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# Cross-correlation bias in lag analysis of aquatic time series

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**Abstract** Cross-correlation analysis is the most valuable and widely used statistical tool for evaluating the strength and direction of time-lagged relationships between ecological variables. Although it is well understood that temporal autocorrelation can inflate estimates of cross correlations and cause high rates of incorrectly concluding that lags exist among time series (i.e. type I error), in this study we show that a problem we term *intra-multiplicity* can cause substantial bias in cross-correlation analysis even in the absence of autocorrelation. Intra-multiplicity refers to the numerous time lags examined and cross-correlation coefficients computed within a pair of time series during cross-correlation analysis. We show using Monte Carlo simulations that intra-multiplicity can spuriously inflate estimates of cross correlations by identifying incorrect time lags. Further, unlike autocorrelation, which generally identifies lags close to the true lag, intra-multiplicity can erroneously identify lags anywhere in the time series and commonly results in a direction change of the correlation (i.e. positive or negative). Using Monte Carlo simulations we develop formulas that quantify the bias introduced by intra-multiplicity as a function of sample size, true cross correlation between the series, and the number of time lags examined. A priori these formulas enable researchers to determine the sample size needed to minimize the biases introduced by intra-multiplicity. A posteriori the formulas can be used to predict the expected bias and type I error rate associated with the data at hand, as well as the maximum number of time lags that can be analyzed to minimize the effects of intra-multiplicity. We examine the relationship between commercial catch of chum salmon and surface temperatures of the North Pacific (1925–1992) to illustrate the problems of intra-multiplicity in fisheries studies and the application of our formulas. These analyses provide a more robust framework to assess the temporal relationships between ecological variables.

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## Introduction

With recent increases in the exploitation and potential collapse of aquatic resources, understanding the extent to which population and community dynamics covary with environmental conditions has become central to the aquatic sciences (Powell 1989; Allen and Hoekstra 1992). For instance, understanding the mechanisms associated with the regulation of fish populations, such as relationships between environmental factors, survival, recruitment, and growth rates of populations, is critical to the management of fish stocks (Beverton and Holt 1957; Royce 1989; Hare and Francis 1995; Quinn and Deriso 1999). Cross-correlation analysis is the most valuable and widely used statistical tool to quantify temporal relationships between variables. Such analysis computes the correlation, expressed as the cross-correlation coefficient, between paired time series at a large number of time lags (commonly ± 25% of the time series length). A time lag refers to a delayed response in the dynamics of a dependent variable following a stimulus, such as changes in species density following fluctuations in a limiting resource or in the dynamics of an interacting species. The time lag with the highest cross-correlation coefficient is then typically taken as the true time lag between the two time series (Wei 1990; Box et al. 1994; Chatfield 1996). Time lags are common in nature and have been reported in numerous aquatic studies. Examples include food web interactions (e.g. Matveev 1995; Shanks 1998; Olden 2000), dynamics of phytoplankton (e.g. Duarte 1990; Pascual and Caswell 1997; Vaque et al. 1997), zooplankton (e.g. Broekhuizen and McKenzie 1995) and plant communities (e.g. Healy 1997) and fish–environment relationships (e.g. Thorrold et al. 1994; Kim et al. 1997; Downton and Miller 1998; Smith et al. 2000). Failure to accurately identify and remove time lags prior to employing statistical analysis can increase the probability that important relationships between ecological variables are masked, or even completely missed. For example, Walters and Collie (1988) discussed how apparently negative stock-recruitment relationships can be observed when favourable environmental conditions cause stock size to increase, but with a lag such that peaks in stock size coincide with periods of deteriorating environmental conditions. It is therefore important that statistical tools are available for researchers to identify time-lagged relationships.

