log-drop structures. The sites were monitored from 1987 or 1988 to 1994 during summer base flow conditions. Brook trout, brown trout, and rainbow trout were sampled by three-pass electrofishing, and abundance was estimated by using a maximum likelihood removal estimator (Otis et al. 1978; White et al. 1982). Only data from the 250-m control sites estimated from their Figures 2, 3, and 4 were used here.

Waters (1999).—Waters (1999) monitored trout populations in a 400-m study section of Valley Creek, Minnesota, annually for 21 years, from 1965 to 1991. The abundance and biomass of all ages of brook trout, brown trout, and rainbow trout were estimated by electrofishing and using the Peterson single-census mark–recapture estimator (Ricker 1975).

Ham and Pearsons (2000).—Ham and Pearsons (2000) monitored salmonids in the Yakima River, Washington, from 1990 to 1998; the number of monitoring years per species varied. The abundance of rainbow trout in the main stem was estimated by using mark–recapture estimates. That of rainbow trout and westslope cutthroat trout *O. c. lewisii* in tributaries was monitored by using electrofishing and a removal estimator. The abundance of bull trout was estimated by means of nighttime snorkeling surveys during 3 years. The authors apparently averaged abundance estimates from all sites within the Yakima basin each year for each species.

Carline (2006).—Carline (2006) monitored age-1 and older brown trout in Spruce Creek, Pennsylvania, for 19 years, from 1985 to 2003. Two segments (602 and 515 m long) were sampled by electrofishing annually in June with a barge electrofishing unit. A Peterson mark–recapture method was used to estimate the population size of age-1 and older individuals (Seber 1982), except in 2 years, when three-pass removal and three-pass Schnabel estimators were used (Seber 1982).