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Serial Correlation and Inter-annual Variability in Relation to the Statistical Power of Monitoring Schemes to Detect Trends in Fish Populations

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Abstract We studied the effects of inter-annual variability and serial correlation on the statistical power of monitoring schemes to detect trends in biomass of bream (*Abramis brama*) in Lake Veluwemeer (The Netherlands). In order to distinguish between 'true' system variability and sampling variability we simulated the development of the bream population, using estimates for population structure and growth, and compared the resulting inter-annual variabilities and serial correlations with those from field data. In all cases the inter-annual variability in the field data was larger than in simulated data (e.g. for total biomass of all assessed bream σ=0.45 in field data, and σ=0.03–0.14 in simulated data) indicating that sampling variability decreased statistical power for detecting trends. Moreover, sampling variability obscured the inter-annual dependency (and thus the serial correlation) of biomass, which was expected because in this long-lived population biomass changes are buffered by the many year classes present. We did find the expected serial correlation in our simulation results and concluded that good survey data of long-lived fish populations should show low sampling variability and considerable inter-annual serial correlation. Since serial correlation decreases the power for detecting trends, this means that even when sampling variability would be greatly reduced, the number of sampling years to detect a change of 15%·year^{-1} in bream populations (corresponding to a halving or doubling in a six-year period) would in most cases be more than six. This would imply that the six-year reporting periods that are required by the Water Framework Directive of the European Union are too short for the existing fish monitoring schemes.

Keywords Bream (*Abramis brama*) · EU Water Framework Directive · Fish monitoring · Netherlands · Sampling variability · Serial correlation · Statistical power · System variability · Trend analysis

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1 Introduction

The EU Water Framework Directive (WFD) aims at protecting surface waters and groundwater by integration of water management throughout the member states of the European Union (European Union, 2000). The Directive requires the member states to comply with far-reaching obligations regarding: (1)

Table 1 Factors influencing the statistical power, and the effect they have

Factor influencing statistical power ($1-\beta$)	Positive/negative effect
Number of samples	+
Effect size	+
Variance (σ^2)	–
α	+

classification of rivers, lakes, transitional waters, and coastal waters; (2) identification of high, good, moderate, poor, and bad ecological status in these waters; and (3) frequency and intensity of monitoring the quality of these water bodies. The Directive aims at reaching at least 'good' or 'potentially good' quality of all surface waters in the EU by 2016. One of the biological quality elements by which the ecological status of most water bodies (except coastal waters) must be assessed is the fish fauna. The structure of the fish community is a most integrative indicator of differences in ecological status between water bodies (classification; e.g. Karr, 1981) and of changes in this status within water bodies through time (monitoring). Its inclusion in the WFD as an indicator of ecological quality is therefore logical.

In order to monitor the development of fish communities in each river catchment, the basic management unit of the WFD, sampling schemes have to be developed that are sensitive enough to detect any change within the fish community, which causes it to shift from one quality class to another (based on a categorisation into five quality classes). Every six years the management of each catchment has to report its results to the European Commission.

In this study we explore the possibilities of some existing fish monitoring schemes in The Netherlands to meet the requirements of the EU-WFD for detecting changes in fish populations.

1.1 Statistical power for trend detection

The monitoring schemes that the WFD requires should be sensitive to the perception of trends in fish community variables. This translates into: 'What is the probability that we can perceive a true trend with this monitoring scheme?' In other words: 'What is the statistical power for perceiving true trends of a particular size (the slope) with this monitoring survey?'

Statistical power is quantified as $1-\beta$, where β is the probability of making a type II error, which is the probability of not detecting a difference that in fact does exist. The other type of error that can be made is detecting a trend that actually does not exist. The probability of making such a type I error is indicated by α (Peterman, 1990). Traditionally, researchers have focused on type I errors, usually setting α at 0.05, but, depending on practical implications, or on the statistical outcome, a low probability of making a type II error (i.e. a small β) can be equally, or even more important (Sheppard, 1999). Especially in environmental issues the failure to detect a harmful, truly existing trend (because of applying a low α) might have more serious consequences than erroneously signalling a non-existing trend (because of applying a higher α).