There are two main concerns associated with cross-correlation analysis. First, researchers are well aware that autocorrelated time series, which violate the assumption of serial independence required for most traditional statistical tests (Hurlbert 1984), can have major consequences for the interpretation of cross correlations among time series. Autocorrelation will inflate type I error rates (i.e. erroneously concluding that a cross correlation is statistically significant), thereby causing the incorrect identification of time lags and spurious inflation of the cross-correlation coefficient (Bayley and Hammersley 1946; Cochrane and Orcutt 1949; Haugh 1976; Haugh and Box 1977). Methods for removing autocorrelation, and consequently the associated cross-correlation biases, are well established in the statistical (e.g. Wei 1990; Box et al. 1994; Chatfield 1996) and ecological literature (e.g. Bence 1995; Pyper and Peterman 1998). A second concern is the effects of "multiplicity" on cross-correlation analysis. Multiplicity refers to the standard statistical problem in which the probability that at least one null hypothesis is rejected by chance alone increases geometrically with the number of statistical tests that are conducted (Tukey 1977; Miller 1981). Here, we distinguish between two forms of multiplicity: *inter*- and *intra-multiplicity*. Inter-multiplicity refers to the bias associated with multiple pair-wise comparisons among time series, whereas what we term intra-multiplicity refers to the numerous time lags examined and cross-correlation coefficients computed within a pair of time series during cross-correlation analysis. Although the effects of inter-multiplicity have been previously acknowledged (e.g. teleconnection studies: Katz 1988; Brown and Katz 1991; Katz and Brown 1991), the bias introduced by intra-multiplicity has not been recognized by researchers. In this study, we were interested in examining the bias introduced by intra-multiplicity in cross-correlation analysis and comparing this to the effects of temporal autocorrelation. Using Monte Carlo simulations, we quantify the cross-correlation bias and type I error rates (i.e. probability of erroneously identifying a time lag) associated with the combined and individual effects of intra-multiplicity and autocorrelation. We develop protocols and construct formulas that predict both the expected bias in the cross-correlation coefficient and type I error rates based on the time series length (i.e. number of observations), true cross correlation, and the number of time lags examined between the series. These methods can be used a priori to design appropriate sampling regimes and a posteriori to calculate the maximum number of lags that can be examined to minimize the effects of intra-multiplicity and obtain an accurate understanding of relationships between biological time series. Finally, we provide an empirical example for the association between chum salmon and ocean surface temperatures of the North Pacific to illustrate the potential degree of cross-correlation bias introduced by intra-multiplicity in fisheries studies and demonstrate the application of our Monte Carlo protocols.

## Methods

### Cross-correlation bias: effects of autocorrelation and intra-multiplicity

We used Monte Carlo simulations to quantify the individual and combined contributions of temporal autocorrelation and intra-multiplicity to the cross-correlation bias. We used simple time series models to generate pairs of ecological variables ($X_t$ and $Y_t$) represented by bivariate stochastic processes, where $X_t$ and $Y_t$ denote observations of the variables $X$ and $Y$, respectively, at time $t$. We considered first-order autoregressive models [AR(1) models] corresponding to a theoretical lag-1 autocorrelation in each of the time series (Box et al. 1994). The models are represented by the following equations:

$$X_t = \phi_X X_{t-1} + \varepsilon_t(X) \quad (1)$$

$$Y_t = \phi_Y Y_{t-1} + \varepsilon_t(Y) \quad (2)$$

where $\phi_X$ and $\phi_Y$ are the first-order autocorrelation coefficients and $\varepsilon_t$ are randomly and normally distributed errors with zero means and variances $1 - \phi_X^2$ and $1 - \phi_Y^2$ for $X$ and $Y$, respectively. We chose AR(1) models because they are the most prevalent models employed and are often successful in describing temporal patterns in fisheries and ecological data (e.g. Bence 1995; Downton and Miller 1998; Pyper and Peterman 1998; Smith et al. 2000).

Pairs of time series ($X$ and $Y$) were generated with different numbers of observations ($n$), degrees of autocorrelations ($\phi$), and levels of cross correlation ($r_{XY}$). We considered sample sizes of $n = 15$, 30, 45, and 60 observations since these are common lengths found in aquatic studies (e.g. Bence 1995; Myers et al. 1995; Pyper and Peterman 1998). Autocorrelation coefficients were set equal to 0.0 (i.e. no autocorrelation), 0.5 (moderate autocorrelation), and 0.8 (high autocorrelation) for both $X$ and $Y$ (e.g. Koslow et al. 1987). Finally, we examined time series with low ($r_{XY} = 0.30$) and moderate ($r_{XY} = 0.60$) levels of cross correlation. Following the methodology of Katz (1988), we introduced the desired level of autocorrelation within each time series by modifying the error terms shown in Eqs. 1 and 2 (i.e. increasing values of $\phi_X^2$ and $\phi_Y^2$ related to decreasing autocorrelation). The desired level of cross correlation between the time series was obtained by adding a second normally distributed error with mean = 0 and variance = $\sigma^2$

