Supplementary material

Evidence for a broad-scale decline in giant Australian cuttlefish (*Sepia apama*) abundance from non-targeted survey data

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Deviance information criterion (DIC) calculation and selection of the negative binomial distribution

Giant cuttlefish counts were overdispersed (i.e. Poisson variance exceeded the mean) with an excess of zeros, so we tested the ability of four distributions (Poisson, zero-inflated Poisson, negative binomial and zero-inflated negative binomial) to account for these data (Martin *et al.* 2005). To ensure that the DIC was calculated appropriately for these hierarchical models, we explicitly specified a partially marginalised likelihood function (Millar 2009; Smith *et al.* 2012) by means of the 'zeros trick' for non-standard likelihoods (Spiegelhalter *et al.* 2003). Preliminary fitting showed that negative binomial distributions provided the best model fit, based on DIC and posterior predictive checks that contrast the fit of replicated data generated from the posterior distribution to that of the observed data (Gelman *et al.* 1996).

Spatial random effects for abundance models

To construct spatial abundance models in WinBUGS, we used the *GeoBUGS* add-on to fit spatial random effects (S_i) that were jointly distributed as a Gaussian CAR (conditional autoregressive) spatial process, such that

$$S_i \mid \boldsymbol{S}_{-i} \sim \mathrm{N}\left(\phi \sum_{j \in N_i} w_{ij} S_j , \frac{1}{w_{ij}\tau^2} \right)$$

where $\boldsymbol{S}_{-i}$ is the vector of all spatial random effects excluding that for the *i*th site, ϕ controls the overall spatial correlation, N_i is the set of neighbours of the *i*th site, and τ is the precision (i.e. inverse of the variance). The weight terms (w_{ij}) were calculated assuming that between-site correlations declined exponentially as a function of distance. On the basis of spatial correlograms, we defined the neighbourhoods N_i as all sites falling within 10 km of the *i*th site. Although CAR models are typically applied to continuous lattices of cells, they can also be used as a computationally efficient means of approximating continuous geostatistical processes (Carroll *et al*. 2010).
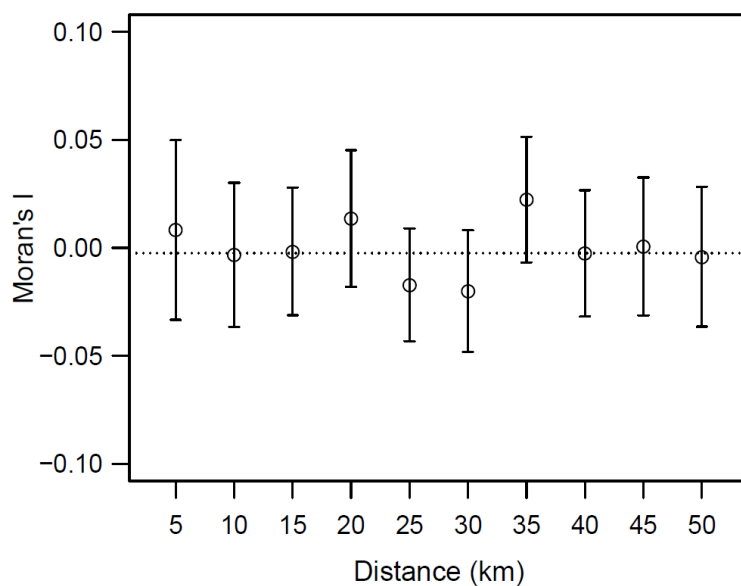

Fig. S1. Spatial correlograms for the residuals of the selected spatial-abundance model (see Table 1 of main text). Points plot Moran's I statistic for different distance lags and error bars represent ± the square root of its variance. The dotted line illustrates the Moran's I statistic expected under the null hypothesis of no spatial autocorrelation.
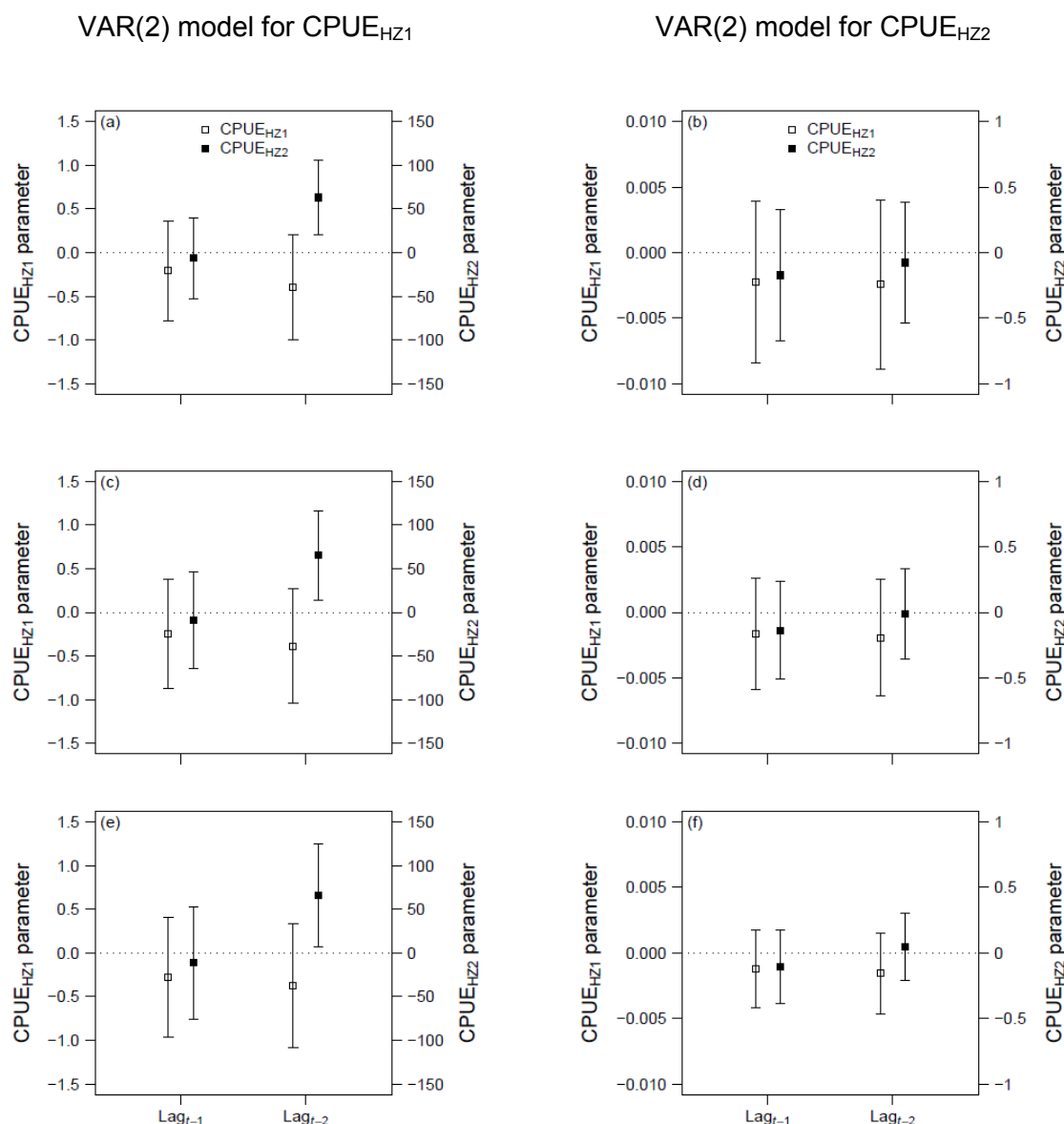
Fig. S2. Sensitivity of vector autoregressive (VAR) models to assumptions regarding the proportional representation of *Sepia apama* in the commercial cuttlefish catch in Harvest Zone 2. Plots show parameter estimates (and 95% confidence intervals) for VAR(2) models assuming (*a*, *b*) no change in catch composition over time, (*c*, *d*) a linear decline from a 100 to 50% contribution from *S. apama* over the time scale of the analysis, and (*e*, *f*) a linear decline from a 100 to 10% contribution from *S. apama*. CPUE$_{HZ1}$ and CPUE$_{HZ2}$ refer to catch per unit effort in Harvest Zones 1 and 2 respectively. Note that the positive, significant relationship between CPUE$_{HZ2}$ lagged by 2 years and CPUE$_{HZ1}$ was not sensitive to assumptions regarding the species composition of CPUE$_{HZ2}$. Panel *a* replicates Fig. 4*b* from the main text.

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