Which variables enhance the statistical power for detecting trends? First, the number of samples (n) has a positive effect on the statistical power (Table 1). In case of annual samples this means that the probability of detecting a true trend increases with the number of years that a monitoring programme is already carried out. The size of the trend (the slope) also has a positive effect on the statistical power: the stronger a true trend is for a given inter-annual variability, the higher the probability that it will be detected. The same holds for the variance in the data. The smaller the variance around a trend of a particular size, the easier it is to detect such a trend. However, the reduction in variance will be less effective in enhancing statistical power when annual samples are not independent from each other (Neter et al., 1996), because of the dependency of the state of the fish population from the state of the population in the preceding year. Hence, annual observations do not vary in a random manner around a possible long-term trend, but are interdependent, which is apparent from serial correlation (correlation between observations of adjacent years) between the residuals around a trend (persistence). In order to correct for this dependency, the variance in the residuals can be expressed as:

$$\sigma^2_{\mathrm{corr}} = \frac{\sigma^2}{1-\rho^2}$$

(Neter et al., 1996), where σ^2_{corr}=variance in the residuals, corrected for the serial correlation (ρ^2).

Finally, with a higher probability level accepted for making a type I error (α), also the statistical power increases. This means that a larger sensitivity for detecting a true trend inevitably involves a higher risk of signalling a non-existing trend.

In this paper we focus on the effects of inter-annual variability and serial correlation in the estimates of fish biomass on the statistical power for trend detection, in order to explore the ability of the monitoring to meet the requirements of the EU-WFD. Our example species is common bream (*Abramis brama* L., Cyprinidae), a fish species which is highly abundant and often dominant in the eutrophic inland waters of north-western Europe. Moreover, the biomass of bream is considered to be an important indicator of the ecological quality of the water body and assessing bream abundance is therefore essential for categorising the water body according to WFD quality classes (STOWA, 2003).

1.2 Variability and serial correlation in the monitoring of fish populations

There are two major sources in annual sampling series: (1) variability due to actual fluctuations in the population (system variability), in which we are in fact interested and (2) variability due to sampling errors (sampling variability), which we try to avoid as much as possible. We consider sampling data to be of good quality if sampling variability is small compared to system variability.

The monitoring of fish populations is especially vulnerable to sampling variability, since fish populations are usually not monitored by direct observation, but by catching them first, thereby introducing the extra source of sampling variability. Large sampling variability increases the overall variability around a possible trend which thus decreases the probability of detecting a true trend, i.e. decreases the statistical power to detect system changes.

In addition, this increased variability is expected to mask the expected interdependency of subsequent annual samples, reflected in the serial correlations of the residuals around a trend. We expect the presence of serial correlation in most annual series for fish biomass, because of the multi-age structure of many fish populations. This serial correlation will be especially marked in populations that belong to long-lived species that have a low, fairly constant annual mortality and slow growth and reproductive rates, resulting in more gradual inter-annual changes in biomass. Large sampling variability increases the total inter-annual variability in the monitoring data, thereby obscuring the underlying, biologically relevant, serial correlation in these series. Hence we expect that with increasing quality of monitoring data (i.e. low sampling variability compared to system variability) random variance decreases and the underlying serial correlation becomes apparent (curved arrow in Fig. 1). In conclusion, high quality data would therefore result in higher power for detecting true trends in fish biomass. However, the power increase would be smaller than expected on the basis of the reduction of variability as such, because of the increased serial correlation in the data series, which, in its turn, decreases the power for trend detection

