Does oyster size matter for modelling trace metal bioaccumulation?

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ABSTRACT

The aim of this study was assessing whether trace metal bioaccumulation models for oysters need to account for the effect of size-structured demography. To achieve this, we used a Bayesian generalised additive mixed modelling (BGAMM) approach. This nonparametric regression approach allowed us to estimate potentially nonlinear size effects of the oysters as well as random and structured spatial effects. Native oysters were collected from ten locations around the shoreline of Moreton Bay, a subtropical estuary in southeast Queensland, Australia. The soft-tissue of these sampled oysters were weighed (dry weight basis) and then analysed for Al, Cu, Fe, Mg, Mn and Zn. Of the six trace metals analysed, only Mg was found to have a significant (negative) effect of soft-tissue mass. The correlated spatial effects for Cu, Mn and Zn indicated that the source of these trace metals in the oysters was from anthropogenic inputs while the correlated spatial effects for Al and Mg indicated natural inputs. The correlated spatial effect for Fe was characterised by ‘hotspot’ concentrations in regions of Moreton Bay where algal blooms have previously occurred and consequently oysters might be useful as an indicator of algal blooms in the Bay. Overall, the absence of an observed size effect for five of the six trace metals indicates that bioaccumulation models do not necessarily need to account for size-structured demography therefore enabling simpler models to be used.

Keywords:

Metal, bioaccumulation, oysters, spatial variation, Bayesian GAMM

INTRODUCTION

Native oysters are widely used to monitor water quality and assess coastal ecosystem health (Brown and McPherson, 1992; Hayes et al., 1998; Lin and Hsieh, 1999) and their application as ‘biomonitors’ or ‘sentinels of the environment’ has previously been well described (Phillips 1980; Phillips and Segar, 1986; Rainbow 1995). Much of their utility arises from their ability to provide an easily measurable and time-integrated indication of contaminants. However, it is often difficult to sample oysters of uniform size both within and across sampling sites (Robinson et al., 2005) and this variability has often (Mackay et al., 1975; Phillips 1980; Frew et al., 1989; Hayes et al., 1998) but not always (Robinson et al., 2005) been a significant factor in the trace metal bioaccumulation patterns that are observed. An implication of this potential size effect is whether oyster bioaccumulation models actually need to account for size-structured demography or whether simpler models that ignore size effects can be used.

In this study, we assess the effect of oyster size on trace metal bioaccumulation using a Bayesian generalised additive mixed modelling approach. This approach allows correlated and uncorrelated spatial effects to be considered simultaneously. Our analysis was carried out using native oysters collected from the intertidal zone of Moreton Bay, which is a large subtropical coastal estuary located in southeastern Queensland, Australia. This analysis provides a basis for developing a better understanding of the effects of variable oyster size and spatial patterns on trace element bioaccumulation in oysters.

MATERIALS AND METHODS

Sampling and laboratory analysis

The study site of Moreton Bay (153°12' E, 27°18' S) is a wave dominated semi-enclosed embayment located in southeast Queensland, Australia (Fig. 1). The western catchment is dominated by grazing and forestry (Capelin et al., 1998) and also features the Queensland state capital city of Brisbane (population 838,000). The eastern catchment is dominated by the sparsely populated Moreton and North Stradbroke Islands.

The selection of native oyster sampling locations was guided by the desire to provide a broad coverage of the shoreline around Moreton Bay. Six adult oysters were sampled from the intertidal zone at ten locations in Moreton Bay during a one-off survey in July 2001 (Fig. 1). Robinson et al., (2005) found that six was the minimum number of samples needed to estimate the mean trace metal concentration for a population of native oysters. Each sampled oyster was carefully removed from local stratum, cleaned in the local seawater, placed in a snap-lock freezer bag, labelled and transferred to a cooler containing ice at the point of collection.

The soft-tissue of the oysters were analysed for Al, Cu, Fe, Mg, Mn and Zn and all concentrations reported on dry weight basis. Oysters were shucked using a stainless steel oyster-shucking knife and the soft-tissue transferred to individual sterile containers. Oysters were dried, weighed, digested with 0.5M redistilled perchloric-nitric acid and then analysed using Inductively Coupled Plasma – Atomic Emission Spectroscopy.

Bayesian regression model

A generalised additive mixed modelling (GAMM) approach was used to explore the effect of size on the soft-tissue concentrations of the six trace metals (Al, Cu, Fe, Mg, Mn and Zn) in the sampled oysters. The GAMM regression models were fitted in a Bayesian inference framework using Markov chain Monte Carlo (MCMC) simulation techniques implemented in the software program Bayes X (Brezger et al., 2005). Bayesian modelling via MCMC simulations is an increasingly used approach for simultaneous estimation of fixed, nonparametric (or nonlinear) and random or structured spatial effects (Fahrmeir and Lang, 2001; Lang and Sunder, 2003; Brezger et al., 2005). The trace metal data generated from the shoreline sampling of oysters were assessed for both correlated (structured) and uncorrelated (random) spatial effects.

All unknown model parameters, including the spatial covariates, are assumed in Bayesian modelling to be random variables and therefore prior distributions need to be specified (Fahrmeir and Lang, 2001). Second-order random walk smoothness priors (Fahrmeir and Lang, 2001; Lang and Sunder, 2003) were used to assess the six trace metals against the soft tissue weight of the oysters. Two-dimensional P-spline surface smoothers (Lang and Sunder, 2003; Augustin et al., 2007) based on the geographical coordinates (latitude and longitude) of each sampling site were used for the structured spatial effects. It was assumed that the site-specific parameters (random spatial effect) were independent gaussian with a common variance (Lang and Sunder, 2003). These are all common priors used in nonparametric Bayesian regression modelling (Lang and Sunder, 2003; Augustin et al., 2007).

Model selection was based on the deviance information criterion (DIC) approach proposed for Bayesian statistical models where the best-fit model is indicated by the lowest DIC (Spiegelhalter et al., 2002). The posterior distribution of the parameter effects for all models was sampled from 50,000 MCMC iterations following an initial burn-in period of 2000 iterations (Brezger et al., 2005). Inference concerning the effects of oyster size was based on the posterior distribution, which was then summarised using the posterior mean, standard deviation, median (50% quantile), and 95% credible intervals based on the posterior 2.5% and 97.5% quantiles. If the 95% credible region for a trace metal could not be fitted with a zero gradient slope then this indicated a significant relationship (see Kneib 2006 p. 790). Conversely if a zero gradient slope could be fitted then this indicated no significant relationship.

RESULTS AND DISCUSSION

The range of soft-tissue masses for the individual oysters sampled from the shoreline of Moreton Bay is presented in Fig. 2 and shows that this ranged from 0.1 to 3.3 g. The mean soft-tissue trace metal concentrations measured at the ten sampling locations are summarised in Table 1 and this data is characterised by considerable within-site and inter-site variation as indicated by the large coefficients of variance (Table 1).

The evaluation of the best-fit model based on the DIC is presented in Table 2.

Spiegelhalter et al., (2002) indicate that a change of 2 or more in DIC is considered an important difference between models. Given this ‘rule of thumb’ measure, size effects

(Model 2) were apparent for Al, Cu and Mg but not for Fe, Mn and Zn. Furthermore a random spatial effect (Model 3) was only apparent for Zn (Table 2). Overall, use of DIC suggested that neither size nor random spatial effects were needed in the model. However, a review of the plots in Fig. 3 shows that while the 95% credible regions for Al, Cu, Fe, Mn and Zn can all be fitted with zero slopes indicating no significant relationship between oyster soft-tissue mass and trace metal concentration, there was a significant (negative) effect of size on Mg concentration. While DIC has been shown to be an effective rapid screening process of model selection (Spiegelhalter et al., 2002), it appears that in this case the importance of a size effect on trace metal concentration is better evaluated from the nonparametric plots. Conversely, other emerging techniques for evaluating Bayesian models could be used in place of DIC (Aitkin et al., 2005).

Robinson et al., (2005) also observed no significant correlation between soft-tissue mass and trace metal concentration for oysters. However, Mackay et al., (1975) found that trace metal concentration in oysters decreased as soft-tissue mass increased in the manner observed here for Mg. Robinson et al., (2006) suggest that oyster soft-tissue mass might not be a significant effect on trace metal concentration if the effect of age is also accounted for. However, age is not always known in native oysters making it difficult to evaluate this effect.