to each observation in $Y$ (but not $X$), with increasing values of $\sigma^2$ related to decreasing cross correlation. Since this second error was random and normally distributed it ensured that the original level of autocorrelation in $Y$ remained unchanged (Note: time series pairs before and after the addition of the second error term were checked to ensure that the autocorrelation structure was maintained). In all cases, we defined $X$ and $Y$ to exhibit a time lag equal to zero (i.e. *true* time lag = 0). We performed 5,000 Monte Carlo trials for each combination of $n$, $\phi$, and $r_{XY}$, and for each trial calculated the cross-correlation coefficients for $k$ lags (where $k$ equaled $\pm 25\%$ of the total length of the time series). The lag was identified by the value of $k$ corresponding to the greatest absolute cross-correlation coefficient that differed significantly from zero. We considered the absolute cross correlation since there is commonly no a priori expectation for the direction of the relationship between the variables. Next, we calculated three summary statistics:

1. *Type I error rate*: the proportion of the 5,000 Monte Carlo trials that an incorrect time lag (i.e. lag $\neq 0$) was chosen.
2. The mean *overall* cross correlation bias: calculated as the mean difference between the estimated cross correlation at the identified lag and the true cross correlation ($r_{XY}$) for all Monte Carlo iterations.
3. The mean *critical* cross-correlation bias: calculated as in (2) but only for the cases when an incorrect time lag was chosen.

Here we define a type I error as erroneously rejecting the null hypothesis of a time lag equal to $k$, which is different from rejecting the null hypothesis of no time lag. We are interested in this null hypothesis since it is more important to identify correctly the value of the true time lag, as compared to identifying correctly the fact that a time lag exists. For simplicity, we simulated the time series to exhibit a time lag equal to zero (i.e. $k = 0$) for all analyses, but the results would be identical for any time lag.

### Quantifying the cross-correlation bias introduced by intra-multiplicity

To isolate the effects of intra-multiplicity we quantified the cross-correlation bias and type I error rates using time series that contained no autocorrelation. Following the Monte Carlo simulations described above (again for 5,000 trials) we examined each combination of $n$ observations (ranging from 10 to 100 by increments of 5), $r_{XY}$ (ranging from 0.1 to 0.95 by increments of 0.05), and $k$ lags examined between the time series (ranging from 5% to 50% of the number of observations ($n$) by increments of 5%). From these data, we modeled patterns in the overall cross-correlation bias and type I error rates as logistic functions of $n$, $r_{XY}$, and $k$.

### Empirical example: Relationship between chum salmon catches and North Pacific temperatures

To demonstrate the effects of intra-multiplicity in aquatic time series, we examined the relationship between chum salmon catches and regional surface temperatures in the North Pacific. Alaska's statewide commercial catch totals were used as a measure of salmon production, and regional temperatures (expressed as anomalies from the 1950–1979 mean) were calculated for each season (see Downton and Miller 1998 for further details). Salmon catch data was $\ln(x + 1)$ transformed to stabilize the variances, whereas the temperature data required no transformation. Both the transformed salmon data and regional temperatures were prewhitened using first-order autoregressive models (Downton and Miller 1998) to remove autocorrelation. The association between chum salmon catches and surface temperatures was examined at five sample sizes: $n = 15$ (4 data sets including data for the years 1925–1939, 1940–1954, 1955–1969, 1970–1984); $n = 30$ (2 data sets for 1925–1954, 1955–1984); $n = 45$ (1925–1969); $n = 60$ (1925–1984), and $n = 68$ (all the data: 1925–1992). Using our Monte Carlo protocols we calculated expected type I error rates, and the overall and critical cross-correlation biases for each sample size. Finally, we calculated the maximum number of time lags that could be examined while maintaining type I error rates of less than 0.20 and an overall cross-correlation bias of less than 10% of the true cross correlation. We assumed that the true cross-correlation coefficient was equal to the cross correlation between the time series based on all the data (i.e. $n = 68$, $r_{XY} = 0.3463$) since the expected type I error rate was the smallest and the overall bias and critical bias was negligible (see Results). All simulations and statistical analyses were performed using the C programming language.

## Results

### Cross-correlation bias: Effects of autocorrelation and intra-multiplicity

The results from the Monte Carlo simulations are summarized in Table 1 and show that both autocorrelation and intra-multiplicity introduced bias into the observed cross correlation between the time series. In general, the cross-correlation bias and type I error rates increased with increasing levels of autocorrelation and decreasing levels of true cross correlation and sample size. For example, at moderate levels of autocorrelation ($\phi_X = \phi_Y = 0.5$) and low true cross correlation ($r_{XY} = 0.30$), the expected bias ranged from 0.06 to 0.20 and type I error rates ranged from 74% to 94% (Table 1). In the absence of autocorrelation (i.e. $\phi_X = \phi_Y = 0.0$), the biases were still substantial. For instance, for a sample size of 15 and a low true cross correlation of 0.30, intra-multiplicity on average inflated estimates of the cross correlation by over 50% with a 92% chance of selecting an erroneous time lag. Figure 1 shows in greater detail the biases introduced by intra-multiplicity. These three-dimensional surfaces show that both the cross-correlation bias and type I error rates increase with decreasing time series length and true cross correlation. The cross-correlation bias associated with intra-multiplicity also increased with the number of comparisons made between the series (i.e. the number of time lags examined; Fig. 2). For example, given a series of $n = 30$ and $r_{XY} = 0.30$, when 12 lags were examined ($\pm 20\%$ of the time series), there was a 75% chance of erroneously rejecting the null hypothesis, with an expected cross-correlation bias of over 27% [$= (0.38 - 0.30)/0.30$]. However, if only 3 lags were examined the type I error rate was less than 30% and the expected cross-correlation bias was less than 2% [$= (0.305 - 0.30)/0.30$; see Fig. 2].

### Quantifying the cross-correlation bias introduced by intra-multiplicity

Given the length of the time series ($n$), true absolute cross correlation between the time series ($r_{XY}$), and the number of lags examined between the series ($k$) expressed as a proportion of $n$, the expected bias in the cross-correlation coefficient and the expected type I

**Table 1** Means and 95% confidence intervals (in parentheses) from the Monte Carlo simulations quantifying the effects of temporal autocorrelation and intra-multiplicity on type I error rates, overall bias, and critical bias (see Methods for definitions). All results are based on 5,000 Monte Carlo trials, where ±25% of the time series length was examined in the cross-correlation analysis. Where no autocorrelation exists ($\phi_X = \phi_Y = 0.0$), the source of the cross-correlation bias and probability of committing a type I error is solely due to intra-multiplicity

| $r_{XY}$ | $n$ | No autocorrelation ($\phi_X = \phi_Y = 0.0$) | | | Moderate autocorrelation ($\phi_X = \phi_Y = 0.5$) | | | High autocorrelation ($\phi_X = \phi_Y = 0.8$) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Type I error rate | Overall bias | Critical bias | Type I error rate | Overall bias | Critical bias | Type I error rate | Overall bias | Critical bias |
| 0.30 | 15 | 0.92 | 0.17 (0.00, 0.41) | 0.19 (0.01, 0.41) | 0.94 | 0.20 (0.00, 0.45) | 0.22 (0.02, 0.45) | 0.96 | 0.26 (0.00, 0.52) | 0.27 (0.03, 0.52) |
| | 30 | 0.82 | 0.08 (0.00, 0.26) | 0.10 (0.01, 0.27) | 0.89 | 0.12 (0.00, 0.32) | 0.13 (0.01, 0.33) | 0.95 | 0.21 (0.00, 0.45) | 0.22 (0.02, 0.46) |
| | 45 | 0.66 | 0.05 (0.00, 0.17) | 0.07 (0.00, 0.19) | 0.80 | 0.08 (0.00, 0.26) | 0.10 (0.01, 0.27) | 0.93 | 0.16 (0.00, 0.38) | 0.18 (0.02, 0.39) |
| | 60 | 0.44 | 0.02 (0.00, 0.11) | 0.05 (0.00, 0.15) | 0.74 | 0.06 (0.00, 0.21) | 0.08 (0.00, 0.22) | 0.90 | 0.14 (0.00, 0.36) | 0.16 (0.00, 0.37) |
| 0.60 | 15 | 0.12 | 0.01 (0.00, 0.11) | 0.06 (0.00, 0.21) | 0.25 | 0.02 (0.00, 0.16) | 0.07 (0.00, 0.24) | 0.48 | 0.05 (0.00, 0.23) | 0.10 (0.00, 0.26) |
| | 30 | 0.01 | 0.00 – | 0.00 (0.00, 0.10) | 0.04 | 0.00 (0.00, 0.03) | 0.05 (0.00, 0.11) | 0.33 | 0.03 (0.00, 0.16) | 0.08 (0.00, 0.21) |
| | 45 | 0.00 | 0.00 – | 0.00 – | 0.01 | 0.00 – | 0.00 (0.00, 0.09) | 0.21 | 0.01 (0.00, 0.11) | 0.06 (0.00, 0.18) |
| | 60 | 0.00 | 0.00 – | 0.00 – | 0.00 | 0.00 – | 0.00 (0.00, 0.02) | 0.15 | 0.01 (0.00, 0.08) | 0.04 (0.00, 0.14) |

error rate were modeled as a logistic function and can be calculated from

$$\text{cross correlation bias} = \frac{1}{2.353 + e^{x}} \tag{3}$$

where $x = 16.68 \cdot r_{XY} + 0.04939 \cdot n - 3.186 \cdot k - 2.480$; and

$$\text{type I error rate} = \frac{1}{1 + e^{y}} \tag{4}$$

where $y = 17.54 \cdot r_{XY} + 0.03797 \cdot n - 4.7042 \cdot k - 5.749$.

We found that the correlation between the predicted and actual cross-correlation bias or type I error rate was 0.94 and 0.93, respectively, based on external model validation (i.e. data not used to develop the equations). Therefore, these functions can be used with high confidence to estimate the expected inflation in the cross-correlation coefficient caused by intra-multiplicity, as well as calculate the expected probability of selecting an incorrect time lag. Furthermore, these functions can be rearranged to solve for the maximum number of time lags ($k$) that can be examined and/or the sample size required ($n$) to maintain a desired level of cross-correlation bias and type I error rate.

### Relationship between chum salmon and North Pacific temperatures

Our analysis of patterns in North Pacific chum salmon catches confirms that a 3-year time lagged response to changes in surface temperature conditions exists and confirms the findings of Downton and Miller (1998). Table 2 summarizes the cross correlation analysis for the five sub-samples of the data. The observed cross-correlation bias (i.e. the difference between the greatest cross correlation and the true correlation of 0.3463 based on all the data) is quite consistent with the expected overall and critical biases (Table 2). In addition, we identified the true time lag of 3 years only 50% of the time for sub-samples of 15 and 30 years, which is consistent with expected rates of type I error. For all sample sizes, to maintain a desired type I error rate less than 0.20, the number of lags examined in the analysis would have to be reduced from the commonly employed 50% of $n$ (±25%), to range from 4% (±2%) to 32% (±16%). Similarly, the number of lags examined would have to be reduced to ensure low levels of cross-correlation bias (i.e. 10% of the true correlation), although this reduction was less significant relative to the type I error rate.

## Discussion

Ecologists and fisheries researchers are well aware of the bias that temporal autocorrelation can introduce into cross-correlation analysis, such as drastically inflating the probability of selecting an incorrect time lag (Bayley and Hammersley 1946; Cochrane and Orcutt 1949; Hurlbert 1984). There are several statistical techniques available for removing (or reducing) temporal autocorrelation in time series, including a number of filtering techniques (e.g. prewhitening, first-differencing) and procedures for adjusting the null hypothesis (see Pyper and Peterman 1998 for recent comparison of methods). In contrast, until now researchers have been