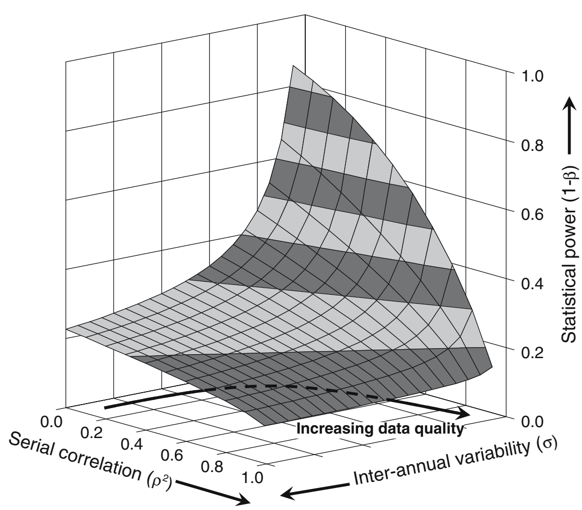

Fig. 1 Theoretical relationship of inter-annual variability and serial correlation of the residuals around a trend with the statistical power to detect the trend. If the quality of the data improves (i.e. if sampling variability decreases), overall inter-annual variability decreases, but serial correlation will increase (*curved arrow*). The decrease of variability will improve statistical power, but to a decreased extent if serial correlation is high

(Fig. 1). This is why we explored the expected inverse relationship between variance and serial correlation and its effects on the statistical power for detecting trends. We did this by comparing field data that encompass both system and sampling variability with simulated data with only system variability. For the simulation we used a size- and age-structured dynamic pool model (Buijse, 1992; Mous, 2000; Pet et al., 1996).

2 Materials and Methods

2.1 Study area

Lake Veluwemeer is an artificial, shallow (1.3 m average depth), 4,000 ha lake in The Netherlands. It originated in 1956 as a result of land reclamation works in the former marine Zuiderzee. Initially the lake was clear and dominated by macrophytes, but in the period 1971–1987 the water was highly eutrophic (mean summer concentrations of total phosphorus ranged from 0.09 to 0.6 mg·l^{-1}) and turbid (mean summer transparency of 0.2–0.5 m), mainly caused by algal blooms (Van Vierssen et al., 1994). The fish community in this period was dominated by cyprinid fish, especially bream, *A. brama* (De Nie & Backx, 1994; Nagelkerke & van Densen, 2001), and was not subject to commercial fisheries. Lake Veluwemeer is largely isolated for the immigration or emigration of fish, which subsequently have no influence on our results.

2.2 Field observations

Lake Veluwemeer was monitored at least once a year by the Department of Fisheries of the Ministry of Agriculture and Fisheries, using a bottom trawl with a 3 m beam and a cod-end stretched mesh size of 10–12 mm. The trawl was towed by boats at a speed of ca. 1 m·s^{-1} (hauls of on average 10 min). All fish caught were counted and the length was measured (from snout tip to fork of the tail: fork length). We only used data from surveys at the end of summer (August–September), when the spatial distribution of bream is more homogeneous (J. Backx, personal communication).

From 1971 to 1976 an average of five trawl hauls were made per survey; from 1977 to 1987 this was exactly five hauls per survey. Hauls were made at evenly spaced sampling stations at fixed positions. The trawl data were kindly made available by the Institute for Inland Water Management and Waste Water Treatment (RIZA).

2.3 Simulating system variability

The conceptual model of the age- and length-based simulation model was adapted from Mous (2000) and shown in Fig. 2. We used recursive numerical integration of state variables over a specified time step, according to model-specific expressions for rates of change (De Wit & Goudriaan, 1978). The elementary state variable in the model was the number of bream of a certain age class contained in a certain length class. The number of fish in that length class increased due to recruitment and growth of smaller fish into the length class. The number of fish in that length class decreased through mortality and also through growth when fish shifted to the next length class. To simulate dispersion in length growth with age the fractional boxcar train method was used (Buijse, 1992; Mous, 2000; Pet et al., 1996).

The bream population in Lake Veluwemeer is characterised by a relatively low natural mortality, the absence of fishing mortality, and by slow individual growth (Backx, 1989; Lourens, 1996). Recruitment, however, was highly variable – the numerical density of zero-group bream in autumn as based on the trawl surveys, fluctuated up to a factor 1,000 (Backx, 1989), with a coefficient of variation of 2.1 – and was expected to have the largest influence on changes in population numbers. A sensitivity analysis of the model showed that also the model is

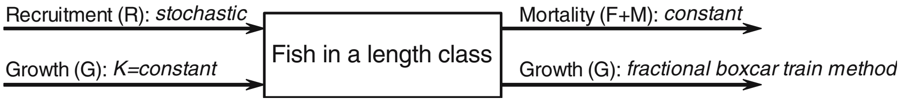

Fig. 2 Conceptual model of the simulation model (adapted from Mous, 2000). *F* Fishing mortality; *M* natural mortality

Table 2 Population dynamics parameters in the simulation models

Parameters	
Recruitment	Random recruitment with: mean $\log_e$(number of 1^+ fish ha^{-1})=5.71; standard deviation=1.21; seed=74; length at recruitment=15.5 cm
Mortality	$M=-2.225+0.601\ A-0.047\ A^2$ where: M = mortality (day^{-1}); A = age (year)
Growth	Von Bertalanffy daily growth with: k=0.00048 day^{-1}; $L_\infty = 55\ cm$
Length–weight relationship	$W=9.80\times10^{-6}\ L^{3.159}$ where: W=weight (kg); L=fork length (cm)

most sensitive to changes in recruitment, and less to deviations in mortality or growth parameters.

The population dynamics parameters that were used in the model were estimated from Backx (1989) (Table 2). Natural mortality was modelled as a 2nd order polynomial function of age. Growth was modelled using a seasonalised Von Bertalanffy growth equation (Sparre & Venema, 1998). Since no positive relationship was found between the numbers of age-0 bream and their presence as older age classes in the years thereafter, recruitment was modelled on the basis of age-1 bream, which did show significant correlations with their numerical presence at higher age. Modelling was done in Turbo-Pascal.

We performed 1,000 model runs of 17 years (equalling the number of sampling years). The model was validated by checking whether the estimates of the mean biomass over the years per length class from the model were similar to the estimates from the field data.

2.4 Data processing

Field observations were converted into numbers per hectre by correcting for the swept area during the haul. These numbers were again converted into a biomass measure (kg·ha^{-1}), using a standard length–weight relationship (W=9.80·10^{-6}· $L^{3.159}$, where W=body mass in kilograms, and L is fork length in centimeters). The output of the model also consisted of numbers of bream per year, age, and length class, which were converted in biomass (kg·ha^{-1}) in the same way as the field observations.

The biomass of bream in the length classes 10–20, 20–30, 30–40 and >40 cm, as well as the total biomass of all groups of bream assessed were $\log_{10}$-transformed and used to calculate inter-annual variability and serial correlations of the residuals around the trend.

Basic statistic analysis and regression analysis were performed in SAS 6.12. Power analysis of trends was partly performed in SAS 6.12 and partly iteratively in a worksheet environment (Microsoft Excel).

3 Results

3.1 Validation of the simulation model

The simulation model was validated by comparing the mean biomass of bream from the field observations

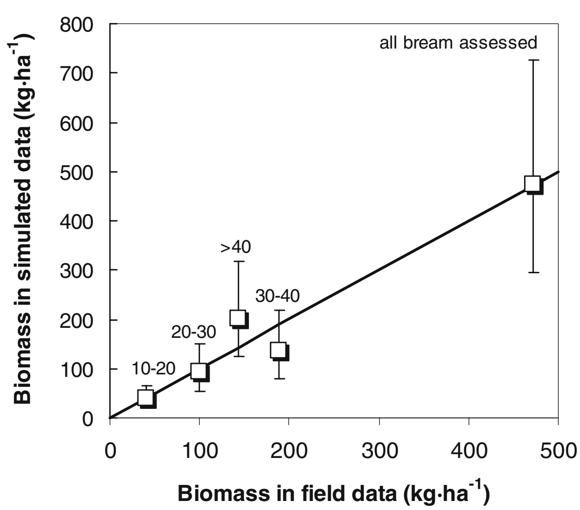

Fig. 3 Validation of the simulation model. Data points show the mean biomass of bream per separate length class and of all bream assessed in the field observations (*horizontal axis*) versus the mean estimated biomass from 1,000 simulation runs. Error bars indicate the 5th and 95th percentile values of the mean biomass from the simulation. The line represents equal biomass values

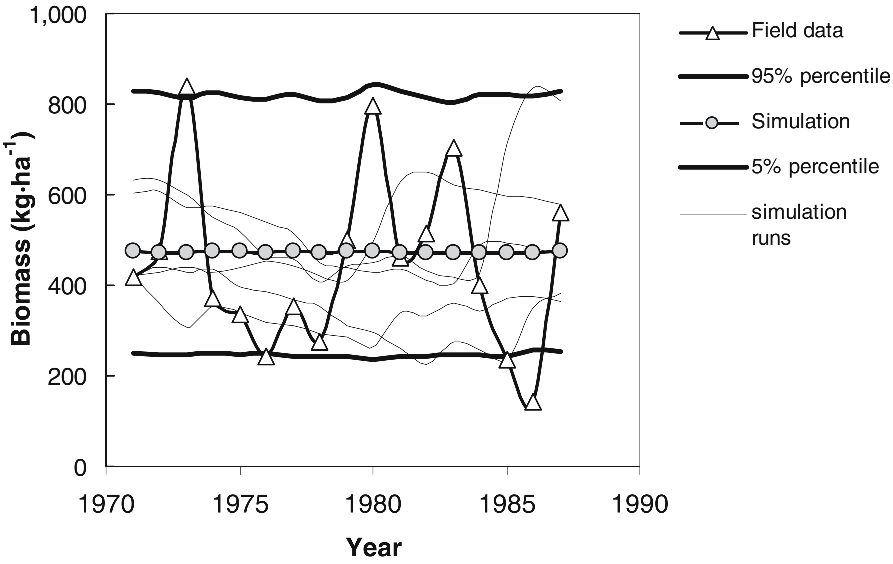

Fig. 4 Time series of the biomass of bream (*Abramis brama*) >10 cm in Veluwemeer in 1971–1987. Field observations are indicated by *triangles*. Mean values from 1,000 simulation runs are shown by *circles*. *Thick solid lines* show the 5th and 95th percentile values of the simulated time series. *Thin solid lines* show five, randomly chosen examples of separate simulation runs

with the mean output biomass from 1,000 simulation runs. Total biomass of all groups assessed (i.e. all bream >10 cm), as well as biomass per separate length class were evaluated (Fig. 3). In all cases the mean values from the field observations were well between the 5th and 95th percentile values of the distribution of the means of the simulations. The estimated mean total biomass of all groups of bream was less than 1% higher in the simulation than in the field observations. Differences between estimates of the biomass from the simulation and field observations were less than 5% for the 10–20 and 20–30 cm length classes. The biomass of 30–40 cm bream was estimated to be on average 28% lower in the simulation runs than in the field observations, while the biomass of bream >40 cm was on average 41% higher in the simulation runs than in the field observations. However, since the values from the field observations were always between the 5th and 95th percentile values of the distribution of the simulation results, the overall fit of the model appeared sufficient and we decided that the model was valid for the questions addressed.

3.2 Variability vs. serial correlations

The modelled biomass of bream, which represents system behaviour, showed a much smoother change between years than the field observations (see the individual simulation runs in Fig. 4). Consequently,

Table 3 Standard deviation in the $\log_{10}$-transformed residuals (σ), serial correlation (ρ^2), number of sampling years needed to detect a trend of 15% year^{-1} (n), and the number of sampling years needed, when corrected for the serial correlation (n_{corr})

Length class	Field observations			Simulation output			
	σ	ρ^2	n	σ	ρ^2	n	n_{corr}
All bream assessed	0.45	0.04	10	0.07 (0.03–0.14)	0.66 (0.28–0.96)	4 (3–6)	5 (3–14)
10–20	1.51	0.14	22	0.41 (0.30–0.54)	0.06 (0.02–0.22)	10 (8–12)	10 (8–12)
20–30	1.19	0.22	19	0.27 (0.17–0.40)	0.31 (0.07–0.63)	8 (6–10)	9 (6–13)
30–40	0.62	0.18	13	0.18 (0.09–0.29)	0.63 (0.36–0.84)	6 (5–8)	8 (5–14)
>40	0.84	0.16	15	0.10 (0.04–0.19)	0.70 (0.41–0.92)	5 (4–6)	7 (4–14)

Data are listed for the biomass of all assessed bream, as well as for separate length classes, both for field observations and for the simulation scenarios. Values in parentheses represent 5th and 95th percentile values from the simulation (for σ and ρ^2), or the most and least favourable cases (for n and n_{corr}).

inter-annual variability, expressed as the standard deviation in the $\log_{10}$-transformed residuals, was smaller for the simulation output than for the field observations for the biomass of all bream, as well as for each separate length class (Table 3; Fig. 5, top). Also, serial correlations in the residuals were larger for the simulation output than for the field observations in case of the total biomass of all bream assessed (Table 3; Fig. 5, bottom), as well as for the larger length classes (30–40 cm and >40 cm), which suffer lower mortality rates and are more buffered against the effect of recruitment variability than the smaller length classes. These findings all corroborate with our expectations about the relationship between inter-annual variability and serial correlation (Fig. 1).

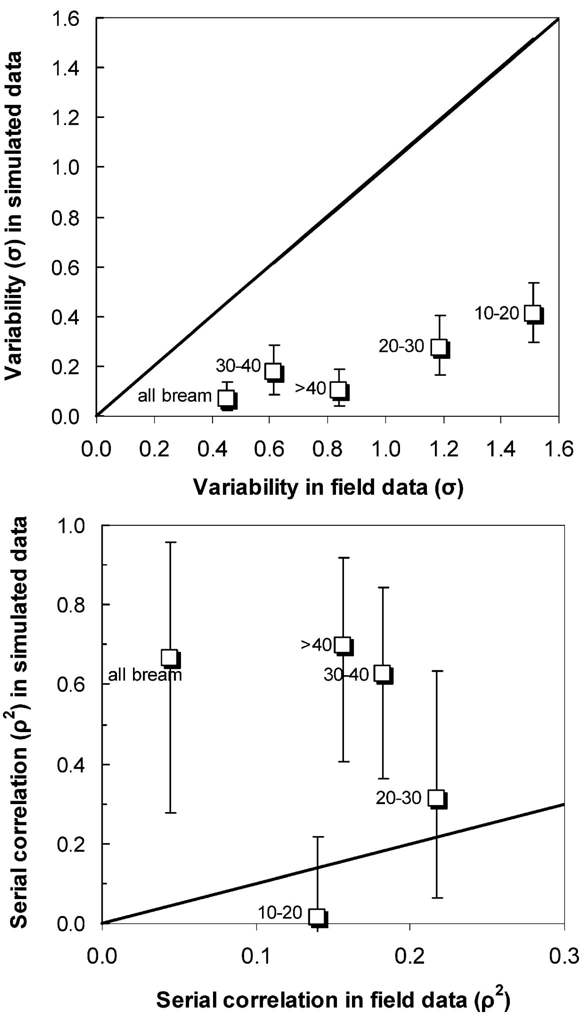

Fig. 5 The relationship between the inter-annual variability (expressed as the standard deviation, σ, of the residuals around the trend through $\log_{10}$-transformed biomass) in the field data and the data from the simulation (*top*), and the relationship between the serial correlation (expressed as the correlation, ρ^2, between adjacent residuals around the trend through $\log_{10}$-transformed biomass) in the field data and the data from the simulation (*bottom*). Error bars indicate the 5th and 95th percentile values from the simulation. *Lines* represent equal variability or equal serial correlation

3.3 Data quality and the statistical power of annual surveys

The simulated data showed the expected higher serial correlation in the residuals than the field observations did. This means that the annual survey data were not independent of each other, which resulted in a lower power for detecting trends (see Fig. 1).

The effects on the statistical power for detecting a trend in survey data were exemplified by taking the inter-annual variability of the residuals around the trend in the field data and calculating what number of sampling years (n) would be needed to detect a 15% increase or decrease per year in the total biomass of all bream assessed, with a generally accepted level for required statistical power ($1-\beta$) of 0.9 (Gerrodette, 1987, 1993; van Densen, 2001). This 15% change roughly equals a doubling or halving of the bream biomass in a six year period. Based on the variability of the field data (σ=0.45: Table 3) this would require 10 sampling years. If the field data would have the same variability as the simulation (mean σ=0.07), then only four years would be needed, if we do not account for serial correlation. However, the simulation resulted in a mean serial correlation of ρ^2=0.66. Hence, $\sigma_{\mathrm{corr}} = \sqrt{(0.07)^2 / (1-0.66)} = 0.12$, and the need for five survey years (n_{corr}, the corrected number of survey years in Table 3). These five survey years were based on the mean variability and serial correlation from 1,000 simulation runs. When we took the 5th and 95th percentile values of inter-annual variability and serial correlation and calculated the number of survey years required, this ranged from 3 (the most favourable situation, i.e. the lowest variability combined with the lowest serial correlation) to 14 (the least favourable situation, i.e. the highest variability combined with the highest serial correlation).

In case of separate length classes of bream, the number of sampling years required ranged from 13 to 22 based on the field data, not taking the serial correlation into account. This means that the six year reporting periods required by the EU-WFD are always too short to detect a halving or doubling with a statistical power of 0.9 with the existing surveys. Based on the simulation, on average 5–10 years would be required if we do not account for serial correlation (4–12 for the most and least favourable situations, based on the 5th and 95th percentile values of inter-annual variability) and 7–10 years if serial correlation is taken into account (4–14 for the most and least favourable situations, based on the 5th and 95th percentile values of inter-annual variability and serial correlation). We therefore concluded that the numbers of required sampling years from the simulation output were, on average, much lower than when calculated from the field data (only about half), because of the smaller inter-annual variability, but to a lesser extent when serial correlation was taken into account. If serial correlation was very high (e.g. ρ^2= 0.96, the 95th percentile value in case of all bream assessed: Table 3) this increased the number of required sampling years to 14. Therefore, even when inter-annual variability would be greatly reduced by completely eliminating sampling variability (as is the case in the simulation), the number of years required to detect such a trend would in most cases (85% of the cases we calculated) still be larger than the six year reporting periods required by the EU-WFD.

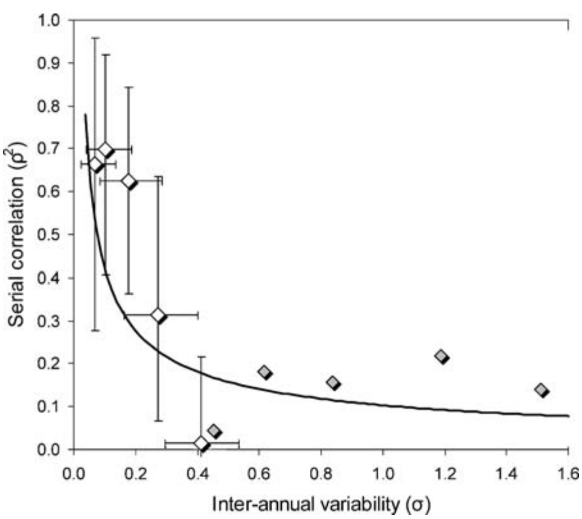

Fig. 6 The relationship between inter-annual variability and serial correlation for field and simulated data. Data-points represent field observations (*filled symbols*), or simulation output (*open symbols*) per length class, or for all assessed bream (see Table 3). Error bars indicate the 5th and 95th percentile values from the simulation for inter-annual variability (*horizontal*) and serial correlation (*vertical*). The curve was fit by eye

These results suggest that increasing the precision of monitoring surveys, i.e. decreasing inter-annual sampling variability, would lead to an increase of statistical power for the detection of trends. However, this increase will be smaller than expected on the basis of decreased variability alone, because of the serial correlation which underlies the true time series. This serial correlation was obscured in the field data, because of additional sampling variability (Fig. 6).

4 Discussion

The European Water Framework Directive prescribes that the progress of water quality developments is reported at six-year intervals (European Union, 2000). In this paper we show that for bream in Veluwemeer six sampling years is too short to report with a statistical power of $1-\beta$=0.9, even a halving or doubling in the total biomass of bream. The main cause for this limited statistical power appears to be the large inter-annual variance due to population and sampling effects (which in themselves are difficult to estimate: Carey & Keough, 2002). We have shown by simulating time series for numbers and biomass of bream in Lake Veluwemeer that the true inter-annual variability of the bream population is probably much lower than the variability we assessed in the field data. This means that fewer sampling years would be needed to detect the trend if inter-annual variability could be reduced. However, even in case of the lowest variabilities (biomass of all bream assessed: σ=0.03–0.14: Table 3) the number of required sampling years was five on average, with a range of 3 to 14 years. In case of the highest variabilities (biomass of bream of 10–20 cm length: σ=0.30–0.54: Table 3) the number of required sampling years was at least eight, that is in the most favourable circumstances, without any additional sampling variability). In addition, we expected and found that the lower the inter-annual variability was, the higher the serial correlation would be (Figs. 1 and 6), resulting in lower statistical power for these time series, and in a higher number of required sampling years (Table 3). This means that in populations of fish species such as bream that are buffered against large variability in annual recruitment (because of their longevity and containing many year classes in their populations), we have to observe the biologically inherent serial correlation to meet minimum requirements for data quality. The absence of serial correlation indicates large sampling variability, i.e. data of poorer quality.

It would be useful to decrease sampling variability in order to increase the statistical power of the bream monitoring surveys. Sampling variability is relatively high in the field observations (Figs. 5 and 6) and will be mainly caused by spatial differences between replicate hauls, heterogeneity of the lake, or by schooling behaviour of the bream, resulting in a clustered occurrence in the lake environment. An additional source of variability could be the trawl nets that were used. It is known that the catchability of large fish is smaller for these trawl nets (STOWA, 2003). This could be a reason for the inter-annual variability to be higher in the largest length class of bream (σ=0.84, Table 3) than in the smaller length class of 30–40 cm (σ=0.62), whereas the simulation suggests that system variability decreases with size. However, even if we would manage to decrease sampling variability considerably, this study suggests that it would be unrealistic to expect the detection of significant trends in bream populations in a six-year period, unless these trends are very large. Similarly, Verhallen et al. (2001) found that in order to have sufficient statistical power to detect trends in total phosphorus concentrations in Dutch–German river catchments concentrations should be at least 1.4 times higher or lower between reporting periods. Both this study and the study on phosphorus concentrations show that the use of existing monitoring schemes for water quality and ecological variables might be problematic in view of the WFD reporting periods.

5 Conclusions

In this study we have shown that: (1) good field observations of long-lived fish populations show low sampling variability and thus high inter-annual serial correlation; (2) serial correlation in time series necessitates an additional number of surveys to acquire a certain statistical power; and (3) it appears to be impossible to catch up with the six-year reporting periods of the EU Water Framework Directive.

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