The estimated correlated spatial effect posterior means for each site observed for each of the soft-tissue trace metals (Fig. 4) were processed to aid visual presentation and interpretation using bicubic interpolation for irregularly spaced data (Akima 1996), which

was implemented using the *akima* package in R (Ihaka and Gentleman, 1996). There was pronounced west-east (high-low) gradients for Cu (Fig. 4b), Mn (Fig. 4e) and Zn (Fig. 4f) that appear to reflect the proximity of the sampled oysters to populated catchment areas of Moreton Bay. The western catchment area of the Bay is heavily populated and dominated by Queensland's capital, Brisbane City, while the eastern catchment of Moreton Island and North Stradbroke Island is sparsely populated. Conversely, an opposite east-west (high-low) gradient was observed for Al (Fig. 4a) and Mg (Fig. 4d) suggesting that the distribution of these metals is a result of natural inputs rather than anthropogenic inputs. Finally, Fe (Fig. 4c) was characterised by 'hotspot' concentrations at Deception Bay to the north and Redland Bay to the south, reflecting the naturally high levels of iron that occur in these regions (Cox and Preda, 2005). Interestingly, algal blooms in both of these regions have been linked to elevated Fe levels (Dennison et al., 1999) and therefore measuring Fe concentrations in oysters might be useful as an indicator of algal blooms in Moreton Bay.

The absence of an observed size effect for five of the six trace metals indicates that oyster bioaccumulation models do not need to include size-structured demography when modelling Al, Cu, Fe, Mn and Zn concentrations. Rather, simpler bioaccumulation models that do not account for size effects can be used in these instances. Models that do account for size effects such as those using a dynamic energetic budget framework (Kooijman and van Haren, 1990) can be difficult to parameterise because of increased complexity. Therefore the use of simpler models is advantageous because of the reduced parameter requirements.

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Table 1. Mean trace element concentrations measured in the soft tissue (dry weight basis) of the collected oysters. Values in parentheses represent coefficient of variation (cv = [standard deviation/mean] x 100).

Metal	Wynnum	Shorncliffe	Wellington	Beachmere	Redland	Cleveland	Cabbage	Myora	Blue	Dunwich
			Point		Bay		Tree Pt		Hole	
Al	31	32	51	107	65	71	70	267	36	136
	(10%)	(146%)	(58%)	(88%)	(71%)	(37%)	(78%)	(60%)	(82%)	(55%)
Cu	681	169	227	203	592	438	274	72	42	111
	(49%)	(62%)	(5%)	(18%)	(11%)	(16%)	(48%)	(29%)	(45%)	(26%)
Fe	408	350	498	2354	2599	690	219	187	56	146
	(67%)	(115%)	(94%)	(81%)	(127%)	(39%)	(55%)	(50%)	(54%)	(22%)
Mg	2371	3188	2826	3367	3140	5137	3643	4390	3454	5110
	(19%)	(46%)	(15%)	(13%)	(26%)	(30%)	(23%)	(28%)	(32%)	(43%)
Mn	11.1	10.8	18.9	20.2	17.1	11.9	13.3	5.3	3.8	5.8
	(20%)	(66%)	(38%)	(48%)	(59%)	(48%)	(40%)	(46%)	(39%)	(31%)
Zn	2459	1360	879	1024	2360	1938	1999	875	562	1271
	(36%)	(26%)	(20%)	(22%)	(19%)	(8%)	(30%)	(32%)	(44%)	(35%)

Table 2. Summary of model selection results for Al, Cu, Fe, Mg, Mn and Zn. The best-fit model is determined by the lowest deviance information criterion (DIC) value, which are shown in **bold**. Model 1 = Global Model; Model 2 = Global Model – size effect; Model 3 = Global Model – size effect – random spatial effect.

Trace Metal	DIC		
	Model 1	Model 2	Model 3
Al	73.22	69.92	69.82
Cu	72.96	70.37	71.03
Fe	69.21	68.53	67.98
Mg	72.95	70.43	70.34
Mn	68.58	68.73	69.13
Zn	72.38	70.78	70.22

Figures

Fig. 1. Map of Moreton Bay indicating the oyster sampling sites.

Fig. 2. Range of soft-tissue mass (dry weight basis) measured in the sampled oysters.

Fig. 3. Estimated non-parametric functions of oyster soft-tissue weight (dry weight basis) for Al, Cu, Fe, Mg, Mn and Zn. Posterior means within the 95% credible regions are shown.

Fig. 4. Correlated spatial effects of trace metal concentrations using two-dimensional p-spline surface smoothers. (a.) Al, (b.) Cu, (c.) Fe, (d.) Mg, (e.) Mn and (f.) Zn.

(a.)

(b.)

(c.)

(d.)

(e.)

(f.)