Multiple covariate distance sampling (MCDS)

- Aim: Model the effect of additional covariates on detection probability, in addition to distance, while assuming probability of detection at zero distance is 1

- References:
- Marques (F) and Buckland (2004) Covariate models for the detection function. Chapter 3 in Buckland et al. (eds). Advanced Distance Sampling.
- Marques (T) et al. (2007) Improving estimates of bird density using multiple covariate distance sampling. The Auk 127: 1229-1243.
- Section 5.3 of Buckland et al. (2015) Distance Sampling: Methods and Applications

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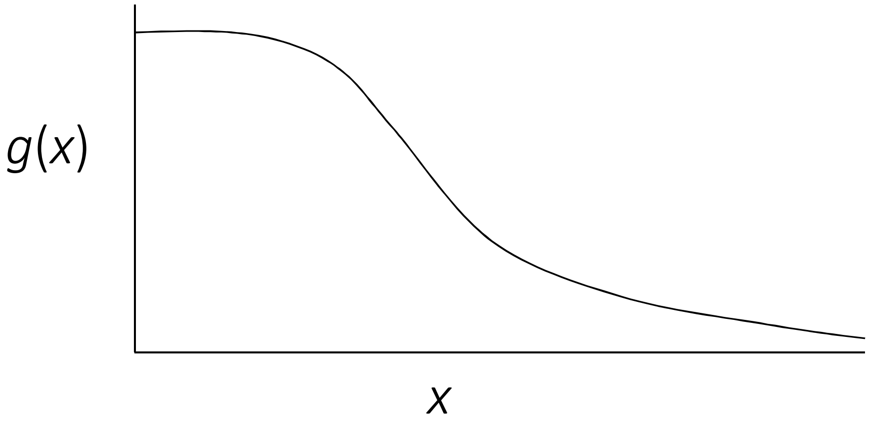
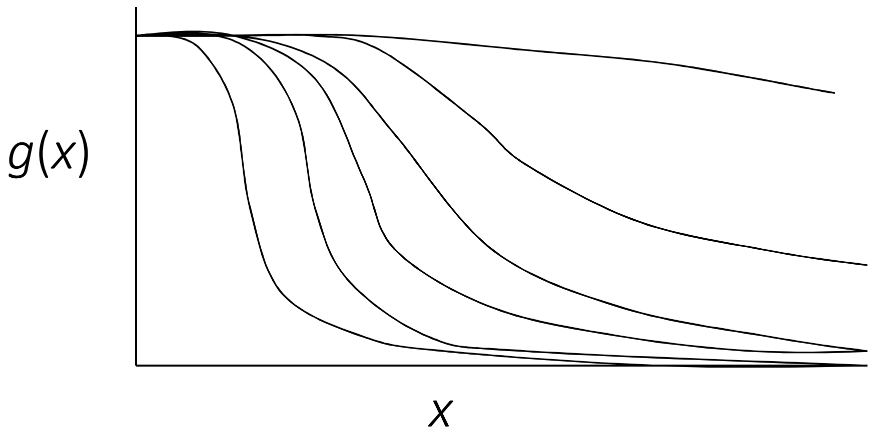
Why additional covariates?

In conventional distance sampling (CDS) analysis all factors affecting detectability, except distance, are ignored



In reality, many factors may affect detectability



Sources of heterogeneity:

Object : species, sex, cluster size

Effort: observer, habitat, weather

Examples of heterogeneity 1

Effect of time of day on Rufous Fantail birds in Micronesia (point transects). Ramsey et. al. 1987. Biometrics 43:1-11

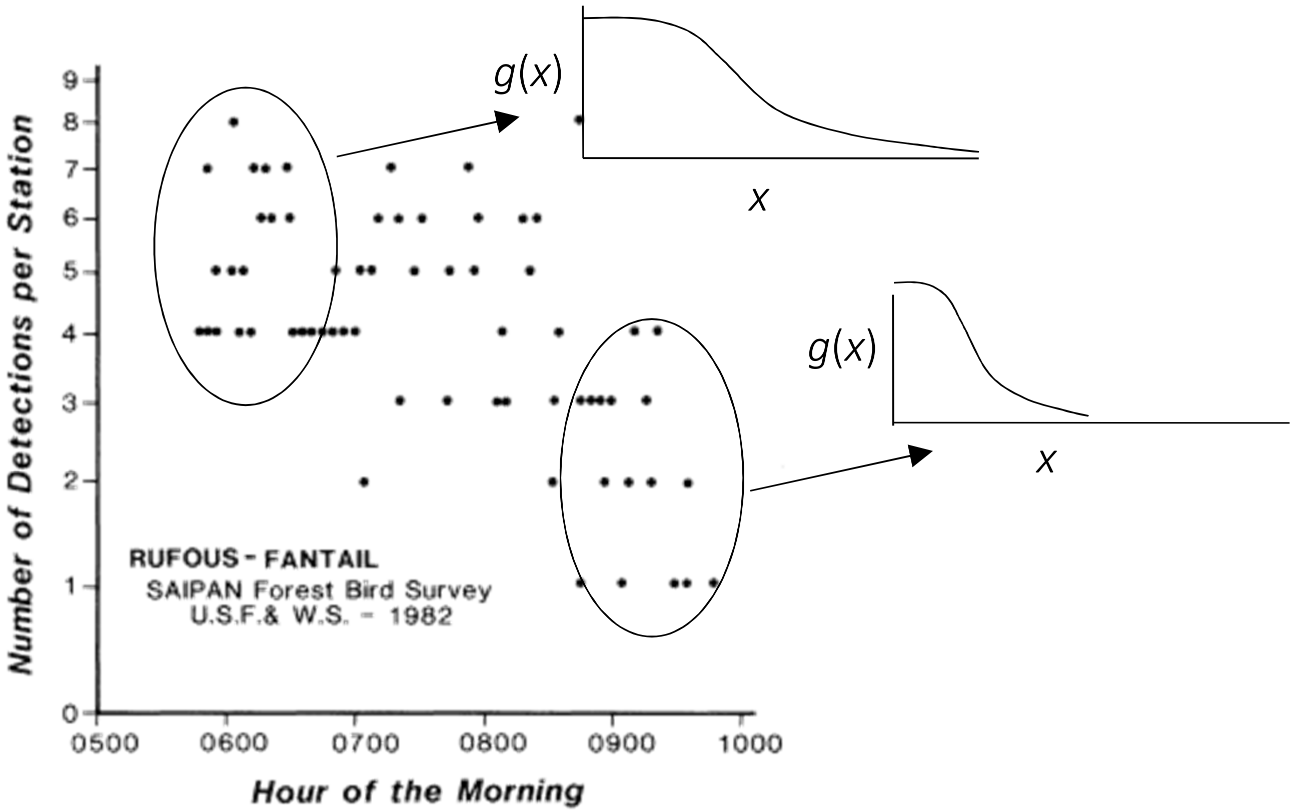


Figure 1. Station counts of Rufous Fantails on Saipan appear higher in the early morning hours than in the late morning ($n = 64$, $r = -.60$).

Examples of heterogeneity 2

Effect of sea state (and other covariates) on sea turtles in the Eastern Tropical Pacific (shipboard line transects). