
7 Relative Abundance and Catch per Unit Effort

Wayne A. Hubert and Mary C. Fabrizio

■ 7.1 INTRODUCTION

Knowledge of the abundance of fish in a stock is a component of the information used in management of fisheries (Ney 1999). Abundance estimates are used along with data on age and length composition and weight–length relations to make judgments regarding the status of fish stocks. Many methods have been developed to estimate the numerical abundance of fish in a stock including counts within isolated segments of a water body, mark and recapture, and removal methods (Chapter 8; Van Den Avyle and Hayward 1999). However, in many freshwater fisheries these methods require more time and money than can be allocated to the assessment. In these cases, fisheries managers use indices of abundance to estimate relative abundance of fishes (Fabrizio and Richards 1996; Hubert 1996; Ney 1999).

The most common indices of relative abundance are computed from catch per unit effort (C/f) data for samples from a fish stock (Fabrizio and Richards 1996; Hubert 1996; Ney 1999). A C/f index is defined mathematically as

$$C/f = qN, \quad (7.1)$$

where C is the number of fish caught, f is the unit of effort expended, q is the catchability coefficient or probability of catching an individual fish in one unit of effort, and N is the absolute abundance of fish in the stock. When numerical abundance cannot be estimated, fisheries scientists often use C/f to make judgments about the abundance of fish in a stock.

Effort (f) is computed in many ways depending on the sampling gear and habitat in which the target species resides. Units of effort may include individual sets or hauls with a gear, the volume or area of habitat sampled, or the temporal duration of sampling. With passive gears (Hubert 1996), such as gill nets and trap nets, effort is generally expressed in terms of the standard “set” with a specific piece of

gear. For example, a gill-net set might involve placing the net on the bottom overnight for 12 h, and the net may be 100 m long and 2 m high, constructed of 2.54-cm-square-mesh monofilament netting, and have a float line and a lead line. With active gears (Hayes et al. 1996), such as trawls, effort is often described in terms of the duration or length of the haul at a given boat speed. Similarly, effort with seines is often quantified relative to the area or length of shoreline over which the seine is pulled. With small larval fish trawls or push nets (Kelso and Rutherford 1996), the volume of water filtered is often computed, and C/f is expressed as the numbers captured per unit of water filtered. The C/f of electrofishing samples (Reynolds 1996) is often described in terms of the number of fish caught in a given amount of time (minutes or hours) or length of shoreline sampled.

7.1.1 General Applications in Freshwater Fisheries

Applications of C/f to assessment of stocks of freshwater fish occur in both sport and commercial fisheries. A stock is a group of fish or other aquatic animals that can be treated as a single unit for management purposes (Lackey and Hubert 1976). A stock is generally considered to be a self-contained and self-perpetuating population of a single species with no mixing from the outside and within which biological characteristics and impact of fishing are uniform. This definition is accurate when applied to populations in small lakes and impoundments. However, the geographic boundaries of many freshwater fish stocks are vague and unknown, as in streams, rivers, large reservoirs, or large lakes. Consequently, defined areas and not biological populations are sometimes used as the management units.

Catch per unit effort data are commonly used to monitor or assess stocks when the boundaries of the populations are unknown. Sport fisheries are often assessed by sampling with active or passive gears (Hayes et al. 1996; Hubert 1996) or by surveying recreational anglers and sampling creel fish (Malvestuto 1996). Commercial fisheries are often assessed using onboard or port-side sampling of the catch (Fabrizio and Richards 1996), but sampling protocols with active or passive gears are also used. Commercial fishery sampling programs are often used to estimate the catch of species in a fishery and the amount of fishing effort (Gillis and Peterman 1998). All of these sampling approaches can generate C/f data that can be used to assess temporal and spatial trends of fish stocks.

7.1.1.1 *Monitoring of Stock Abundance over Time*

One of the earliest applications of C/f data in inland waters was a description of annual changes in relative abundance of sport fish in Clear Lake, Iowa from 1947 to 1968 based on gill-net data (Carlander 1953; Bulkley 1970). Similarly, the temporal patterns in relative abundance of prey fishes in Lake Michigan from 1973 to 1993 have been described using C/f data from trawl sampling (Fabrizio et al. 2000). Also, cyclic patterns in abundance of yellow perch in an oligotrophic lake have been described using C/f data (Sanderson et al. 1999). Many similar monitoring programs have been conducted by state, provincial, and federal management agencies.

Most commonly, time series of C/f data are used to assess the efficacy of fisheries management actions, such as the response of largemouth bass and bluegill populations to the removal of excess vegetation in lakes (Pothoven et al. 1999). Monitoring of C/f is also conducted to determine declines or increases in abundance of rare species, such as Atlantic sturgeon in the Hudson River (Peterson et al. 2000). Other C/f monitoring efforts may be used to evaluate restoration efforts, such as those for lake trout in Lake Superior (Hansen et al. 1995). Similarly, the response of fisheries to introductions of exotic species can be assessed using C/f , as has been done for Lake Erie fishes relative to the appearance of zebra mussels in the lake (Trometer and Busch 1999).

Several measures of annual variation in C/f have been developed to predict the future abundance of fish or the quality of a fishery. For example, C/f of small yellow perch in trawls in the southern portion of Lake Michigan has been used to predict the future abundance of fish acceptable to anglers (Shroyer and McComish 1998). Similarly, C/f of walleye in gill nets during the fall can be a predictor of angler catch rates the following summer (Isbell and Rawson 1989). Also, C/f of age-0 fish has been used as a predictor of recruitment of age-1 fish of some species in reservoirs (Willis 1987; Sammons and Bettoli 1999).

7.1.1.2 *Evaluation of Spatial Distribution Patterns within Stocks*

Another common application of C/f data is the evaluation of spatial distribution patterns or patchiness of fish within a stock. For example, C/f data have been used to describe spatial distributions of fishes in large (Ward et al. 2000) and small (Hi and Lodge 1990) lakes, as well as reservoirs of various sizes (Hubert and O'Shea 1992; Van Den Avyle et al. 1995; Michaletz and Gale 1999). Habitat associations of fishes may be identified using C/f data obtained from different habitats in both lentic (Irwin et al. 1997; Sammons and Bettoli 1999) and lotic (Jackson 1995; Johnson and Jennings 1998) waters. Seasonal patterns in fish distributions have also been described using C/f data. For example, seasonal abundance of fishes in tributaries to the Missouri River has been described in this manner (Braaten and Guy 1999). Fisheries scientists also use C/f data to ascertain the effects of habitat mitigation efforts on the spatial distribution of fishes (e.g., Moyer et al. 1995; Chipps et al. 1997).

7.1.1.3 *Assessment of Stocks Relative to Other Stocks*

Comparison of fish stocks in two or more water bodies based on C/f data obtained by standard fish sampling protocols has also been applied by freshwater fishery managers. For example, among biologists managing small impoundments there is general consensus that electrofishing C/f is a good measure of largemouth bass abundance (Flickinger et al. 1999).

7.1.1.4 *Surveys*

Surveys are sometimes conducted in which C/f data are used to describe the fish assemblage in a water body. However, the catchability coefficient (q) with a particular gear differs among species, so the actual composition of a fish assemblage

is generally not well represented by C/f data. Nevertheless, researchers have attempted to consider the effects of differential encounter probabilities, fish size, fish swimming speed, and retention probabilities of a specific gear to provide a better indicator of actual assemblage composition. For example, Spangler and Collins (1992) made such adjustments to C/f data from gill nets to describe fish assemblages in different portions of Lake Huron. Parsley et al. (1989) computed capture efficiencies for small fishes sampled with beach seines to achieve a better estimate of assemblage structure in a reservoir.

7.1.2 Underlying Assumptions

An underlying assumption of using C/f as an index of abundance is that the number of fish captured is proportional to the amount of effort expended. When a population is closed, one unit of sampling effort removes a fixed proportion of the total population (Seber 1982). As the population declines in abundance, the number of animals captured by one unit of effort declines. This simple linear relation between C/f and abundance has been extended to research and monitoring surveys such that C/f data are typically treated as a measure of abundance. However, when the assumption of a linear relation fails, C/f can be a misleading indicator of stock abundance.

7.1.2.1 *Density As an Index of Abundance*

The classic catch equation expresses catch as a proportion of abundance, and this proportion varies with the amount of effort:

$$C = fq (N/A), \quad (7.2)$$

where C is catch, f is fishing effort, q is (constant) catchability, N is abundance, and A is the area in which the stock occurs (Gulland 1969). This equation can be re-arranged to $C/f = q(N/A)$, so if catchability is known, C/f is a measure of fish density (N/A).

Assumptions of this model are (1) the population is in equilibrium (i.e., birth, recruitment, and immigration rates are balanced by death and emigration rates); (2) units of effort (such as individual trap or net sets) operate independently (one unit of fishing gear does not interfere with other units); (3) q is constant throughout the sampling period; and (4) every individual in the stock has the same probability of capture (Seber 1982). The fourth assumption concerns the spatial distribution of fish and is met when fish are uniformly distributed within the boundaries of the stock. Additionally, when sampling of fish within a stock is without replacement (i.e., live fish are not returned to the water), it is assumed that the effects of such removals are negligible.

7.1.2.2 *Constant Catchability*

Technically, the constancy of the catchability coefficient (q) determines how well C/f serves as an index of abundance (Gulland 1969). The assumption of equal

capture probability for each fish in the population implies that fish are uniformly distributed in space and that all occupied areas are accessible to the gear and are randomly sampled. However, neither fishing effort nor fish are uniformly distributed (Paloheimo and Dickie 1964). Even when effort is uniform, such as in research studies using standardized sampling methods, variation in catchability arises when changes occur in the spatial distribution of fish. It has long been recognized that C/f data reflect changes in animal distributions as often as they reflect changes in abundance (Paloheimo and Dickie 1964). Changes in fish distribution (and availability to the gear) may occur vertically (e.g., changes in the thermocline affecting the vertical distribution of fish) or horizontally (e.g., different habitats are occupied such that the proportion of a population occurring outside the survey area changes). Catch-per-unit-effort data are further confounded when changes in spatial distribution occur concurrently with changes in abundance. For example, at low abundance a relatively greater proportion of Atlantic cod were found in shallow regions outside a survey area and were unavailable to the trawl, thereby reducing catchability during times of low abundance (Swain et al. 1994).

Care must be taken to restrict interpretations of C/f estimates to the portion of a stock actually sampled. For example, when fish in a stock are spatially distributed among exploited and unexploited regions, and individuals move from an unexploited to an exploited region, C/f estimates from the exploited segment are not a good measure of total stock abundance (Sampson 1991). Catch-per-unit-effort estimates from the exploited region are representative of the entire stock only when the rates of movement between the two regions are random. Effects of shifts in distribution on C/f estimates have been recognized for some time and have been incorporated into equilibrium models of production for exploited fisheries (Die et al. 1990).

Variations in catchability decrease the accuracy of C/f estimates as indices of abundance. Catchability can vary with size, sex, or other intrinsic characteristics of fish. Catchability can also vary with time of day, season, sampling site, water temperature, dissolved oxygen levels, or other environmental features that may affect the ability of the gear to capture fish or the distribution of fish relative to the gear (i.e., availability).

There are several ways to address departures from the constant catchability assumption. One approach is to stratify sampling of a stock according to the feature of interest. For example, when catchability varies with fish length, then an estimate of catchability for a stock is really the average q for all fish in the stock. As long as the length structure of the fish in the stock does not change, the average q will be a reasonable estimate for the entire stock. However, the length structure of fish in a stock is generally not constant, and catchability may best be estimated separately for individual length-classes in the sample (Seber 1982). Another approach is to adjust C/f data to account for changes in extrinsic factors such as changes in fishing power (Kimura 1981). For example, trawlers with larger engines consistently catch more fish and have greater fishing power than do trawlers with smaller engines, all other things being equal (Gulland 1977). Still another approach is to estimate catchability independently, for example, from a tagging

study that yields estimates of stock abundance through time (e.g., Paloheimo 1963). Whichever approach is taken, the factors affecting catchability should be measured and used to adjust C/f data.

Numerous relationships between catchability and environmental factors have been found by examining correlations between C/f and these factors. For instance, swimming speed of fish generally decreases at lower temperatures and fish become more vulnerable to capture by a trawl. At the same time, the spatial distribution of fish in a stock may change as temperature decreases, thereby changing their availability to the gear. However, although C/f may be significantly correlated with environmental conditions, catchability may not be affected by those factors (Swain et al. 2000). Careful examination and appropriate experimental designs are needed to understand the nature of the relationship between catchability and environmental factors.

7.1.2.3 *Validation of Assumptions*

The distinction between density and abundance is often overlooked, but the key to understanding their difference is the validity of the constant area assumption. Typically, the area occupied by a stock is assumed to remain constant. As abundance changes, the expectation is that density will also change, and C/f estimates will remain proportional to abundance. Although the proportional relation between C/f estimates and abundance is convenient, it is not universal (e.g., Crecco and Savoy 1985). In some cases, as abundance increases, fish may increase their spatial distribution and spread into adjacent nonsampled areas.

In other cases, C/f may exhibit “hyperdepletion” in relation to abundance (Hilborn and Walters 1992). In this situation, the rate of change for C/f is higher than it is for abundance. This relation is observed when C/f decreases faster than abundance because the most vulnerable animals are captured first, leaving behind less vulnerable individuals (Ricker 1975; Miller 1990; Hilborn and Walters 1992).

An opposite effect is “hyperstability,” which occurs when C/f remains high even as abundance decreases (Hilborn and Walters 1992). This relationship occurs when the search for fish is highly efficient, effort is concentrated in areas of high densities, and the fish remain concentrated as abundance declines (Hilborn and Walters 1992). This has been observed among commercial (Rose and Kulka 1999) and recreational (Peterman and Steer 1981) fisheries. Aggregation of fish in a small portion of the stock’s boundaries during a period of declining abundance is termed hyperaggregation (Rose and Kulka 1999). For example, anglers experienced high catchabilities of Chinook salmon during periods of low riverine abundance because both fish and anglers were concentrated in small areas of the river (Peterman and Steer 1981).

The assumption of constant catchability has been investigated for commercial fisheries because of known changes in fishing efficiency associated with vessel power, learning by crews, and technological improvements in commercial fleets through time (Fabrizio and Richards 1996). These factors increase catchability and introduce systematic error in C/f data. Thus, long-term C/f data from commercial fisheries must be adjusted prior to computation of C/f estimates. Without

such adjustments, increased catchability leads to overestimation of stock abundance from commercial fishery statistics. Variations in fishing power may also characterize research surveys when more than one crew, vessel, or unit of gear is used (Munro 1998). Often, such variations must be explored experimentally to derive conversion coefficients (e.g., Pelletier 1998). When C/f data are adjusted for differences in catchability there is a tendency to overestimate the variance of C/f ; thus, Munro (1998) developed a method to determine when adjustments are warranted.

The assumption of independence of fish-sampling units (i.e., no interference of one unit of gear with another) has been considered in a few studies. Interference among highly aggregated gill nets has been documented (Rose and Leggett 1989). Among anglers, interference is commonly observed when total effort is high (e.g., during holidays when crowding can lead to lower catchabilities; Ricker 1975). In general, data are insufficient to determine how frequently interference may occur (Gillis 1999). Simulation studies show that when stock abundance is low, C/f estimates can fail to reflect abundance even under low levels of interference (Gillis and Peterman 1998).

In some instances, mark-recapture experiments can be conducted to estimate stock abundance (N) and relate these estimates to C/f data to obtain an estimate of the catchability: $q = (C/f)/N$. For example, electrofishing catchability has been related to largemouth bass abundance estimated by mark-recapture methods in small impoundments (Hall 1986) and lakes (Coble 1992).

■ 7.2 SAMPLING DESIGN

The importance of sampling design cannot be overemphasized when using C/f estimates as an index of stock abundance. Catch per unit effort can vary widely because fish distributions are patchy and fish exhibit spatial and temporal variation in their distribution and activity patterns. Mean C/f estimates often have high variance (Peterman and Bradford 1987; Allen et al. 1999), thereby introducing uncertainty when using C/f to assess differences in stock abundance. Thus, sampling designs that minimize variation in C/f should be used. For example, in an effort to reduce the variation in C/f , fisheries scientists often sample with the same gear, in the same locations, and at the same time each year when assessing annual changes in abundance of fishes (e.g., Fabrizio et al. 2000).

Generally, sampling designs are developed to minimize variation in C/f that is due to factors other than the true abundance of fish. Sampling locations and times are selected based on knowledge of the life history, movement, and habitat associations of a species (Pope and Willis 1996). Substantial literature is dedicated to identifying where and when to sample different species. For example, Mero and Willis (1992) assessed seasonal variation in gill-net catches of walleye and sauger from Lake Sakakawea, North Dakota, to determine when C/f was highest and the coefficient of variation of the C/f data was lowest. Similarly, variation in C/f data for largemouth bass sampled by electrofishing is minimized when sampling only shoreline areas (McInerny and Cross 2000).

A study is dependent on the objectives of the fisheries scientist, and objectives must be clearly identified. For example, objectives may be to (1) define annual trends in abundance of walleye in a prairie lake, (2) evaluate changes in relative abundance of channel catfish in a river in response to implementation of a minimum-length limit, or (3) determine effects of shoreline restoration efforts on the relative abundance of largemouth bass in a small impoundment. Each objective may require a different sampling design dependent not only on the question but also on the species and type of water body.

The experimental designs described in Chapter 3 have the potential of being used in studies in which C/f estimates are the response variable. Simple random sampling is generally not appropriate when C/f estimates are used to assess fish stocks because low precision generates C/f data that are too variable to detect trends or differences that may occur. Within the fisheries literature, we have found no examples of simple random sampling where C/f estimates were the response variable, but it is possible that situations may occur for which such a design may be applicable, particularly in small water bodies with homogeneous habitat features.

There is a strong tendency among fisheries scientists to use stratified random sampling designs, especially when assessing temporal trends in C/f . Four general reasons for using stratified random sampling to assess fish stocks are (see Cochran 1977) (1) calculation of C/f statistics may be required for different portions of a stock, such as different bays within a large lake; (2) sampling constraints may necessitate using different sampling methods in different areas, such as trawling in offshore areas and beach seining in nearshore areas of a large lake; (3) stratification may result in a gain in precision of C/f estimates for the whole stock; and (4) administrative convenience may require stratification in different areas, such as different states or provinces around one of the Great Lakes. Michaletz and Gale (1999) provide an example of the application of stratified random sampling where C/f estimates were used to assess both spatial and temporal patterns of abundance (also, see example in section 7.5.2).

A systematic sampling design is another approach that may be considered for studies based on C/f data. In this approach, sampling begins at a randomly selected site or time and continues at equally spaced locations or time intervals. Systematic sampling may be used effectively in rivers to gather information on the relative abundance of organisms along a gradient of environmental conditions (Karr 1999). Although several estimators exist for the variance of the mean from a systematic sample, all estimators require data from replicated systematic samples (Cochran 1977). The variance of the mean from a single systematic sample may be estimated, but estimators studied to date are biased and inconsistent (Skalski et al. 1993). For example, when mean abundance estimates are obtained from hydroacoustic surveys, systematic designs may (Simmonds and Fryer 1996) or may not (Jessop and Harvie 1990; Skalski et al. 1993) yield highly precise estimates of abundance. In general, systematic sampling provides less precise estimates of the mean than does stratified random sampling (Cochran 1977) and should be considered only when the objectives of the study are not compromised by the lower precision of systematic sampling estimators or when preliminary analyses indicate

that lower sampling costs associated with systematic designs outweigh the need for precision. Systematic sampling designs are probably most useful when combined with stratified random sampling in a two-stage approach (Schweigert et al. 1985; Chapter 3). Additional sampling designs may be applicable to assessment of C/f (see Chapters 2 and 3).

■ 7.3 ASPECTS OF SAMPLING EFFORT

Design and construction of a sampling gear and factors associated with its operation contribute to variations in gear efficiency. For instance, catch rates for traps are affected by soak time and the type of bait used to attract animals (Miller 1990). In addition, gear efficiency may be affected by the interaction of captured animals and the gear itself (the saturation effect) and may vary according to life stage of the target species (Miller 1990). When conducting research or monitoring, care must be taken to standardize gear, not just in terms of the design and construction, but also in terms of the operation. Standardization also pertains to techniques used by operators of the gear. It is widely recognized that even though using the same gear, some operators can obtain a higher catch than others. By standardizing gear design, construction, and operation, fisheries scientists minimize variation in catchability and C/f data.

Often, preliminary sampling is necessary to identify factors associated with variation in catchability of a target species. A good example of an informative preliminary analysis is described in Bernard et al. (1991). They examined diurnal changes in catchability, optimal baiting strategies, optimal soak duration, and hoop-net size effects (among other factors) on the efficacy of hoop nets for capturing burbot in Alaskan lakes. These results were used to design surveys of stocks of burbot in 15 Alaskan lakes (Bernard et al. 1993).

7.3.1 Selectivity and Saturation

Gear performance is species and habitat specific (Choat et al. 1993). For example, light-trap selectivity for larval fish sampling depends on the attraction of different species to light, and not all taxa are equally phototactic (Choat et al. 1993). Encounter rates of some species or sizes can be increased by deploying the gear in appropriate habitats and exploiting behavioral differences among species or life stages. However, encounters with gear do not necessarily result in capture. Fish are captured when they encounter the gear and are also retained. The probability of retention is termed selectivity. With some gear, retention of organisms will vary with mesh size and the likelihood of extrusion through the mesh. Body size, body shape, and pressure exerted by fish across the net mesh are three factors that determine the likelihood of extrusion.

Gear saturation is another factor affecting gear efficiency and catchability. Saturation occurs when the present catch reduces the potential for additional catch by reducing the number of new captures, increasing escapement, or both (Miller 1990). As a gear becomes saturated, the likelihood of capturing additional animals

decreases. Good examples of saturation effects can be found for gill nets (the presence of entangled fish may scare other fish away), longlines (as more fish are captured, the number of vacant hooks decreases, and eventually no additional fish are caught), and baited pots or traps (captured animals deplete the bait or discourage other animals from entering the trap). In traps, reduced entry is thought to be due to intimidation by trapped organisms using odor, posture, or sound to prevent entry of additional animals into the trap (Miller 1990). Longlines are notoriously prone to the effects of saturation and interspecific competition for hooks. Under these conditions, time fished is not a good indicator of true effort. An extreme example occurs when all hooks bear fish at time t but the longline is retained in place until $t + i$; in this case, C/f is biased low because true effort was (over) estimated by $t + i$. New methods have been developed to more accurately estimate effort associated with longlines based on time to capture as measured by fish-activated timing devices placed on each hook (Somerton and Kikkawa 1995).

7.3.2 Sampling Issues Specific to Gear Types

7.3.2.1 *Passive Gears*

Passive gears rely on the movement of organisms, either schooling or more directed migrations such as spawning, to bring organisms in contact with the gear (Hubert 1996). Schooling behavior creates density differences that affect the estimation of relative abundance. About one-fourth of teleosts are obligate schoolers and exhibit schooling behavior throughout their life, and about half of all teleost species school as juveniles (Shaw 1978). Schooling increases the vulnerability of fish to capture by fishing gear. Increased vulnerability of individuals in schools leads to less time expended in capturing fish, thus leading to biased C/f estimates. For example, catch rates with passive gears may be higher when environmental factors cause fish movements and increase their vulnerability to capture (Rose and Leggett 1989).

Because the effective area fished by passive gear is impossible to measure, effort is measured in terms of soak time. Although it may seem that longer soak times should produce greater catches, in fact, as soak time increases, the gear may become saturated and catch per unit of time will decrease. At this point, C/f does not provide an index of relative abundance (Hansen et al. 1998). For traps and pots, as soak time increases, the catch actually may decrease as more organisms escape than enter (Miller 1990). For baited longlines, saturation begins to occur as the odor concentration from baited hooks decreases (Sigler 2000).

The relation between catch and soak time is specific for particular gear types (Miller 1990) and must be determined experimentally. When designing experiments or surveys involving traps, Miller (1990) suggests the following: (1) determine the relation between catch and soak time; (2) ensure that catch rates are uniform throughout the study area; (3) standardize bait quantity and quality; (4) standardize time of setting and hauling; (5) standardize trap spacing; (6) maintain

traps in good repair; and, if following an experimental protocol, (7) randomize sampling spatially and temporally within strata.

With other passive gears such as gill nets and drift nets, catchability may be related to the visual acuity of fish, which, in turn, is affected by turbidity, light intensity, or other environmental conditions (e.g., Cui et al. 1991). Light intensity varies over a daily cycle, but lunar phase also affects light intensity. In addition, the visibility of the net depends on the color of the mesh.

Catchability of passive gears may be affected by changes in activity of fish associated with light levels. For example, most decapods are more active during dawn, dusk, or generally at night, and catchability increases during these times (Miller 1990). Some fish are also more active at night, increasing their vulnerability to passive gear. However, this relation of increased activity and light intensity may change seasonally. For example, burbot are nocturnal in spring and summer but diurnal in the fall (Bernard et al. 1993).

7.3.2.2 *Active Gears*

Active gears often have different catchabilities depending on light intensity. This may be due to diel vertical movements of fish or reduced visibility (Walsh 1991; Casey and Myers 1998; Korsbrette and Nakken 1999). Catchability may also be affected by the ability of fish to escape, and that ability depends on the behavior of individuals during herding and capture (Godø et al. 1999).

Electrofishing is a highly effective active sampling gear for fish in streams and littoral zones of lakes (Reynolds 1996). Electrofishing tends to be more effective for larger fish and for species that float at the surface when stunned. Some species exhibit relatively low catchabilities to electrofishing gear. For instance, benthic fishes exhibit low catchabilities because the likelihood of seeing immobilized individuals is low, whereas other pelagic species avoid the electric field (Bohlin et al. 1989), thereby reducing their catchability. Additionally, increasing water levels can reduce electrofishing catchabilities in rivers (Bohlin et al. 1989). Standardization of electrofishing techniques is important when using C/f as an index of abundance.

7.3.3. **Standardization of Effort**

The appropriate units for measuring effort for a given gear can vary depending on the target species and habitat sampled. For example, electrofishing C/f is usually reported as catch per minute (e.g., Tillma et al. 1998), especially for highly abundant species or life stages such as age-0 bluegills in Midwestern lakes. At times, electrofishing C/f may be reported as catch per hour (e.g., Paragamian 1989; Miranda et al. 1996), but this usually occurs when the species of interest is rarely captured. In some cases the shoreline of a lake or reservoir may serve as the sampling unit in an electrofishing survey and C/f is measured as catch per area (e.g., fish per 100 m² of littoral zone) or catch per length of shoreline (e.g., fish per 100 m).

Fishing power should be standardized to maintain constant catchability. For example, C/f estimates from trawl surveys can change with vessel speed, so vessel speed must be constant. With all types of sampling, fisheries scientists must consider how procedural changes may affect fishing power. For example, electrofishing equipment is typically standardized by using constant voltage or constant amperage. Variations in electrical power (wattage) have caused 12–15% increases in variation in electrofishing catch rates (Burkhardt and Gutreuter 1995).

7.3.3.1 *Multiple Gears*

In some instances it is desirable to use two or more gear types to sample organisms and to combine C/f estimates from the different gears (Seber 1982). However, care must be taken to ensure that catchability of each gear remains constant. Although catchability may be constant through time for one gear, it may not be for another (e.g., gill nets and trap nets for Atlantic cod, Rose and Leggett 1989). At times it may be possible to calibrate C/f from multiple gears, but patterns of variation in C/f may be due to behavioral characteristics of the species under study (Methven and Schneider 1998).

7.3.3.2 *Effects of Seasonal and Daily Variation*

Catch per unit effort can change seasonally due to variations in recruitment, growth, and mortality, but such changes may not be the same for all species or for a given species in all habitats (Pope and Willis 1996; Richards et al. 1996). For example, seasonal variation in C/f for the virile crayfish was observed in Minnesota lakes but not for the northern clearwater crayfish in streams (Richards et al. 1996). For some species, catchability may increase temporarily during a particular season as fish increase activity levels in response to environmental factors such as temperature and photoperiod (e.g., Bernard et al. 1993; Braaten and Guy 1999; Gordoa et al. 2000). Also, seasonal patterns in C/f may not be observed every year due to climate variability (Gordoa et al. 2000).

When collecting C/f data over time to examine trends, care must be exercised to sample at appropriate times if seasonal variation in density exists. In the case of sampling during a seasonal spawning migration, annual C/f data will reflect relative abundance only if the seasonal timing of the migration remains the same from year to year (Fréon and Misund 1999). Thus, when sampling migratory species, the timing within the run is critical. For example, two-thirds of the annual emigration of Chinook salmon smolts occurred during a new or waning moon (Roper and Scarnecchia 1999). If using C/f data to compare abundance of a species from various areas, then care must be exercised to sample the areas of interest during the same time. For example, a comparative survey of bluegill abundance in Minnesota lakes found that data collected at different times of the year should not be compared because about 40% of the variation in C/f was explained by day of the year (Cross et al. 1995).

Daily or circadian variations in C/f are well known (e.g., Walsh 1991). Such variations may be related to the visual acuity of fish or diel vertical movements in lentic systems (Stoner 1991). Similarly, electrofishing catchability may (Paragamian

1989; Dumont and Dennis 1997) or may not (Maceina et al. 1995; Van Zee et al. 1996; Dumont and Dennis 1997) increase at night depending on the target species or the habitat in which the species occurs (Kessler 1999).

7.3.3.3 *Consideration of Life History and Behavior*

Catchability may be affected by life history or physiological stage of the target species. This is illustrated among decapod crustaceans. Typically, the increased activity levels of decapods during warm temperatures increase their vulnerability to capture in baited traps, but their vulnerability ceases during molting (e.g., Somers and Green 1993; Richards et al. 1996). Similarly, catchability of the American lobster in traps decreases to near zero during molting, and because males and females may molt at different times of the year, sex-specific catchability varies (Miller 1990). In Minnesota streams, catchability of northern clearwater crayfish in baited traps was highest between molting periods when animals were actively feeding (Richards et al. 1996). Thus, behavioral changes associated with life history events should be taken into account when interpreting C/f estimates.

Some of the most effective fishing gears use the behavioral responses of organisms to maximize encounter rates and retention. A pertinent example is how olfactory cues can be used to elicit behavioral responses of fish to enhance encounter probabilities. For example, when Gerhardt and Hubert (1989) baited hoop nets, the C/f of channel catfish was doubled during the postspawning period.

Some species or life stages are photopositive, so gear catchability can be increased by using light lures at night. While lighted traps and other nets may increase nocturnal catches of certain fishes or life stages, the phase of the moon may interact with catchability if fish activity varies with lunar phase. For example, Rooker et al. (1996) found that nocturnal catches of larval fishes increased significantly when lighted lift nets were used during the new moon.

The presence of predators or competitors may influence catchability. For example, in Ontario lakes, crayfish catchability in baited traps declined in the presence of rock bass and smallmouth bass and with increasing numbers of co-occurring crayfish species (Collins et al. 1983; Somers and Green 1993). These effects were noted only in lakes with relatively high abundance of predatory fishes (Collins et al. 1983).

Habitat preferences and behavior of organisms contribute to variation in C/f (Fréon and Misund 1999). Juvenile and adult fish may be distributed in areas varying in depth (Hubert and Sandheinrich 1983; Bernard et al. 1993). Individuals of some species may segregate spatially on the basis of sex (Miller 1990). If a substantial portion of a stock occupies a habitat that is inaccessible to the sampling gear, then the proportion available to the gear is likely to vary through time depending on environmental factors that alter habitat selection (Fréon and Misund 1999). For example, tidal currents in the Barents Sea have been shown to influence the vertical distribution of cod and haddock such that they are available to bottom trawls only during periods of low or decreasing tidal currents (Michalsen et al. 1996).

Habitat preferences of fish are sometimes exploited to enhance catchability. For example, some species prefer areas with cover and fisheries scientists may

purposefully sample in these areas. Often, nets are set or gear is towed in areas likely to contain fish, and the sampling locations are not truly standardized or random. This type of selection mimics the manner in which commercial fisheries operate by locating areas with potentially high densities of fish and fishing only in these areas. If the objective is to compare changes through time in an impoundment or lake, then such judgment sampling may be appropriate (Hubbard and Miranda 1988). When sampling for largemouth bass, electrofishing in areas near weed beds, stump fields, or flooded timber in the littoral zone would constitute judgment sampling (Hubbard and Miranda 1988). As long as the judgment sampling sites are constant over time (i.e., permanent sampling sites), this approach can yield an efficient means to assess temporal trends in relative abundance within a given water body.

7.3.3.4 *Consideration of Gear Efficiency in Different Habitats*

The efficiency of a given gear can vary substantially among habitat types. For example, electrofishing efficiency can vary widely among habitat types. In habitats with low water clarity (transparencies less than 1 m) and depths greater than a few meters, electrofishing is not very efficient (Bohlin et al. 1989). For example, Dewey (1992) reported that in turbid, highly vegetated waters, electrofishing was less efficient than were other gears because low visibility and entanglement of fish in the vegetation reduced capture efficiency.

7.3.4 **The Need to Minimize Variance and Bias**

One of the most common approaches to increasing the precision of C/f estimates is to increase the number of samples. Assuming the sampling design is appropriate (see section 7.2; Chapters 2 and 3) and catchability is constant, increasing sample size will likely increase precision. However, factors affecting catchability must remain constant during the sampling period. For instance, if catchability varies greatly with light intensity and samples are collected throughout a 24-h period without regard to this factor, then an increase in the number of samples may not improve precision. We recommend that variation in catchability be studied with respect to factors that influence the magnitude of C/f estimates including those that influence availability of animals to the gear and vulnerability to capture. Once these factors are known, then the value of increasing the number of samples can be determined.

In stratified random sampling designs the optimal sampling plan may not involve equal sampling among all strata, but rather optimal sampling intensity may vary according to stratum size. Minimizing the variation of C/f data is particularly important when these data are used to evaluate changes in relative abundance. Trends in abundance may be difficult to discern or detect when the data are highly variable (see Box 7.1).

The considerations we discussed to maximize precision of C/f estimates are not exhaustive, and additional considerations should be made. For example, only fully recruited age-classes should be considered in deriving C/f estimates;

Box 7.1 Detection of Changes in Relative Abundance with Highly Variable Catch per Unit Effort (C/f) Data

The time series data below illustrate the effects of highly variable C/f data on the ability to detect relative abundance changes for a hypothetical fish population that is declining through time. The first column is the year; the second column, population abundance (N), shows a decline of 5% each year; the third column gives C/f as $0.001N$; the fourth column shows C/f varying randomly by 5% or 10% above or below $0.001N$; and the fifth column is C/f varying randomly by 20% or 40% above or below $0.001N$.

Table Times series data for a hypothetical fish population.

Year	Population abundance (N)	C/f	$C/f \pm 5\%$ or 10%	$C/f \pm 20\%$ or 40%
1	10,000	10.0	10.5	6.0
2	9,500	9.5	8.6	13.3
3	9,025	9.0	8.1	5.4
4	8,573	8.6	7.7	10.3
5	8,145	8.1	7.7	4.9
6	7,739	7.7	6.9	4.6
7	7,351	7.4	8.1	5.9
8	6,983	7.0	7.7	5.6
9	6,634	6.6	7.2	9.2
10	6,302	6.3	6.0	8.8
11	5,987	6.0	6.3	8.4
12	5,688	5.7	5.4	3.4
13	5,404	5.4	5.7	6.5
14	5,133	5.1	4.8	3.1
15	4,877	4.9	5.4	6.9

A significant correlation ($r = 0.64$; $P < 0.001$) is observed between N and the $C/f \pm 5$ or 10% measurement error, but the correlation ($r = 0.33$; $P = 0.23$) between N and the $C/f \pm 20\%$ or 40% measurement error is not significant. Note that with the $C/f \pm 20\%$ or 40% measurement error the C/f in year 15 exceeds the C/f in year 1.

Both levels of measurement error used in this example are within the range of what may be encountered in the field when sampling fish populations and obtaining C/f data. This illustrates how C/f measurement error can mask changes in actual abundance of fish populations.

otherwise, recruitment variability will induce variation in catchability (Seber 1982). A single gear will not capture all components of a stock in proportion to their abundance, so a key piece of information is the selectivity of the gear for various life stages or length-classes of the target species. In addition, all habitats inhabited by a species will not be equally sampled. Sampling should be conducted during a time when factors affecting catchability are similar if C/f data are used to compare across time or space (Richards and Schnute 1986; Miller 1990). A good approach is to focus the unit of study and define it properly, and then consider gains in precision through replication.

7.3.5 Assessment of Sample Sizes Prior to Initiation of Sampling

A power analysis allows the researcher to determine the level of effort (i.e., sample size) necessary to detect a change of a predetermined magnitude given a measure of the variability in the factor of interest (see Box 7.2). For instance, the number of trap-nights necessary to detect a 25% change in relative abundance of bluegill can be determined using an estimate of the variance of the mean C/f . In general, power analysis requires the assumption that C/f data follow a normal distribution. If the C/f data are not normally distributed, it becomes important to identify a transformation that yields an approximately normal distribution (Gryska et al. 1997). An example of statistical power analysis applied to C/f data from electrofishing samples is given in Paller (1995). In general, many samples will be necessary to detect small (<20%) differences among means, but when C/f is low, an even greater number of samples is necessary (Paller 1995).

■ 7.4 STATISTICAL ANALYSIS

A common approach to analysis of C/f data has been to compute means and assume normal distributions of the data. However, the frequency distributions of C/f data are seldom normal. This is not surprising because C/f is a ratio estimator having catch and effort as random variables (Cochran 1977). Testing hypotheses regarding C/f generally involve application of statistical tests that assume the variables have a continuous scale of measure, the data exhibit a normal frequency distribution, and standard deviations are independent of the mean. Statistical analyses that require these assumptions can lead to reductions in power and misleading results when the assumptions are not met. Nonparametric statistical procedures have less restrictive assumptions regarding distributions, but it is difficult to assess the magnitude of difference between treatments or change over time based on nonparametric procedures.

7.4.1 Normalization of C/f Distributions

The shapes of C/f sample distributions can vary widely and may include normal frequency distributions and negative binomial distributions. It is common for C/f distributions to have standard deviations that are about equal to the mean, to be positively skewed (Moyle and Lound 1960), and to have standard deviations that increase proportionally with the mean—indications of distributions that are not normal. Among 703 published studies on larval fish abundances estimated from replicated sampling, Cyr et al. (1992) found many positive relationships between the variance and the mean, indicating that C/f frequency distributions were not normal in many studies. It has been suggested that the shape of C/f sample distribution changes with fish abundance (see Hubert 1996). At very high fish densities, C/f data may be normally distributed, but as fish densities decline, the mode shifts to the left and the distribution becomes skewed to the right. At relatively

Box 7.2 Power Analysis Assessment of Sampling Effort

Preliminary sampling of channel catfish in two hypothetical small impoundments is conducted with traps in early summer to obtain C/f data as the first step in establishing an annual monitoring program to assess temporal variation in mean C/f . In each reservoir, 20 traps are set at randomly selected locations, left overnight, and retrieved the following day. The following C/f data (i.e., fish/trap-night) and statistics are obtained for each impoundment. Each C/f value is transformed as $\log_{10}(C/f + 1)$ to assess the effects of data transformation on C/f statistics and estimates of needed sampling effort.

Table Catch per unit effort data and summary statistics for channel catfish in two hypothetical impoundments.

Net set and summary statistic	Impoundment A		Impoundment B	
	C/f	$\log_{10}(C/f + 1)$	C/f	$\log_{10}(C/f + 1)$
1	0	0	1	0.301
2	0	0	1	0.301
3	0	0	2	0.477
4	0	0	2	0.477
5	0	0	3	0.602
6	0	0	3	0.602
7	0	0	3	0.602
8	0	0	4	0.699
9	1	0.301	4	0.699
10	1	0.301	4	0.699
11	1	0.301	4	0.699
12	1	0.301	5	0.778
13	2	0.477	5	0.788
14	2	0.477	5	0.788
15	3	0.602	6	0.845
16	3	0.602	6	0.845
17	7	0.903	8	0.954
18	9	1.000	10	1.041
19	12	1.114	12	1.114
20	20	1.322	20	1.322
Mean	3.1	0.385	5.4	0.731
SD	5.2	0.422	4.4	0.254

Observation of the data and the summary statistics suggests that the C/f data for Impoundment A are highly skewed and substantially depart from a normal distribution; furthermore, the logarithmic transformation did little to affect the shape of the distribution. For both forms of C/f data the standard deviation exceeds the mean. The C/f data for Impoundment B are less severely skewed, and a logarithmic transformation reduces the standard deviation and creates a frequency distribution that more closely resembles a normal distribution.

Power analysis allows definition of the required sampling effort to determine specified changes in mean C/f at predetermined levels of significance (α) and power ($1 - \beta$) to guard against type I

(Box continues)

Box 7.2 (continued)

(rejecting the null hypothesis of no difference when it is true) and type II (failing to reject the null hypothesis of no difference between the means when it is false) errors (Brown and Austen 1996; Gryska et al. 1997). Power analysis is conducted by computing needed sampling effort at various levels of significance, power, and detectable effect sizes. Means and variances of C/f data from previous or preliminary sampling periods are used in the computations. The detectable effect size is the specified difference in two means when the null hypothesis is rejected at a specified α and β (Cohen 1969). For example, if the mean C/f is 3.1 fish/trap-night (as was observed for Impoundment A during the preliminary sampling) and the fisheries scientist specifies that the desire is to detect a change in C/f in either direction of 10% or more, the detectable effect size is 0.31 fish/trap-night. The desire is that the null hypothesis would be rejected if future sampling means differ from the preliminary sampling mean by 0.31 fish/trap night or more. How much sampling effort is needed to detect such a difference at various probabilities of type I and type II error?

Calculations are performed using the formula of Snedecor and Cochran (1989):

$$n = 2 (z_{\alpha} + z_{\beta})^2 (s^2/d^2);$$

n = number of samples needed;

z_{α} = standard normal deviation for the probability of a type I error at a given level of probability (significance);

z_{β} = standard normal deviation for the probability of a type II error at a given level of probability (power = $1 - \beta$);

s = standard deviation of the preliminary C/f data; and

d = the detectable effect size as an absolute number.

Standard normal deviations, or z scores, are easily obtained from tables in reference books or programs in various statistical software packages.

An example computation is conducted using the logarithmic transformation of C/f data from Impoundment B because it most closely resembles a normal distribution and yields the smallest estimates of needed sampling effort. The mean $\log_{10}(C/f + 1)$ is 0.731 and SD (s) is 0.254. If it is specified that the detectable effect size is 10% of the mean, or 0.0731, α is 0.05, and β is 0.10, then $z_{\alpha} = 1.65$, $z_{\beta} = 1.28$, and

$$n = 2 (1.65 + 1.28)^2 (0.254^2/0.0731^2) = 207 \text{ trap nights.}$$

It is unlikely that the needed sampling effort could be achieved by practicing fisheries scientists as part of a routine monitoring program.

If the specified criteria are relaxed, lesser amounts of sampling effort are needed. For example, if it is specified that the detectable effect size is 20% of the mean, or 0.146, α is 0.10, and β is 0.20, then

$$n = 2 (1.28 + 0.84)^2 (0.254^2/0.146^2) = 27 \text{ trap nights.}$$

Although substantially less sampling effort is needed, the magnitude of change in C/f that would occur before that change is detected is doubled, and the probabilities of both type I and type II errors are doubled.

low fish densities, the most frequent catch is no fish and the distribution is likely to approximate a negative binomial probability (Power and Moser 1999). Because most fish stocks occur in relatively low densities and have patchy spatial distributions, C/f sample distributions that resemble negative binomial probability distributions are fairly common.

The negative binomial distribution is widely recognized as a descriptor of animal distribution patterns, and it has been argued that the negative binomial distribution is a reasonable probability distribution for the overall description of C/f data (Moyle and Lound 1960; Power and Moser 1999). Often, C/f data are characterized by a high frequency of zeroes (Bannerot and Austin 1983; Power and Moser 1999), and occasionally one or more C/f values are excessively large, thereby exerting excessive influence on the arithmetic mean (Pennington 1996; Kappenman 1999). The variance of the mean C/f is often large; thus, it is difficult to discern if mean C/f estimates differ among groups or over time using parametric statistical testing (e.g., a t -test or analysis of variance [ANOVA]; Bannerot and Austin 1983). In addition, if the mean C/f is small and the variance is large, the probability of observing zero catches will be high (Power and Moser 1999) if the fisheries scientist assumes that data are from a normal probability distribution. For these reasons, mean C/f calculated from data distributed as a negative binomial distribution may not provide a reasonable statistic for comparison of samples.

Because the occurrence of negative binomial distributions of C/f data have been recognized, logarithmic transformations ($y = \log_e [x + 0.001]$ or $y = \log_{10} [x + 0.001]$) have been applied frequently in an attempt to normalize distributions (Bulkley 1970; Bagenel 1972) but with quite variable success. It has become common practice to apply logarithmic transformations to C/f data prior to conducting statistical tests and to assume that the transformation sufficiently normalizes the distribution so that test assumptions are not grossly violated. Fisheries scientists who follow this practice seldom carry out statistical tests to determine if normal distributions are achieved by the transformation. It is our experience that logarithmic transformations of C/f data seldom yield a normal distribution but can reduce the variance relative to the mean (see Box 7.2). Other transformations of C/f data have been applied in attempts to normalize the distributions (Shroyer and McComish 1998), but none was found to have wide success.

7.4.2 Appropriate Sample Statistics

Fisheries scientists occasionally use statistics other than the arithmetic mean to describe C/f distributions, primarily the geometric mean, median, and the frequency of occurrences of the target species among samples.

The back-transformed mean of the logarithmically transformed C/f data is called the geometric mean (Sokal and Rohlf 1981) and is used by fisheries scientists as a measure of central tendency for C/f data (Craig and Fletcher 1982; Hamley and Howley 1985; Hansen et al. 1995). It seems to be a logical expression of C/f when the data are logarithmically transformed for analysis. However, because the scale

is not familiar to many, it is difficult to grasp the magnitude of difference or change using the geometric mean.

The median of the C/f data distribution has an equal number of observations on either side of it (Sokal and Rohlf 1981) and also has been used by fisheries scientists as a measure of central tendency (Moyle and Lound 1960; Moyer et al. 1995). Moyle and Lound (1960) provided a method for computing confidence limits around median C/f estimates.

Another statistic applied to C/f data is based on enumeration of the frequency of occurrence of the target species among individual units of effort (Bannerot and Austin 1983; Counihan et al. 1999). If the frequency distribution of C/f data resembles a negative binomial, Bannerot and Austin (1983) suggested comparing the frequency of zero catches, which they found was a less biased index of abundance than mean C/f . The frequency of zero catches was more responsive to changes in stock abundance than mean C/f for a marine fishery (Bannerot and Austin 1983). Similarly, Counihan et al. (1999) stated that an index based on the proportion of individual units of effort when a target species is captured may have advantages over mean C/f because it is robust to biases and errors in sampling and insensitive to extremely high C/f values. Presence–absence indices generate proportional data that can be analyzed for differences among groups or over time (Sokal and Rohlf 1981). This approach circumvents issues of normal distributions associated with using the mean C/f and statistical tests requiring the assumption of normal C/f frequency distributions.

7.4.3 Bootstrap and Jackknife Techniques

Bootstrap and jackknife techniques are used to answer the same question: how precise is a particular statistic? These techniques can provide estimates of precision of C/f statistics (Dixon 1993). These techniques release fisheries scientists from the restrictive assumption that C/f data conform to a normal frequency distribution (Krebs 1989). Because both techniques compute a standard error for a statistic, they allow us to compute t -tests.

Bootstrap and jackknife techniques can be applied to statistics computed from C/f data, including the arithmetic mean, geometric mean, and median. They provide measures of the precision of the statistics and enable statistical comparisons of two samples. For statistics that are bounded in range (such as any of the three C/f statistics mentioned above, which are always greater than or equal to zero), these techniques may work more satisfactorily if the data are subjected to logarithmic transformation. Programs for bootstrap and jackknife routines are available, but some computational shortcuts may yield erroneous results. We recommend that fisheries scientists who want to apply these techniques work with statisticians to develop programs appropriate for their applications. It should be noted that the bootstrap and jackknife techniques will not usually yield the same answer (Dixon 1993), and there is no agreement on which technique is “better” for analysis of C/f data (Krebs 1989).

Some examples of using bootstrapping to obtain estimates of precision from C/f data can be found in the fisheries literature. In one example, Kimura and Balsiger (1985) applied bootstrapping to estimate the precision of C/f data for sablefish captured in pot gear off the Pacific Coast. Estimates of precision (i.e., coefficient of variation) of C/f data were obtained from different sampling areas and water depths and were then used to develop recommendations for the number of locations that should be sampled. Kimura and Balsiger (1985) also used the bootstrap technique to compute Z -statistics to estimate the statistical significance of observed differences in C/f between years within specified locations and depths. Similarly, Stanley (1992) used bootstrapping to estimate the variance and confidence limits for C/f data from four trawl fisheries along the Pacific Coast, and this information was then used to estimate the number of hauls needed to estimate mean C/f at $\pm 25\%$ of the actual rate 80% of the time ($\alpha = 0.2$). Bernard et al. (1993) applied bootstrapping to an assessment of burbot in Alaskan lakes. The bootstrap procedure was used to generate an empirical sampling distribution from which the variance was estimated for individual lakes. More recently, Smith (1997) developed bootstrap confidence limits for groundfish trawl survey estimates of mean C/f .

7.4.4 Comparison of Two Samples

In a classical statistical approach, a comparison of two samples is undertaken by testing the equality of means. Assuming the observations are selected randomly from a normal frequency distribution, the arithmetic mean provides a measure of central tendency. Because the mean is computed from a sample (and not the entire population), the uncertainty of the mean can be measured by the variance, another characteristic of the distribution. Under these conditions, a comparison of two samples is fairly simple: estimates of the variance are used to calculate standard errors, and confidence intervals around the means are constructed. However, as mentioned earlier, C/f data generally violate many of the assumptions of classical statistical approaches. For example, using traditional statistical approaches (t -tests and analysis of covariance) and logarithmically transformed data, only order-of-magnitude differences in larval fish abundance could be detected among sampling areas or time periods (Cyr et al. 1992).

To compare mean C/f values from different sampling locations or across time, an estimate of the variance (hence, standard error) is needed. Although some investigators advocate estimating the variance with regression methods (e.g., regressing catch on effort, Smith 1980) or jackknifing the variance of the ratio (Smith 1980), these approaches assume a linear relation between catch and effort. Because this assumption is not often met, we recommend seeking alternate approaches. One such approach uses maximum-likelihood methods to estimate C/f and its variance from the bivariate distribution of catch and effort (Richards and Schnute 1992).

Recently, Power and Moser (1999) applied an approach based on the assumption that the distribution of the catch data follows a negative binomial and variances

need not be homogeneous. Their generalized linear model permits comparison of catch rates among two or more samples and allows catch rates to vary as linear (or nonlinear) functions of exogenous variables. Generalized linear models share the same structure as general linear models (GLMs), but unlike general linear models, generalized linear models are not constrained by the assumption of normality. Using bootstrap simulations, Power and Moser (1999) demonstrated that the linear model with negative binomial errors performed better than the t -test in detecting differences between the means of two samples; furthermore, this was true when the t -test was applied to either raw data or logarithmically transformed data.

7.4.5 Analysis of Variance

7.4.5.1 Comparisons Based on Blocked Designs

When testing hypotheses based on ecological experiments, particularly field experiments, experimental units are sometimes grouped together in blocks. The purpose of this is to identify groups of similar experimental units so there is more similarity within blocks than among blocks. Blocks are not randomly assigned (as are treatments) but are either intrinsic characteristics of the experimental units (e.g., year-classes of a particular species, where the species is the experimental unit) or arbitrary segments of the experimental unit (e.g., 0.5-ha area of sandy bottom, where sections of sandy areas are the experimental units in a lake; Newman et al. 1997). In fisheries fieldwork, the blocking factors most likely to be encountered are areas fished (e.g., station or individual lakes), length-classes, or age-classes. The purpose of blocking is to improve the precision of the estimator. The example in Box 7.3 demonstrates how blocking can improve the ability to detect effects associated with factors of interest to fisheries scientists.

7.4.5.2 Other Analysis of Variance Models

Catch-per-unit-effort data are frequently collected from surveys and are intended to measure changes in abundance of fish in a stock. Depending on the design, ANOVA can be used to analyze these data under certain assumptions and constraints. Because surveys typically consist of repeated measures (e.g., C/f is estimated from a set of fixed or random stations through time), a repeated-measures ANOVA could be used to analyze such data (see Maceina et al. 1994). This approach accommodates temporal autocorrelation among observations—that is, it explicitly accounts for the fact that two observations taken closely apart in time will likely be correlated, and the correlation is likely to decrease as observations further apart in time are considered. The repeated-measures approach is recommended when (1) the study includes only fixed effects, (2) the data are balanced, and (3) the variance–covariance structure of the data conforms to a restrictive form (i.e., compound symmetry; Neter et al. 1996). Some adjustments exist for incorporating random effects into a repeated-measures ANOVA and for relaxing the assumption of compound symmetry (Neter et al. 1996). However, in many fishery surveys, C/f measures are repeated not just across time but also through space. In these cases, a different approach must be taken to accommodate correlations in

Box 7.3 Illustration of Blocked Design in One-Way Analysis of Variance (ANOVA)

An investigator wishes to determine if the abundance of bluegill differs among vegetated and nonvegetated areas of lakes. Bluegills are sampled using trap nets set within a vegetated and a nonvegetated area in each of eight lakes. In this study, the vegetation (presence or absence) is a fixed effect, the blocking factor is lake, and the response is the *C/f* of bluegill (fish/trap-night). Using the following hypothetical data set, we show how ignoring the blocking factor (lake) can lead to erroneous conclusions about the effect of vegetation on the relative abundance of bluegill.

Table Catch per unit effort data for bluegills.

Vegetation	Lake							
	A	B	C	D	E	F	G	H
Absent	63	45	30	50	80	67	48	55
Present	70	56	42	68	87	75	49	62

Program

The following SAS program is employed.

```
data bluegill;
input lake $ vegetation $ cpue;
lines;
[input data]
proc glm data=bluegill;
class lake vegetation;
model cpue=lake vegetation;
title 'One-Way ANOVA, Block Design';
prog glm data=bluegill;
class vegetation;
model cpue=vegetation;
title 'ANOVA without Blocking';
run;
```

Results

Table Results of one-way ANOVA with block design. The number of observations in the data set is 16. Abbreviations are as follows: mean square error (MSE); coefficient of variation (CV); and sum of squares (SS).

Class Level Information					
Class	Levels	Values			
Lake	8	A	B	C	D E F G H
Vegetation	2	absent	present		

Analysis of Variance					
Source	df	SS	Mean square	F-value	P > F
Model	8	3339.000	417.375	34.20	0.0001
Error	7	85.438	12.205		
Corrected	15	3424.438			
R ²	0.975	Root MSE	3.494		
CV	5.903	C/f mean	59.188		

(Box continues)

Box 7.3 (continued)

Analysis of Variance (continued)					
Source	<i>df</i>	Type I SS	Mean square	<i>F</i> -value	<i>P</i> > <i>F</i>
Model	8	3339.000	417.375	34.20	0.0001
Lake	7	3023.938	431.991	35.39	0.0001
Vegetation	1	315.063	315.063	25.81	0.0014

Table Results of ANOVA without blocking. The number of observations in the data set is 16.

Class Level Information		
Class	Levels	Values
Vegetation	2	absent present

Analysis of Variance					
Source	<i>df</i>	SS	Mean square	<i>F</i> -value	<i>P</i> > <i>F</i>
Model (vegetation)	1	315.063	315.063	1.42	0.253
Error	14	3109.375	222.098		
Corrected total	15	3424.438			
<i>R</i> ²	0.092	Root MSE	14.903		
CV	25.179	C/ <i>f</i> mean	59.188		

Interpretation

A cursory examination of the data reveals that within a lake, bluegill *C/f* is higher in vegetated areas than in nonvegetated areas. However, on closer inspection, we see that bluegill *C/f* in nonvegetated areas of lakes A and F was just as high as *C/f* in vegetated areas of lakes H and D. Results from the blocked ANOVA indicate that vegetation significantly affects the mean relative abundance of bluegills (vegetation is a significant factor in the ANOVA). In addition, the relative abundance of bluegills varied significantly among lakes (lake is a significant factor in the ANOVA). Thus, by blocking the design and accounting for lake to lake differences in the relative abundance of bluegills, the investigator was able to examine the effect of vegetation on bluegill abundance within lakes. Incidentally, if the investigator had randomly sampled one set of lakes (say lakes L, M, N, O, P) to estimate bluegill *C/f* in vegetated areas, and another set of lakes (say lakes Q, R, S, T, U) to estimate bluegill *C/f* in nonvegetated areas, then lake would not be a blocking factor because the treatment (vegetated versus nonvegetated) was randomly applied across lakes. In our blocked design, the treatment (vegetated versus nonvegetated) occurred in the same lake; because of this, the response to the two treatment levels was measured from the same lake. In this respect, data from a blocked design could also be analyzed as a paired *t*-test (see Sokal and Rohlf [1981] for further discussion).

In the second analysis, blocking is ignored, and it is not possible to detect the effect of vegetation on bluegill abundance. This occurs because in the unblocked design, the variation associated with lakes is considered part of the error term (compare the sums of square error terms from both models). By ignoring the blocking effect, we would interpret the results of this ANOVA in the following manner: on average across all lakes sampled, variation in relative abundance of bluegills is not affected by the presence of vegetation.

space in addition to serial correlations in time. Fabrizio et al. (2000) demonstrated how the mixed-model procedure (MIXED) in SAS (SAS Institute 1998) can be used to study changes in fish abundance from a complex repeated-measures design. Procedure (PROC) MIXED was used to fit a linear model with correlated errors to a 20-year time series of catch data from Lake Michigan, but the approach is applicable to other fixed-station fishery surveys. The linear model used by Fabrizio et al. (2000), $y = X\beta + e$, is similar to a GLM (one fit with SAS' PROC GLM) except that in the GLM, the vector e is a vector of independent random variables, and in the linear model with correlated errors, e is a vector of possibly correlated random errors with covariance matrix R (Littell et al. 1996). In this notation, y is a vector of observations, X is a matrix of fixed effects values, and β is a vector of fixed effects coefficients. Another difference between the two models is that instead of simply modeling the mean and a single variance of y (the GLM), the mean, variance, and covariance of y are modeled in the linear model with correlated errors.

Procedure MIXED is a flexible approach that works well for unbalanced data. It can be used to fit a variety of models, including mixed models that contain both fixed effects and random effects: $y = X\beta + Z\mu + e$, where y , X , β , and e are defined as before, Z is the design matrix (usually a matrix of 0s and 1s), and μ is a vector of random effects parameters (Littell et al. 1996). To use PROC MIXED, the investigator must identify and specify the type of the variance–covariance structure that defines the error term of the model. Version 6.12 of SAS offers about 20 options for the structure of the variance–covariance matrix, and Wolfinger (1996) discusses useful variance–covariance structures for models fit to repeated-measures data. A new procedure, PROC NLMIXED, available with SAS version 7 and higher, can fit nonlinear models using likelihood-based methods (Wolfinger 1999).

7.4.6 Nonparametric Alternatives to Analysis of Variance

Because nonparametric tests do not require the assumption that the data come from a normal distribution, these tests have been recommended when assumptions of parametric statistics cannot be met. Standard parametric tests such as the t -test and ANOVA have nonparametric counterparts that can be easily implemented once the raw data are rank transformed. For example, the counterpart to the t -test is the Mann–Whitney U -test or Wilcoxon's rank-sum test. However, it should be noted that the null hypothesis of a nonparametric test is not equivalent to that tested by the analogous parametric method. In the case of the Mann–Whitney or Wilcoxon test, the null hypothesis is that two distributions are identical. Nonparametric tests will detect differences not just in central tendency but also differences in the spread or shape of distributions (Johnson 1995). When performing a nonparametric comparison of two samples, a significant test result provides no information on whether the difference is due to the mean, variance, shape, or some other characteristic of the distribution (Johnson 1995).

Although nonparametric techniques obviate the need for normally distributed data and appear to be well suited for analysis of C/f data, relations between C/f and other variables must still be considered. For example, Richards and Schnute (1986) found that C/f data had to be standardized prior to applying a Kruskal–

Wallis test when evaluating the effects of sea surface condition, time of day, and tidal phase on C/f . These data were standardized by working with observations from a restricted time (only when sea surface conditions were calm) when catches were thought to be most reliable.

With nonparametric tests investigators still must apply a priori significance levels to tests and consider the trade-offs between type I and type II errors. Because some fisheries scientists perceive the power of nonparametric tests to be low, larger alpha levels (e.g., $\alpha = 0.10$ or 0.15) are sometimes used in significance testing. However, nonparametric tests often have as much power as their parametric counterparts.

7.4.7 Time Series Analysis

Fish abundance measures that are estimated repeatedly through time are typically examined for patterns of change through time by means of regression analysis. The relation between observations close in time may be similar—that is, values in a given year may be influenced by values in the previous year. This relationship generally decreases with increasing time intervals. Such data are said to exhibit positive autocorrelation. The presence of autocorrelation (or serial dependence) in fish abundance data compromises statistical interpretation of correlation and regression analyses that may be undertaken to relate changes in fish abundance to environmental or biological variables (Pyper and Peterman 1998). The reason is that most parametric statistical tests assume independence (correlation equals 0) of observations. Hypothesis tests on autocorrelated data require adjustments to the degrees of freedom to reflect the lack of independence among observations (Pyper and Peterman 1998).

For predictive modeling or exploratory analyses, autocorrelated data must be transformed. Several transformations have been used with autocorrelated data, including smoothing, first-differencing, and prewhitening. A smoothed data series results from the computation of a series of weighted averages from nearby points. A simple smoothing technique is the running average (moving average). Smoothing is an effective transformation for removing high-frequency variation, which appears as rapid changes over short time scales. An example of high-frequency variation is measurement error. Sometimes it may be desirable to remove the signal associated with slow, long-term changes from a time series of C/f data. These changes are typical of low-frequency variation and first-differencing or prewhitening may be used to transform the data series (Pyper and Peterman 1998). In first-differencing, the observation at time $t - 1$ is subtracted from the observation at time t . Prewhitening is typically applied when the analyst wishes to relate C/f data to one or more environmental variables. For example, to determine if the pattern of variation in C/f is associated with the pattern of variation in temperature data, the time series of temperature data are modeled with an appropriate time series model. That model is then applied to the series of C/f data to prewhiten the C/f series. Model identification, parameter estimation, and diagnostic checking procedures are beyond the scope of this chapter but are

well described in Box and Jenkins (1976). Additional information on smoothing, first-differencing, and prewhitening is available in Pyper and Peterman (1998), along with an effective method for adjusting the degrees of freedom for statistical testing of autocorrelated data.

It should be noted, however, that the decision to employ any of the transformations should be taken with extreme caution. Pyper and Peterman (1998) point out that if low-frequency variation is removed from a time series of data, the effect of a slowly changing variable on the dynamics of the population will be difficult to detect, but the effect of a quickly changing variable (high-frequency variability) will be well detected if it is the dominant source of covariation. When the dominant source of covariation is low frequency, Pyper and Peterman (1998) recommend adjusting the degrees of freedom because this approach has greater statistical power.

7.4.8 Assessment of Relationships between C/f and Other Variables

Regression analysis is commonly applied to C/f data to make predictions. For example, Isbell and Rawson (1989) found that C/f of walleye captured in experimental gill nets was a predictor of angler catch rates in western Lake Erie. Mean C/f in gill nets was used as the predictor variable, and mean C/f among anglers was used as the response variable. Similarly, Shroyer and McComish (1998) predicted the future C/f of quality-length (>200 mm total length) yellow perch based on C/f of stock-length (>130 mm total length) yellow perch in trawl samples in Indiana waters of Lake Michigan.

Regression analysis has also been used to predict C/f of fish from various habitats. For example, Johnson and Jennings (1998) assessed the habitat associations of small fishes around islands in the upper Mississippi River based on C/f as an index of abundance. They predicted C/f from measures of habitat. Similarly, Irwin et al. (1997) assessed the habitat associations of age-0 largemouth bass along the shoreline of a large reservoir. Regression analysis was used to determine if measured habitat features accounted for variation in C/f of age-0 largemouth bass among 43 discrete shoreline sections.

These approaches are fairly straightforward when habitat variables are static characteristics of the environment. However, when habitats or environmental conditions are dynamic (such as salinity and water temperature), it is advisable to remove the high frequency (<24 h) variation of these dynamic physical variables prior to using such data in a regression (Rose and Leggett 1989).

Fishery scientists have long recognized the problem of using C/f as a predictor variable in regression analysis (see Ricker 1975) because the predictor variable is assumed to be known accurately. This is an untenable assumption with C/f data that are fraught with measurement errors. Measurement errors in C/f data are a good example of what statisticians call the "errors in variables" problem. In general, errors in variables tend to flatten the probability density function and increase dispersion; such changes lead to upwardly biased variance estimates and downwardly

biased estimates of the mean (Chesher 1991). Ricker (1975) demonstrated how to use functional regression analysis to estimate regression parameters from C/f data, but Ricker's approach is now considered ad hoc (Hilborn and Walters 1992). A good review of the fisheries-related work on the errors in variables problem is provided in Hilborn and Walters (1992). Although errors in variables are unavoidable in fisheries modeling, the magnitude of the bias associated with the errors in variables problem can be investigated using Monte Carlo simulation techniques (Hilborn and Walters 1992). When modeling the stock–recruitment relation, even small measurement error (mean = 0 and SD = 0.2) can lead to erroneous conclusions about the nature of the relationship (Walters and Ludwig 1981). Several other approaches have been proposed to work with C/f data subject to the errors in variables problem, including techniques for data containing measurement error in both the dependent and independent variables (e.g., Richards and Schnute 1986; Kimura 2000).

Most linear models, including regression analysis, do not address extra-Poisson or extra-binomial variation, and, because of this, such models may not provide reliable confidence intervals or significance tests for parameters of interest (Casey and Myers 1998). As discussed in section 7.4.3, the jackknife or bootstrap approach may be useful in estimating precision of regression parameters. Another approach is to use simulation modeling. In addition to these techniques, the randomization approach may be used to estimate confidence intervals for a regression parameter, particularly if the standard significance levels or standard errors of the parameter estimates are not reliable (Casey and Myers 1998).

Detection of trends in C/f data has been recently pursued with regression tree methods (Watters and Deriso 2000). Observed trends were ascribed to changes in catchability and to actual changes in abundance. This regression tree application required estimation of 139 parameters for 30 years of monthly data on bigeye tuna from the Pacific Ocean, so it is not likely to be appropriate for short time series. Regression trees are useful in examining the interaction of factors such as area (e.g., latitude–longitude grids) and time (e.g., specific months) and may be more parsimonious (fewer parameters) than GLMs or spatially explicit models that account for variations in environmental conditions (Watters and Deriso 2000).

■ 7.5 INTERPRETATION AND APPLICATION OF C/f STATISTICS

Monitoring changes in fish stock abundance through time is a costly activity undertaken typically by federal and state agencies. The goal of these surveys is to provide long-term information on the status of species so that changes in abundance can be detected. These surveys require an investment in gear and personnel as well as an institutional commitment to multiyear support. Analysis of data collected from monitoring surveys is often difficult due to the nature of the C/f data, which may also reflect the vagaries of the weather and the reliability of the equipment and gear.

7.5.1 Example of a Temporal Monitoring Program

In this section, we illustrate how to assess patterns of change in C/f over time. We use mean C/f of bay anchovy from two regions of a mid-Atlantic estuary as an example (see Box 7.4). The C/f data were collected from fixed stations along a salinity gradient in the estuary and are considered repeated measures. To begin analysis, components that represent the treatment structure and those representing the design structure must be designated so that the appropriate statistical model can be identified. In general, the treatment structure refers to the components of the experimental design whose effects are of interest. In a temporal monitoring program, this typically includes effects of time and may also include effects of other factors such as region (in this example), habitat type, or habitat manipulation. Design structure components are elements necessary to conduct or construct the experiment and assist in addressing the components of the treatment structure. Randomization and blocking are two examples of design structure elements. Statistical testing is focused on components of the treatment structure and generally not on the design structure. In this example, we use PROC MIXED to examine changes in mean C/f between two regions in the estuary and through time. The treatment structure consists of two fixed effects: region (bay versus river) and time. The design structure incorporates a random component (i.e., stations, which are nested within regions).

In a typical repeated-measures design, the response is measured from the same subject multiple times. In this temporal monitoring example, the “subjects” are stations from which C/f data were sampled; the repeated measures are C/f . To designate stations as the experimental units, we must restrict our inferences to the two regions sampled and assume that the C/f data from the two regions are uncorrelated. (Technically, because our treatment [region] cannot be applied to each station, the stations are not independent experimental units, and further investigation of the dependency among stations may be pursued prior to modeling. However, this line of inquiry is beyond the scope of this example and will not be illustrated here.)

Although PROC GLM provides several approaches for analyzing repeated-measures data (using split-plot or multivariate approaches), we advise against using this SAS procedure to analyze fisheries survey data such as these. The split-plot and multivariate approaches to analysis of repeated measures are useful for analysis of some ecological data, but in those cases, the experimental units are typically groups of organisms or samples that can be randomly assigned a treatment. In addition, the split-plot repeated-measures design has been used to analyze fisheries data obtained at various points in time before and after an experimental manipulation, where the manipulation affects all possible sample sites within a water body (e.g., to test the effects of vegetation removal on length structure of fish in a small lake; Maceina et al. 1994). The split-plot approach is well suited to surveys of individual water bodies from which replicates are taken and treatments can be applied to each experimental unit (station and replicate). The split-plot approach

Box 7.4 Analysis of C/f Data from a Temporal Monitoring Program

Bay anchovies were sampled with an otter trawl every 6 months from November 1996 through May 2000 for a total of eight sampling periods. Trawl tows were taken at 13 randomly selected sites in the river and 11 randomly selected sites in the bay. A single 5-min tow was completed at each station during each sampling period, the area swept was calculated, and C/f was computed as the number captured per unit of area swept. The analysis was designed to address two questions. Did mean C/f change through time? Did mean C/f differ between the river and bay?

The data set contained 192 otter trawl samples, but 134 samples contained no bay anchovies. Because the C/f data contained many zeros, had a large coefficient of variation, and had a variance that exceeded the mean, the C/f observations were transformed as $\log_e(x + 0.0001)$. River sites were coded as 0 and bay sites as 1 in a variable termed region. Sampling periods were coded 1 through 8 in a variable termed time. Sampling sites were coded 1 to 13 in the river and 1 to 11 in the bay in a variable termed station.

We first identified the type of covariance matrix that best described the random component (i.e., stations sampled repeatedly) in this study. The keyword TYPE identifies the covariance matrix in the repeated statement of PROC MIXED. Because the C/f data are repeated measures, temporal correlation among samples from a site may occur with the correlation decreasing as the time interval increases. If the decrease is exponential, then the covariance structure can be modeled using a first-order autoregressive structure (TYPE = AR[1]). If the correlations are equal across time intervals, the covariance can be modeled using a compound symmetric structure (TYPE = CS). For maximum flexibility in modeling the correlations, an unstructured covariance matrix may be specified (TYPE = UN). We fitted these three covariance structures to the data and compared the model fit using a likelihood-based criterion, Akaike's Information Criterion (AIC; Littell et al. 1996). The best model provides the smallest AIC, which is reported in a SAS output under "Fit Statistics." We found TYPE = AR(1) provided the best description of the covariance structure for these data.

Procedure MIXED was used to test for region and time effects. Before fitting the model to the data we examined the interaction plot to determine the relation between region and time.

Program

The following SAS program was employed.

```

/* Plot the mean data through time for each region - Interaction Plot */
proc univariate noprint data=cpue.anchovy;
var lcpue_a;
by region t;
output out=anc_out mean=ybar;
proc plot data=anc_out;
plot ybar*t=region/box;
proc mixed data=cpue.anchovy;
class region station t;
model lcpue_a = region t region*t / outp=predict1;
random station(region) / s;
/* This is the error term for testing the region effect */
repeated / subject=station type=ar(1);
ods listing exclude solutionr;
ods output solutionr=randsoln;
title 'Proc Mixed Results for Anchovy Data';

/* Assess residuals for approximate normality at the whole plot (region)
level. Actually, these are estimated random effects. */
proc univariate data=randsoln plot normal;
var tvalue;
probplot tvalue / normal;
title 'Residuals - Estimated Random Effects';

```

```

/* Assess residuals for approximate normality at the subplot (time) level. */
proc univariate data=predict1 plot normal;
var resid;
probplot resid / normal;
title 'Residuals - From Predicted'; run;

```

In the PROC MIXED statements, note that region, station, and time are class variables. The model statement includes region, time, and the region \times time interaction, which we suspect may be significant. The output option (outp=) in this statement specifies that the output SAS data set is called predict1. All the modeled effects are fixed effects. The single random effect identified in the random statement was station nested within region. The s option in the random statement requests estimation of the solution, which will be used to evaluate normality of random effects. The repeated statement defines the subjects of this repeated-measures analysis, which were stations. Two statements are included to control the output delivery system (ods). The first (listing exclude solution) suppresses the listing of the model estimates for each of the 24 random effects. The ods output statement places the random effects estimates in a SAS data set (randsoln). Portions of the output from the PROC MIXED analysis are given below.

Results

Table Portion of results for mixed-model ANOVA of bay anchovy *C/f*. Abbreviations are first-order autoregressive structure (AR[1]); time (*t*); numerator (Num); and denominator (Den).
Covariance Parameter Estimates

Covariance Parameter Estimates				
Covariance parameter		Subject	Estimate	
Station (region)			0.5511	
AR(1)		Station	0.2283	
Residual			4.4531	

Type 3 Tests of Fixed Effects				
Source	Num <i>df</i>	Den <i>df</i>	<i>F</i> -value	<i>P</i> > <i>F</i>
Region	1	22	2.81	0.1077
<i>t</i>	7	154	7.01	<0.0001
Region* <i>t</i>	7	154	2.79	0.0093

Interpretation

The interaction plot indicated that mean *C/f* may be changing differently in the two regions, hinting that an interaction of time and region may occur (see Quinn and Keough 2002). The output reveals the estimate of the variance of the mean *C/f* among stations nested within regions (0.5511). The correlation coefficient (0.2283) indicates a relation in *C/f* between adjacent 6-month sampling times. The *F*-test identifies a significant interaction of region and time (region**t*, *F* value = 2.79, *P* > *F* = 0.0093), as suggested by the interaction plot, making interpretation of region and time effects difficult to assess. The interaction indicates that processes contributing to changes in mean *C/f* differ in the river and bay. Options for further analysis may be to test for the presence of trends in *C/f* for each region separately or omit the distinction between regions and assess the collective data set for temporal trends.

cannot be applied to our example data set because each whole plot (station in bay or river) would need to contain both treatments (regions). Furthermore, for some moderately complex designs, the GLM procedure is known to compute incorrect standard errors. When analyzing repeated-measures data with PROC GLM, the analyst should be aware of potential problems that occur with missing data, especially when the random statement is used or when modeling multivariate contrasts (Littell et al. 1996). We note that for most field studies, missing data are common due to experimental failures, weather-related loss of sampling opportunity, and other unplanned problems. Procedure MIXED was developed to address some of the limitations of PROC GLM for modeling data from experiments that incorporate random components either in the design structure, treatment structure, or both.

7.5.2 Example of an Assessment of Spatial Patterns

Fisheries scientists are frequently faced with the need to identify spatial patterns in fish distributions. Given the target species and type of water, an approach may entail the use of C/f . A hypothetical example of an assessment of spatial distribution patterns of a fish stock based on C/f data may be illustrated by means of yellow perch in a stratified Midwestern lake (Box 7.5). The fisheries scientists wanted to know if the midday depth distribution patterns of yellow perch differed between June and August. A stratified random sampling design was used. The strata were the two sampling months and five sampling depths (2.5, 5, 10, 15, and 20 m). Within each depth stratum, three redundant locations were randomly selected for sampling during each sampling month. Gill nets were set perpendicular to the shore 1 h before midday and retrieved 2 h later. Fish/net/h was used as an index of yellow perch relative abundance. Two-way ANOVA (i.e., PROC GLM) was used to assess variation in C/f among months and sampling depths (see Box 7.5). No significant difference in mean C/f was found between June and August, but mean C/f differed significantly among sampling depths. Sampling month and depth exhibited no significant interaction, indicating that patterns in the depth distribution of yellow perch were similar in June and August. The mean C/f was greatest at the 10-m sampling depth during both months. The data suggest that yellow perch are most abundant between 5 and 15 m with lower numbers near shore (2.5 m) and at 20 m.

7.5.3 Example of the Use of a Regression Estimator

A common problem encountered by fisheries scientists is the need to identify relations between fish abundance and habitat features. Such relationships help define habitat features needed by a species, determine habitat quality, or define the likely responses of aquatic organisms to improvement or degradation of habitat (Orth and White 1999; Summerfelt 1999). Because experiments involving manipulation of habitat are difficult, time-consuming, and expensive to conduct,

Box 7.5 Assessment of Depth Distribution Patterns of Yellow Perch Based on C/f Data

Data on C/f (fish//net/h) of yellow perch captured with gill nets in a Midwestern lake were obtained during midday at five depths during 2 months with three randomly selected sites sampled at each depth during each month. A two-way ANOVA was used to assess effects of sampling depth and month as well as the interaction between the two.

Table Data on C/f of yellow perch in a Midwestern lake. Three sites were sampled at each of five depths during two dates (June = 1 and August = 2).

Month	Depth (m)	C/f	Month	Depth(m)	C/f
1	2.5	2	2	2.5	0
1	2.5	4	2	2.5	2
1	2.5	7	2	2.5	0
1	5.0	6	2	5.0	10
1	5.0	10	2	5.0	10
1	5.0	12	2	5.0	9
1	10.0	8	2	10.0	13
1	10.0	12	2	10.0	40
1	10.0	33	2	10.0	46
1	15.0	10	2	15.0	6
1	15.0	10	2	15.0	5
1	15.0	17	2	15.0	12
1	20.0	0	2	20.0	0
1	20.0	2	2	20.0	0
1	20.0	3	2	20.0	0

Program

The following SAS program was employed.

```

data yelperch;
input month depth catch;
cards;
[input data]
proc glm;
class month depth;
model catch=month depth month*depth;
proc sort;
by month depth;
proc means mean stderr;
by month depth;
var catch;

```

Results

The ANOVA indicated that C/f varied significantly among sampling depths, but no significant difference occurred among sampling months and no interaction occurred.

(Box continues)

Box 7.5 (continued)**Table** Two-way ANOVA of *C/f* data for yellow perch. There were 30 observations.

Class Level Information					
Class	Levels	Values			
Month	2	1 2			
Depth	5	2.5 5 10 15 20			

Analysis of Variance					
Source	<i>df</i>	SS	Mean square	<i>F</i> -value	<i>P</i> > <i>F</i>
Model	9	2659.633333	295.514815	5.48	0.0008
Error	20	1079.333333	53.966667		
Corrected total	29	3738.966667			
<i>R</i> ²	0.711328	Root MSE	7.346201		
CV	76.25814	Catch mean	9.633333		

Source	<i>df</i>	Type I SS	Mean square	<i>F</i> -value	<i>P</i> > <i>F</i>
Month	1	9.633333	9.633333	0.18	0.6772
Depth	4	2249.800000	562.450000	10.42	<0.0001
Month*depth	4	400.200000	100.050000	1.85	0.1582

The mean *C/f* and SE for each sampling month and depth are given below so that comparisons can be made between months.

Table Mean *C/f* and SE for yellow perch data.

Depth (<i>m</i>)	June		August	
	Mean <i>C/f</i>	SE	Mean <i>C/f</i>	SE
2.5	4.33	1.45	0.66	0.66
5.0	9.33	1.76	9.66	0.33
10.0	17.67	7.75	33.00	10.15
15.0	12.33	2.33	7.67	2.19
20.0	1.66	0.88	0	0

fisheries scientists often rely on a regression analysis to make inferences on the relationships between fish abundance and habitat features. Many examples exist in the literature in which a regression analysis was used to identify habitat features that might be related to fish abundance, particularly as measured by *C/f* (Irwin et al. 1997; Tillma et al. 1998; Braaten and Guy 1999). Cause and effect relations between measured habitat features and *C/f* cannot be proven by means of a

regression analysis, but substantial insight and predictive capabilities can be generated if studies are designed properly and analyses are conducted carefully.

We provide a hypothetical example to illustrate application of a regression design to examine habitat quality when C/f data are used to index fish abundance. In this example, fisheries scientists wanted to identify habitat features that may affect the abundance of age-0 smallmouth bass in shoreline areas and to develop the ability to predict abundance from measured habitat features. Box 7.6 contains a hypothetical data set for age-0 smallmouth bass and demonstrates how habitat features along the shoreline of a small natural lake may be associated with C/f of age-0 fish. Twenty sites representing the range of shoreline habitats were selected from the periphery of the lake. At each site, a 50-m segment was sampled between the shoreline and the 1-m-depth contour in late July. The mean bottom slope, proportion of the bottom composed of gravel–cobble substrate, and proportion of the bottom covered by aquatic macrophytes were measured at each site. Over each 50-m segment, one pass was made at night with a boat-mounted electrofishing unit, and all age-0 smallmouth bass captured during the pass were counted. The C/f (number/50 m of shoreline) was used as an index of age-0 smallmouth bass abundance at each site.

Pearson's correlation coefficients were computed to assess relations among the three habitat features. A significant correlation was found between the proportion of gravel and the bottom slope indicating that these two independent variables may be redundant measures of the same ecological feature, which may or may not be important to age-0 smallmouth bass. Linear regression analysis was next used to evaluate relationships between C/f and each habitat feature. A $\log_{10}(x + 1)$ transformation of the C/f data was made to improve the linear relation. Gravel accounted for significant variation in C/f (see Box 7.6). When C/f was transformed, the coefficient of determination (r^2) increased and the probability (P) that the relation was due to chance declined, indicating a more linear relationship. Vegetation, which was not correlated with gravel, did not account for additional variation in C/f when included in a multiple-regression model with gravel. Based on the high coefficient of determination ($r^2 = 0.84$), the relation between gravel and $\log_{10}(C/f + 1)$ would be judged as a good predictor of age-0 smallmouth bass abundance in shoreline areas. However, fisheries scientists using this model should note that cause and effect relations were not defined by the regression model. In this case, it is likely that small gravel is a suitable spawning substrate for smallmouth bass and that age-0 fish are abundant where spawning was concentrated not necessarily because gravel is a needed habitat feature for age-0 fish. The model should be tested with several independent data sets before it is used for management decisions.

■ 7.6 SUMMARY

When assessing temporal or spatial trends in fish stocks, freshwater fisheries scientists often use C/f as an index of relative abundance. Underlying assumptions associated with the relationship between C/f data and actual population abundance

Box 7.6 Regression Analysis to Assessment of Habitat Features when C/f Data Are Used As the Response Variable.

This hypothetical problem focuses on defining the habitat features affecting the densities of age-0 smallmouth bass around the shoreline of a natural lake in the Midwestern United States.

Table Data: for 20 sites sampled along 50-m segments of shoreline of a Midwestern natural lake in late July. The mean bottom slope, proportion of the bottom composed of gravel–cobble substrate, and proportion of the bottom covered by aquatic macrophytes were measured at each site, and one pass was made at night with a boat-mounted electrofishing unit for age-0 smallmouth bass.

C/f (fish/50 m)	Gravel (%)	Vegetation (%)	Slope (%)
0	0	0	7.3
5	5.2	10.1	1.5
1	0.3	1.1	2.2
10	5.5	13.6	1.2
12	6.7	7.3	1.7
0	0.8	10.9	5.3
1	0.1	10.0	8.3
3	1.9	0	3.0
25	8.3	0	1.5
0	0.5	5.0	4.3
98	11.1	1.8	1.5
2	0.9	4.0	4.3
15	6.6	1.3	1.1
60	10.0	11.0	1.4
0	3.0	0	5.9
1	1.0	7.7	8.0
7	5.9	1.0	1.3
1	1.0	4.0	4.4
0	4.0	0	8.7
5	4.3	7.6	1.4

The data were entered into a spreadsheet, and the C/f data were transformed [$\log_{10}(C/f + 1)$] to create a second response variable. Correlations were assessed among the habitat features to avoid inclusion of redundant variables in regression models. Simple linear regressions were computed between each of the three habitat features and each of the two measures of relative abundance.

Program

The following SAS program was employed.:

```
data bass;
input cpue logcpue gravel vegetation slope;
gravveg=gravel*vegetation;
cards;
[...input .data...]
proc corr;
var gravel slope vegetation;
proc reg;
model cpue=gravel;
model cpue=slope;
model cpue=vegetation;
model logcpue=gravel;
model logcpue=slope;
model logcpue=vegetation;
```

Results

The correlation analysis indicated that the proportion of gravel and the shoreline slope were negatively correlated ($r = -0.649, P = 0.002$).

Table Pearson's correlation coefficients (r), ($n = 20$) for habitat variables and the probability of a greater $|r|$ under the null hypothesis that $\rho = 0$.

	Gravel	Slope	Vegetation
Gravel	1.00000	0.03204 0.8933	-0.64916 0.0020
Slope	0.03204 0.8933	1.00000	-0.09309 0.6963
Vegetation	-0.64916 0.0020	-0.09309 0.6963	1.00000

The regression analyses indicated that the strongest linear relationship between relative abundance and a measured habitat feature occurred between $\log_{10} C/f$ and the proportion of gravel ($r^2 = 0.837, P < 0.0001$).

Table Regression analysis of $\log_{10}(C/f + 1)$ of smallmouth bass and the proportion of gravel.

Analysis of Variance					
Source	<i>df</i>	SS	Mean square	<i>F</i> -value	<i>P</i> > <i>F</i>
Model (gravel)	1	5.93149	5.93149	92.59	<0.0001
Error	18	1.15315	0.06406		
Corrected Total	19	7.08464			
R^2	0.8372	Root MSE	0.25311		
Adjusted R^2	0.8282	Dependent mean	0.66490		
CV	38.06690				

Parameter Estimates					
Variable	<i>df</i>	Parameter estimate	SE	<i>t</i> -value	<i>P</i> > $ t $
Intercept	1	0.04083	0.08608	0.47	0.6410
Gravel	1	0.16189	0.01682	9.62	<0.0001

Interpretation

The model that used the untransformed C/f as the response variable and gravel as the dependent variable was significant (<0.0001), but the amount of variability in C/f accounted for by gravel was substantially less ($r^2 = 0.636$).

Multiple-regression models were computed with both the proportion of gravel and the proportion of vegetation as habitat variables, as well as with the interaction term ($\text{gravveg} = \text{gravel} \times \text{veg}$). The following SAS program was employed:

```
Proc reg;
  model logcpue=gravel vegetation;
  model logcpue=gravel vegetation gravveg;
```

Results

Neither the proportion of vegetation nor the interaction term was significant. Slope was not included in the multiple-regression model because it was significantly correlated with the proportion of gravel. Therefore, the regression analysis suggests that the relative abundance of age-0 smallmouth bass can be predicted from the proportion of gravel along shoreline areas.

must be considered, or C/f can be a misleading indicator of abundance. While there are several assumptions to be considered, the assumption of constant catchability may be the most critical and commonly violated. Substantial effort should be made to assure constant catchability in management assessments and research designs. In order to minimize uncontrolled sources of variation (error) in C/f , stratified random and systematic sampling designs are commonly used. Such designs incorporate standardization of gear and effort and identification of sampling times and locations. Assessing the extent of variability in C/f with a particular design and identifying the sampling effort required to detect changes over time or to detect differences among sampling sites through preliminary sampling are necessary components of management and research efforts.

A major problem in the application of C/f sampling data is that the distribution is seldom normally distributed. Negative binomial distributions are common among C/f data sets, but they cannot be assumed to occur. A variety of descriptive statistics have been used to characterize the distribution of C/f data, but none are universally applicable. The power of classical statistical methods is substantially reduced when C/f data are incorrectly assumed to be normally distributed. Furthermore, changes in C/f over time or among different locations may not be detectable when, in fact, differences in fish abundance exist. However, recent applications of general linear models and mixed models that incorporate temporally and spatially autocorrelated errors into C/f analyses provide substantial promise for more powerful analyses. Similarly, advances in regression analyses beyond classic least-squares regression are providing better descriptors of relations between C/f and other variables. The historic and emerging statistical methods described in this chapter have utility in management and research; however, users of these techniques are advised to seek consultation of professional statisticians to assure that the most appropriate analytical methods are used and to avoid misleading results or interpretations.

■ 7.7 REFERENCES

- Allen, M. S., M. M. Hale, and W. E. Pine, III. 1999. Comparison of trap net and otter trawls for sampling black crappie in two Florida lakes. *North American Journal of Fisheries Management* 19:977–983.
- Bagenel, T. B. 1972. The variability in the number of perch, *Perca fluviatilis* L., caught in traps. *Freshwater Biology* 2:27–36.
- Bannerot, S. P., and C. B. Austin. 1983. Using frequency distributions of catch per unit effort to measure fish-stock abundance. *Transactions of the American Fisheries Society* 112:608–617.
- Bernard, D. R., J. F. Parker, and R. Lafferty. 1993. Stock assessment of burbot populations in small and moderate-size lakes. *North American Journal of Fisheries Management* 13:657–675.
- Bernard, D. R., G. A. Pearse, and R. H. Conrad. 1991. Hoop traps as a means to capture burbot. *North American Journal of Fisheries Management* 11:91–104.

- Bohlin, T., S. Hamrin, T. G. Heggberget, G. Rasmussen, and S. J. Saltveit. 1989. Electrofishing—theory and practice with special emphasis on salmonids. *Hydrobiologia* 173:9–43.
- Box, G. E. P., and G. M. Jenkins. 1976. *Time series analysis, forecasting and control*. Holden-Day, Oakland, California.
- Braaten, P. J., and C. S. Guy. 1999. Relations between physiochemical factors and abundance of fishes in tributary confluences of the lower channelized Missouri River. *Transactions of the American Fisheries Society* 128:1213–1221.
- Bulkley, R. V. 1970. Fluctuations in abundance and distribution of common Clear Lake fishes as suggested by gillnet catch. *Iowa State Journal of Science* 44:413–422.
- Burkhardt, R. W., and S. Gutreuter. 1995. Improving electrofishing catch consistency by standardizing power. *North American Journal of Fisheries Management* 15:375–381.
- Carlander, K. D. 1953. Use of gill nets in studying fish populations, Clear Lake, Iowa. *Proceedings of the Iowa Academy of Science* 60:621–625.
- Casey, J. M., and R. A. Myers. 1998. Diel variation in trawl catchability: is it as clear as day and night? *Canadian Journal of Fisheries and Aquatic Sciences* 23:579–586.
- Chesher, A. 1991. The effect of measurement error. *Biometrika* 78:451–462.
- Chipps, S. R., D. H. Bennett, and T. J. Dresser, Jr. 1997. Patterns of fish abundance associated with a dredge disposal island: implications for fish habitat enhancement in a large reservoir. *North American Journal of Fisheries Management* 17:378–386.
- Choat, J. H., P. J. Doherty, B. A. Kerrigan, and J. M. Leis. 1993. A comparison of towed nets, purse seine, and light-aggregation devices for sampling larvae and pelagic juveniles of coral reef fishes. *U.S. National Marine Fisheries Service Fishery Bulletin* 91:195–209.
- Coble, D. W. 1992. Predicting population density of largemouth bass from electrofishing catch per effort. *North American Journal of Fisheries Management* 12:650–652.
- Cochran, W. G. 1977. *Sampling techniques*, 3rd edition. Wiley, New York.
- Collins, N. C., H. H. Harvey, A. J. Tierney, and D. W. Dunham. 1983. Influence of predatory fish density on trapability of crayfish in Ontario lakes. *Canadian Journal of Fisheries and Aquatic Sciences* 40:1820–1828.
- Counihan, T. D., A. I. Miller, and M. J. Parsley. 1999. Indexing the relative abundance of age-0 white sturgeons in an impoundment of the lower Columbia River from highly skewed trawling data. *North American Journal of Fisheries Management* 19:520–529.
- Craig, J. F., and J. M. Fletcher. 1982. The variability in the catches of charr, *Salvelinus alpinus* L., and perch, *Perca fluviatilis* L., from multi-mesh gill nets. *Journal of Fish Biology* 20:517–526.
- Crecco, V. A., and T. F. Savoy. 1985. Density-dependent catchability and its potential causes and consequences on Connecticut River American shad, *Alosa sapidissima*. *Canadian Journal of Fisheries and Aquatic Sciences* 42:1649–1657.
- Cross, T. K., M. C. McInerney, and D. H. Schupp. 1995. Seasonal variation in trap-net catches of bluegill in Minnesota lakes. *North American Journal of Fisheries Management* 15:382–389.
- Cui, G., C. S. Wardle, C. W. Glass, A. D. F. Johnstone, and W. R. Mojsiewicz. 1991. Light level thresholds for visual reaction of mackerel, *Scomber scombrus* L., to coloured monofilament nylon gillnet materials. *Fisheries Research* 10:255–263.

- Cyr, H., J. A. Downing, S. Lalonde, S. B. Baines, and M. L. Pace. 1992. Sampling larval fish populations: choice of sample number and size. *Transactions of the American Fisheries Society* 121:356–368.
- Dewey, M. R. 1992. Effectiveness of a drop net, pop net, and an electrofishing frame for collecting quantitative samples of juvenile fishes in vegetation. *North American Journal of Fisheries Management* 12:808–813.
- Die, D. J., V. R. Restrepo, and W. W. Fox, Jr. 1990. Equilibrium production models that incorporate fished area. *Transactions of the American Fisheries Society* 119:445–454.
- Dixon, P. M. 1993. The bootstrap and the jackknife: describing the precision of ecological indices. Pages 290–318 in S. M. Scheiner and J. Gurevitch, editors. *Design and analysis of ecological experiments*. Chapman and Hall, New York.
- Dumont, S. C., and J. A. Dennis. 1997. Comparison of day and night electrofishing in Texas reservoirs. *North American Journal of Fisheries Management* 17:939–946.
- Fabrizio, M. C., J. Raz, and R. R. Bandekar. 2000. Using linear models with correlated errors to analyze changes in abundance of Lake Michigan fishes: 1973–1992. *Canadian Journal of Fisheries and Aquatic Sciences* 57:775–788.
- Fabrizio, M. C., and R. A. Richards. 1996. Commercial fisheries surveys. Pages 625–650 in B. R. Murphy and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Flickinger, S. A., F. J. Bulow, and D. W. Willis. 1999. Small impoundments. Pages 651–588 in C. C. Kohler and W. A. Hubert, editors. *Inland fisheries management in North America*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Fréon, P., and O. A. Misund. 1999. Dynamics of pelagic fish distribution and behavior: effects on fisheries and stock assessment. *Fishing News Books*, Blackwell Scientific Publications, Malden, Massachusetts.
- Gerhardt, D. R., and W. A. Hubert. 1989. Effectiveness of cheese bait to capture channel catfish in hoop nets. *North American Journal of Fisheries Management* 9:343–351.
- Gillis, D. M. 1999. Behavioral inferences from regulatory observer data: catch rate variation in the Scotian Shelf silver hake (*Merluccius bilinearis*) fishery. *Canadian Journal of Fisheries and Aquatic Sciences* 56:288–296.
- Gillis, D. M., and R. M. Peterman. 1998. Implications of interference among fishing vessels and the ideal free distribution to the interpretation of CPUE. *Canadian Journal of Fisheries and Aquatic Sciences* 55:37–46.
- Godø, O. R., S. J. Walsh, and A. Englanddås. 1999. Investigating density-dependent catchability in bottom-trawl surveys. *ICES Journal of Marine Science* 56:292–298.
- Gordoa, A., M. Maso, and L. Voges. 2000. Monthly variability in the catchability of Namibian hake and its relationship with environmental seasonality. *Fisheries Research* 48:185–195.
- 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.
- Gulland, J. A. 1969. *Manual of methods for fish stock assessment*. Part 1. Fish population analysis. FAO (Food and Agriculture Organization of the United Nations) Manuals in Fisheries Science 4, Rome.
- Gulland, J. A. 1977. *Fish population dynamics*. John Wiley and Sons, New York.

- Hall, T. J. 1986. Electrofishing catch per hour as an indicator of largemouth bass density in Ohio impoundments. *North American Journal of Fisheries Management* 6:397–400.
- Hamley, J. M., and T. P. Howley. 1985. Factors affecting variability of trapnet catches. *Canadian Journal of Fisheries and Aquatic Sciences* 42:1079–1087.
- Hansen, M. J., R. G. Schorfhaar, J. W. Pcek, J. H. Selgeby, and W. W. Taylor. 1995. Abundance indices for determining the status of lake trout restoration in Michigan waters of Lake Superior. *North American Journal of Fisheries Management* 15:830–837.
- Hansen, M. J., R. G. Schorfhaar, and J. H. Selgeby. 1998. Gill-net saturation by lake trout in Michigan waters of Lake Superior. *North American Journal of Fisheries Management* 18:847–853.
- Hayes, D. B., C. P. Ferreri, and W. W. Taylor. 1996. Active fish capture methods. Pages 193–220 in B. R. Murphy and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Hi, X., and D. M. Lodge. 1990. Using minnow traps to estimate fish population size: the importance of spatial distribution and relative species abundance. *Hydrobiologia* 190: 9–14.
- Hilborn, R., and C. J. Walters. 1992. *Quantitative fisheries stock assessment: choice, dynamics and uncertainty*. Chapman and Hall, New York.
- Hubbard, W. D., and L. E. Miranda. 1988. Competence of non-random electrofishing sampling in assessment of structural indices. *Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies* 40 (1986):79–84.
- Hubert, W. A. 1996. Passive capture techniques. Pages 157–192 in B. R. Murphy and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Hubert, W. A., and D. T. O’Shea. 1992. Use of spatial resources by fishes in Grayrocks Reservoir, Wyoming. *Journal of Freshwater Ecology* 7:219–225.
- Hubert, W. A., and M. B. Sandheinrich. 1983. Patterns of variation in gill-net catch and diet of yellow perch in a stratified Iowa lake. *North American Journal of Fisheries Management* 3:156–162.
- Irwin, E. R., R. L. Noble, and J. R. Jackson. 1997. Distribution of age-0 largemouth bass in relation to shoreline landscape features. *North American Journal of Fisheries Management* 17:882–893.
- Isbell, G. L., and M. R. Rawson. 1989. Relations of gill-net catches of walleyes and angler catch rates in Ohio waters of western Lake Erie. *North American Journal of Fisheries Management* 9:41–46.
- Jackson, D. C. 1995. Distribution and stock structure of blue catfish and channel catfish in macrohabitats along riverine sections of the Tennessee–Tombigbee Waterway. *North American Journal of Fisheries Management* 15:845–853.
- Jessop, B. M., and C. J. Harvie. 1990. Evaluation of designs of periodic count surveys for the estimation of escapement at a fishway. *North American Journal of Fisheries Management* 10:39–45.
- Johnson, B. L., and C. A. Jennings. 1998. Habitat associations of small fishes around islands in the upper Mississippi River. *North American Journal of Fisheries Management* 18:327–336.

- Johnson, D. H. 1995. Statistical sirens: the allure of nonparametrics. *Ecology* 76:1998–2000.
- Karr, J. R. 1999. Defining and measuring river health. *Freshwater Biology* 41:221–234.
- Kappenman, R. F. 1999. Trawl survey based abundance estimation using data sets with unusually large catches. *ICES Journal of Marine Science* 56:28–35.
- Kelso, W. W., and D. A. Rutherford. 1996. Collection, preservation, and identification of fish eggs and larvae. Pages 255–302 in B. R. Murphy and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Kessler, R. K. 1999. Potential influence of predator presence on diel movements of small riverine fishes in the Ohio River, Kentucky. *Journal of the Kentucky Academy of Science* 60:108–112.
- Kimura, D. K. 1981. Standardized measures of relative abundance based on modeling log(c.p.u.e.), and their application to Pacific Ocean perch (*Sebastes alutus*). *Journal du Conseil International pour l'Exploration de la Mer* 39:211–218.
- Kimura, D. K. 2000. Using nonlinear functional relationship regression to fit fisheries models. *Canadian Journal of Fisheries and Aquatic Sciences* 57:160–170.
- Kimura, D. K., and J. W. Balsiger. 1985. Bootstrap methods for evaluating sablefish pot index surveys. *North American Journal of Fisheries Management* 5:47–56.
- Korsbrekke, K., and O. Nakken. 1999. Length and species-dependent diurnal variation of catch rates in the Norwegian Barents Sea bottom-trawl survey. *ICES Journal of Marine Science* 56:284–291.
- Krebs, C. J. 1989. *Ecological methodology*. Harper and Row, New York.
- Lackey, R. T., and W. A. Hubert. 1976. *Analysis of exploited fish populations*. Virginia Polytechnic Institute and State University, Sea Grant Extension Division, VPI-SG-76-04, Blacksburg.
- Lawson, G. L., and G. A. Rose. 1999. The importance of detectability to acoustic surveys of semi-demersal fish. *ICES Journal of Marine Science* 56:370–380.
- Littell, R. C., G. A. Milliken, W. W. Stroup, and R. D. Wolfinger. 1996. *SAS system for mixed models*. SAS Institute, Cary, North Carolina.
- Maceina, M. J., P. W. Bettoli, and D. R. DeVries. 1994. Use of a split-plot ANOVA design for repeated measures fishery data. *Fisheries (Bethesda)* 19(3):14–20.
- Maceina, M. J., W. B. Wrenn, and D. R. Lowery. 1995. Estimating harvestable largemouth bass abundance in a reservoir with an electrofishing catch depletion technique. *North American Journal of Fisheries Management* 15:103–109.
- Malvestuto, S. P. 1996. Sampling the recreational creel. Pages 591–624 in B. R. Murphy and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- McInerny, M. C., and T. K. Cross. 2000. Effects of sampling time, intraspecific density, and environmental variables on electrofishing catch per effort of largemouth bass in Minnesota lakes. *North American Journal of Fisheries Management* 20:328–336.
- Mero, S. W., and D. W. Willis. 1992. Seasonal variation in sampling data for walleye and sauger collected with gill nets from Lake Sakakawea, North Dakota. *Prairie Naturalist* 24:231–240.
- Methven, D. A., and D. C. Schneider. 1998. Gear-independent patterns of variation in catch of juvenile Atlantic cod (*Gadus morhua*) in coastal habitats. *Canadian Journal of Fisheries and Aquatic Sciences* 55:1430–1442.

- Michaletz, P. H., and G. M. Gale. 1999. Longitudinal gradients in age-0 gizzard shad density in large Missouri reservoirs. *North American Journal of Fisheries Management* 19:765–773.
- Michalsen, K., O. R. Godø, and A. Fernö. 1996. Diel variation in the catchability of gadoids and its influence on the reliability of abundance indices. *ICES Journal of Marine Science* 53:389–395.
- Miller, R. J. 1990. Effectiveness of crab and lobster traps. *Canadian Journal of Fisheries and Aquatic Sciences* 47:1228–1251.
- Miranda, L. E., W. D. Hubbard, S. Sangare, and T. Holman. 1996. Optimizing electrofishing sample duration for estimating relative abundance of largemouth bass in reservoirs. *North American Journal of Fisheries Management* 16:324–331.
- Moyer, E. J., M. W. Halon, J. J. Sweatman, R. S. Butter, and V. P. Williams. 1995. Fishery responses to habitat restoration in Lake Tohopekaliga, Florida. *North American Journal of Fisheries Management* 15:591–595.
- Moyle, J. B., and R. Lound. 1960. Confidence limits associated with means and medians of series of net catches. *Transactions of the American Fisheries Society* 89:53–58.
- Munro, P. T. 1998. A decision rule based on the mean square error for correcting relative fishing power differences in trawl survey data. *U.S. National Marine Fisheries Service Fishery Bulletin* 96:538–546.
- Neter, J., M. H. Kutner, C. J. Nachtsheim, and W. Wasserman. 1996. *Applied linear statistical models*, 4th edition. Richard D. Irwin, Chicago.
- Newman, J. A., J. Bergelson, and A. Grafen. 1997. Blocking factors and hypothesis tests in ecology: is your statistics text wrong? *Ecology* 78:1312–1320.
- Ney, J. J. 1999. Practical use of biological statistics. Pages 167–192 in C. C. Kohler and W. A. Hubert, editors. *Inland fisheries management in North America*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Orth, D. J., and R. J. White. 1999. Stream habitat management. Pages 249–284 in C. C. Kohler and W. A. Hubert, editors. *Inland fisheries management in North America*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Paller, M. H. 1995. Interreplicate variance and statistical power of electrofishing data from low-gradient streams in the southeastern United States. *North American Journal of Fisheries Management* 15:542–550.
- Paloheimo, J. E. 1963. Estimation of catchabilities and population size of lobsters. *Journal of the Fisheries Research Board of Canada* 20:59–88.
- Paloheimo, J. E., and L. M. Dickie. 1964. Abundance and fishing success. *Rapports et Procès-Verbaux des Réunions du Conseil International pour l'Exploration de la Mer* 155:152–163.
- Paragamian, V. L. 1989. A comparison of day and night electrofishing: size structure and catch per unit effort for smallmouth bass. *North American Journal of Fisheries Management* 9:500–503.
- Parsley, M. J., D. E. Palmer, and R. W. Burkhardt. 1989. Variation in capture efficiency of a beach seine for small fishes. *North American Journal of Fisheries Management* 9:239–244.
- Pelletier, D. 1998. Intercalibration of research survey vessels in fisheries: a review and an application. *Canadian Journal of Fisheries and Aquatic Sciences* 55:2672–2690.

- Pennington, M. 1996. Estimating the mean and variance from highly skewed marine data. U.S. National Marine Fisheries Service Fishery Bulletin 94:498–505.
- Peterman, R. M., and M. J. Bradford. 1987. Statistical trends in fish abundance. Canadian Journal of Fisheries and Aquatic Sciences 47:2–15.
- Peterman, R. M., and G. J. Steer. 1981. Relation between sport-fishing catchability coefficients and salmon abundance. Transactions of the American Fisheries Society 110:585–593.
- Peterson, D. L., M. B. Bain, and N. Haley. 2000. Evidence of declining recruitment of Atlantic sturgeon in the Hudson River. North American Journal of Fisheries Management 20:231–238.
- Pope, K. L., and D. W. Willis. 1996. Seasonal influences on freshwater fisheries sampling data. Reviews in Fisheries Science 4:57–73.
- Pothoven, S. A., B. Vondracek, and D. L. Pereira. 1999. Effects of vegetation removal on bluegill and largemouth bass in two Minnesota lakes. North American Journal of Fisheries Management 19:748–757.
- Power, J. H., and E. B. Moser. 1999. Linear model analysis of net catch data using the negative binomial distribution. Canadian Journal of Fisheries and Aquatic Sciences 56:191–200.
- Pyper, B. J., and R. M. Peterman. 1998. Comparison of methods to account for autocorrelation in correlation analyses of fish data. Canadian Journal of Fisheries and Aquatic Sciences 55:2127–2140. (See also Pyper, B. J., and R. M. Peterman. 1998. Erratum: Comparison of methods to account for autocorrelation in correlation analyses of fish data. Canadian Journal of Fisheries and Aquatic Sciences 55:2710.)
- Reynolds, J. B. 1996. Electrofishing. Pages 221–254 in B. R. Murphy and D. W. Willis, editors. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Richards, C., F. J. Kutka, M. E. McDonald, G. W. Merrick, and P. W. Devore. 1996. Life history and temperature effects on catch of northern orconectid crayfish. Hydrobiologia 319:111–118.
- Richards, L. J., and J. T. Schnute. 1986. An experimental and statistical approach to the question: is CPUE an index of abundance? Canadian Journal of Fisheries and Aquatic Sciences 43:1214–1227.
- Richards, L. J., and J. T. Schnute. 1992. Statistical models for estimating CPUE from catch and effort data. Canadian Journal of Fisheries and Aquatic Sciences 49:1315–1327.
- Ricker, W. E. 1975. Computation and interpretation of biological statistics of fish populations. Fisheries Research Board of Canada Bulletin 191.
- Rooker, J. R., G. D. Dennis, and D. Goulet. 1996. Sampling larval fishes with a nightlight lift-net in tropical inshore waters. Fisheries Research 26:1–15.
- Roper, B. B., and D. L. Scarnecchia. 1999. Emigration of age-0 chinook salmon (*Oncorhynchus tshawytscha*) smolts from the upper South Umpqua River basin, Oregon, U.S.A. Canadian Journal of Fisheries and Aquatic Sciences 56:939–946.
- Rose, G. A., and D. W. Kulka. 1999. Hyperaggregation of fish and fisheries: how catch-per-unit-effort increased as the northern cod (*Gadus morhua*) declined. Canadian Journal of Fisheries and Aquatic Sciences 56 (Supplement 1):118–127.
- Rose, G. A., and W. C. Leggett. 1989. Predicting variability in catch-per-effort in Atlantic cod, *Gadus morhua*, trap and gillnet fisheries Journal of Fish Biology 35 (Supplement A):155–161.

- Sammons, S. M., and P. W. Bettoli. 1999. Spatial and temporal variation in electrofishing catch rates of three species of black bass (*Micropterus* spp.) from Normandy Reservoir, Tennessee. *North American Journal of Fisheries Management* 19:454–461.
- Sampson, D. B. 1991. Local catch per unit effort as an index of global fish abundance. Pages 275–284 in I. G. Cowx, editor. *Catch effort sampling strategies: their application in freshwater fisheries management*. Fishing News Books, Blackwell Scientific Publications, Cambridge, Massachusetts.
- Sanderson, B. L., T. R. Hrabik, J. J. Magnuson, and D. M. Post. 1999. Cyclic dynamics of a yellow perch (*Perca flavescens*) population in an oligotrophic lake: evidence for the role of intraspecific interactions. *Canadian Journal of Fisheries and Aquatic Sciences* 56: 1534–1542.
- SAS Institute. 1998. *SAS/Stat user's guide, version 6: volumes 1 and 2*. SAS Institute, Cary, North Carolina.
- Schweigert, J. F., C. W. Haegele, and M. Stocker. 1985. Optimizing sampling design for herring spawn surveys in the Strait of Georgia, British Columbia. *Canadian Journal of Fisheries and Aquatic Sciences* 42:1806–1814.
- Seber, G. A. F. 1982. *The estimation of animal abundance and related parameters*, 2nd edition. Charles Griffin & Co., London.
- Shaw, E. 1978. Schooling fishes. *American Scientist* 66:166–175.
- Shroyer, S. M., and T. S. McComish. 1998. Forecasting abundance of quality-size yellow perch in Indiana waters of Lake Michigan. *North American Journal of Fisheries Management* 18:19–24.
- Sigler, M. F. 2000. Abundance estimation and capture of sablefish (*Anoplopoma fimbria*) by longline gear. *Canadian Journal of Fisheries and Aquatic Sciences* 57:1270–1283.
- Simmonds, E. J., and R. J. Fryer. 1996. Which are better, random or systematic acoustic surveys? A simulation study using North Sea herring as an example. *ICES Journal of Marine Sciences* 53:39–50.
- Skalski, J. R., A. Hoffman, B. H. Ransom, and T. W. Steig. 1993. Fixed-location hydroacoustic monitoring designs for estimating fish passage using stratified random and systematic sampling. *Canadian Journal of Fisheries and Aquatic Sciences* 50:1208–1221.
- Smith, S. J. 1980. Comparison of two methods of estimating the variance of the estimate of catch per unit effort. *Canadian Journal of Fisheries and Aquatic Sciences* 37: 2346–2351.
- Smith, S. J. 1997. Bootstrap confidence limits for groundfish trawl survey estimates of mean abundance. *Canadian Journal of Fisheries and Aquatic Sciences* 54:616–630.
- Snedecor, G. W., and W. G. Cochran. 1989. *Statistical methods*. Iowa State University Press, Ames.
- Sokal, R. R., and F. J. Rohlf. 1981. *Biometry*, 2nd edition. W. H. Freeman, San Francisco.
- Somers, K. M., and R. H. Green. 1993. Seasonal patterns in trap catches of the crayfish *Cambarus bartoni* and *Orconectes virilis* in six south-central Ontario lakes. *Canadian Journal of Zoology* 71:1136–1152.
- Somerton, D. A., and B. S. Kikkawa. 1995. A stock survey technique using the time to capture individual fish on longlines. *Canadian Journal of Fisheries and Aquatic Sciences* 52:260–267.
- Spangler, G. R., and J. J. Collins. 1992. Lake Huron fish community structure based on

- gill-net catches corrected for selectivity and encounter probabilities. *North American Journal of Fisheries Management* 12:585–597.
- Stanley, R. D. 1992. Bootstrap calculation of catch-per-unit-effort variance from trawl log-books: do fisheries generate enough observations for stock assessment? *North American Journal of Fisheries Management* 12:19–27.
- Steel, R. G. D., and J. H. Torrie. 1960. Principles and procedures of statistics, with special reference to the biological sciences. McGraw-Hill, New York.
- Stewart-Oaten, A. 1995. Rules and judgments in statistics: three examples. *Ecology* 76:2001–2009.
- Stoner, A. W. 1991. Diel variation in the catch of fishes and penaeid shrimps in a tropical estuary. *Estuarine, Coastal and Shelf Science* 33:57–69.
- Sullivan, P. J. 1991. Stock abundance estimation using depth-dependent trends and spatially correlated variation. *Canadian Journal of Fisheries and Aquatic Sciences* 48:1691–1703.
- Summerfelt, R. C. 1999. Lake and reservoir management. Pages 285–320 in C. C. Kohler and W. A. Hubert, editors. *Inland fisheries management in North America*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Swain, D. P., G. A. Nielsen, A. F. Sinclair, and G. A. Chouinard. 1994. Changes in catchability of Atlantic cod (*Gadus morhua*) to an otter-trawl fishery and research survey in the southern Gulf of St. Lawrence. *ICES Journal of Marine Science* 51:493–504.
- Swain, D. P., G. A. Poirier, and A. F. Sinclair. 2000. Effect of water temperature on catchability of Atlantic cod (*Gadus morhua*) to the bottom-trawl survey in the southern Gulf of St. Lawrence. *ICES Journal of Marine Science* 57:56–68.
- Tillma, J. S., C. S. Guy, and C. S. Mammoliti. 1998. Relations among habitat and population characteristics of spotted bass in Kansas streams. *North American Journal of Fisheries Management* 18:886–893.
- Trometer, E. S., and W.-D. N. Busch. 1999. Changes in age-0 fish growth and abundance following the introduction of zebra mussels *Dreissena polymorpha* in the western basin of Lake Erie. *North American Journal of Fisheries Management* 19:604–609.
- Van Den Avyle, M. J., J. Boxrucker, P. Michaletz, B. Vondracek, and G. R. Ploskey. 1995. Comparison of catch rate, length distribution, and precision of six gears used to sample shad populations. *North American Journal of Fisheries Management* 15:940–955.
- Van Den Avyle, M. J., and R. S. Hayward. 1999. Dynamics of exploited fish populations. Pages 127–166 in C. C. Kohler and W. A. Hubert, editors. *Inland fisheries management in North America*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Van Zee, B. E., D. W. Willis, and C. C. Stone. 1996. Comparison of diel sampling data for sauger collected by electrofishing. *Journal of Freshwater Ecology* 11:139–143.
- Walsh, S. J. 1991. Diel variation in availability and vulnerability of fish to a survey trawl. *Journal of Applied Ichthyology* 7:147–159.
- Walters, C. J., and D. Ludwig. 1981. Effects of measurement errors on the assessment of stock-recruitment relationships. *Canadian Journal of Fisheries and Aquatic Sciences* 38:704–710.
- Ward, C., R. L. Eshenroder, and J. R. Bence. 2000. Relative abundance of lake trout and burbot in the main basin of Lake Michigan in the early 1930s. *Transactions of the American Fisheries Society* 129:282–295.

- Watters, G., and R. Deriso. 2000. Catches per unit of effort of bigeye tuna: a new analysis with regression trees and simulated annealing. *Bulletin of the Inter-American Tropical Tuna Commission* 21:531–552.
- Willis, D. W. 1987. Use of gill-net data to provide a recruitment index for walleyes. *North American Journal of Fisheries Management* 7:591–592.
- Wolfinger, R. D. 1996. Heterogeneous variance–covariance structures for repeated measures. *Journal of Agricultural, Biological, and Environmental Statistics* 1:205–230.
- Wolfinger, R. D. 1999. Fitting nonlinear mixed models with the NLMIXED procedure. *SAS Users Group International Conference Proceedings* 24: Paper 287.