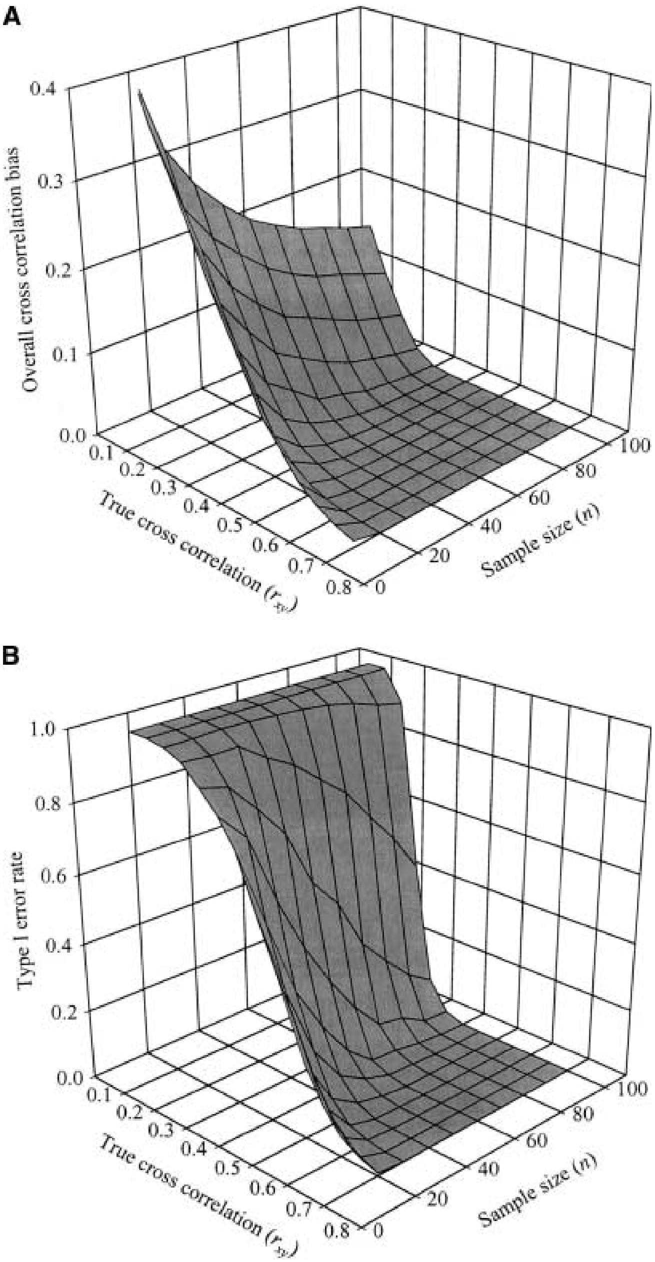


**Fig. 1** Overall cross correlation bias (**A**) and type I error rates (**B**) due to intra-multiplicity as functions of sample size ($n$) and true cross correlation ($r_{XY}$) based on 5,000 Monte Carlo trials. All results are based on examining $k$ time lags where $k$ equals $\pm 25\%$ of the time series length ($n$)

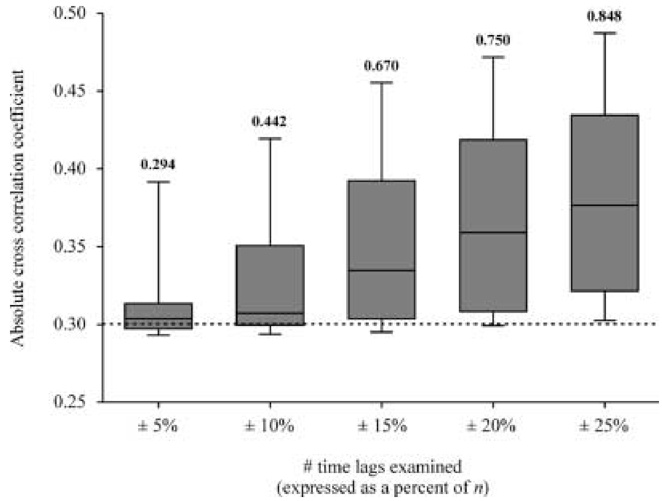


**Fig. 2** Observed cross correlations (*box plots*) and type I error rates (*value above box plots*) as a function of the number of time lags examined (shown for $n = 30$ and $r_{XY} = 0.30$) based on 5,000 Monte Carlo trials. Time lags are expressed as a percentage of the time series length ($n$). Within box plots the *solid line* represents mean cross-correlation coefficient and *whiskers* delineate the 2.5 and 97.5 percentiles. *Dotted line* represents the true cross correlation ($r_{XY}$)

unaware of the cross-correlation bias caused by intra-multiplicity. Intra-multiplicity refers to choosing the largest cross correlation between a pair of series out of many computed when searching for time-lagged relationships. We have shown that intra-multiplicity, independent of autocorrelation, significantly inflates estimates of cross-correlation coefficients and increases the probability that an incorrect time lag is identified. Of special concern is the fact that most ecological time series are less than 25 observations in length (series containing more than 25 are considered long and are rare in surveys of the literature: Kendall et al. 1998, 1999). In these cases, intra-multiplicity can significantly bias cross-correlation analysis and lead to inaccurate inferences about the strength and type of relationships between time series.

The cross-correlation biases introduced by temporal autocorrelation and intra-multiplicity are governed by different processes. The source of the bias from temporal autocorrelation is due to the temporal dependency among the observations of each time series and the probability that a small shift in one time series away from the true time lag results in a higher cross-correlation coefficient. As such, the majority of the selected time lags will be close to the true lag and will almost always be in the same direction (i.e., positive or negative correlation). In contrast, the bias introduced from intra-multiplicity is strictly due to the chance event that shifting one time series results in a higher cross correlation. In this case, the direction of the correlation is just as likely to be positive as negative and therefore represents a serious concern for interpretation of correlative analyses. This phenomenon is illustrated in our empirical example, where at low sample sizes a negative cross correlation was identified between chum catches and surface temperatures even though the relationship was actually positive. The source of the bias from intra-multiplicity can be viewed as being analogous to the biases associated with multiple comparisons between variables (e.g. Tukey 1977; Miller 1981), such as inflated type I error rates due to multiple independent statistical tests (Peres-Neto 1999) and inclusion of random variables during regression model selection (Olden and Jackson, 2000). In the context of cross-correlation analysis, the more extensive the search for time lags, the

**Table 2** Results from the cross-correlation analysis of chum salmon catches and regional temperatures in the North Pacific for five sample sizes. Reported values are the greatest observed cross-correlation coefficient between the time series, the time lag at which it was observed, expected type I error rate, overall bias, and critical bias, and the maximum number of time lags that could be examined to ensure type I error rate less than 0.20 and overall cross correlation bias less than 10% of the true cross correlation (i.e. 0.035). "–" indicates that a type I error rate of 0.20 could not be achieved

| *n* | Years | Greatest cross correlation | Lag (*k*) | Expected | | | Maximum number of lags | |
|---|---|---|---|---|---|---|---|---|
| | | | | Type I error rate | Overall bias | Critical bias | Type I error rate <0.20 | Overall bias <10% |
| 15 | 1925–1939 | −0.386 | 1 | 0.811 | 0.072 | 0.089 | – | 4 (±13%) |
| | 1940–1954 | 0.437 | 3 | | | | | |
| | 1955–1969 | 0.471 | −1 | | | | | |
| | 1970–1984 | 0.456 | 3 | | | | | |
| 30 | 1925–1954 | 0.270 | 3 | 0.708 | 0.038 | 0.053 | 1 (±2%) | 13 (±22%) |
| | 1955–1984 | 0.435 | 2 | | | | | |
| 45 | 1925–1969 | 0.314 | 3 | 0.579 | 0.019 | 0.033 | 7 (±8%) | 22 (±25%) |
| 60 | 1925–1984 | 0.362 | 3 | 0.438 | 0.010 | 0.021 | 15 (±13%) | 30 (±25%) |
| 68 | 1925–1992 | 0.346 | 3 | 0.365 | 0.006 | 0.017 | 22 (±16%) | 34 (±25%) |

more cross-correlation coefficients that are calculated, and the greater the chance is of identifying an erroneous lag.

The effects of intra-multiplicity are dependent on the length of the time series, number of time lags examined, and true cross correlation between the time series. Using either the derived formulas or the Monte Carlo protocol developed in this article, researchers can now determine a priori the sample size required to minimize the cross-correlation bias and rates of type I error. Conversely, researchers can a posteriori calculate the expected cross-correlation bias for their data, thus providing an estimate of confidence in their results. Furthermore, the maximum number of lags that can be examined while maintaining acceptable levels of the cross-correlation bias and probabilities of committing a type I error can be determined. For example, we showed this application with the chum salmon–temperature data.

Quantifying cross-correlation bias and type I error rates requires information on the length of the time series, the number of time lags examined, and the true cross correlation. Since it is unlikely that the true cross correlation will be known, researchers may wish to estimate the expected cross correlation, for example, based on previous knowledge, or examine a number of different levels that likely encompass the true correlation. Regardless of the true cross correlation, the bias associated with intra-multiplicity can be reduced by (1) increasing the sampling frequency employed to construct the time series or (2) reducing the total number of time lags examined in the cross correlation analysis. Increasing the sampling frequency, however, can be costly. Alternatively, reducing the number of total time lags examined between a pair of time series requires knowledge of the range of biologically or ecologically plausible time lags. Such knowledge may include the generation time of the study organism (e.g. Pascual and Caswell 1997; Downton and Miller 1998; Smith et al. 2000) or interacting organism (e.g. Vaque et al. 1997), seasonality (i.e. temporal periodicity) in environmental conditions (e.g. Thorrold et al. 1994) or resource abundance (e.g. Duarte 1990; Pascual and Caswell 1997; Stronge et al. 1998) or inter-year variability in climate or predation (e.g. Post and Stenseth 1998). Smith et al. (2000) provide an example incorporating the life history of steelhead (*Oncorhynchus mykiss*) to reduce the total number of time lags examined to those that are biologically reasonable. Angling success of steelhead were compared to summer and winter upwelling anomalies in British Columbia, and only time lags corresponding to the years that the steelhead are at sea following their entry into the ocean (about 2–3 years of age) were considered. Similarly, our results show that the number of time lags examined between chum salmon catches and ocean surface temperatures must be reduced to maintain type I error rates lower than 20%. Although Downton and Miller (1998) were unaware of the effects of intra-multiplicity, they restricted their analysis to a total of 12 time lags (±6 time intervals), since this range encompassed the range of generation times for the salmon species. More generally, however, there is a tendency for researchers to search intensively for time lags by examining and calculating large numbers of cross correlations between the time series (commonly ±25% of the time series length). By reducing the total number of time lags examined between a pair of series, and assuming that the subset includes the true lag, researchers can reduce the bias effects of intra-multiplicity, thus enhancing the accuracy of their analyses. Researchers may therefore wish to consider both sampling frequency and the number of time lags examined when conducting cross-correlation analysis.

In the present study we used Monte Carlo simulations to examine the effects of intra-multiplicity on the expected cross correlation bias and type I error rates in cross-correlation analysis. Similar to approaches used to develop correction factors for adjusting the estimate of functional relationships between stock sizes and recruitment (Walters 1985, 1990) and for adjusting confidence intervals of the mean and parameters of a linear regression for autocorrelation in time series (Bence 1995), our approach provides formulas for predicting the magnitude of the cross-correlation bias and rates of type I error given characteristics of the data. We found that when the time series contain no autocorrelation (i.e. prewhitened time series), our formulas were highly accurate. However, using our Monte Carlo protocols directly (available from the authors upon request) can provide more accurate estimates of cross-correlation bias and type I error rates. For example, one possible application would be to use the formulas developed here to a priori determine the minimum time series length for a given study (i.e. the number of observations) and then use our Monte Carlo protocols a posteriori to estimate the cross-correlation bias, type I error rates, and the maximum number of times lags that should be analyzed.

## Conclusion

The findings from this study have highlighted the importance of accounting for temporal autocorrelation and specifically intra-multiplicity prior to employing correlative approaches to assess the degree of association between variables measured in time. The fact that autocorrelation introduces a bias in cross-correlation analysis is not new; however, the demonstration that intra-multiplicity also biases such analyses is previously unknown. By quantifying this bias we have provided an important tool that can be utilized a priori and a posteriori for minimizing the cross correlation bias introduced by intra-multiplicity. These methods in addition to those previously available for autocorrelation will enable researchers to make accurate inferences regarding ecological relationships in nature and will be especially valuable for the monitoring and management of our aquatic resources.

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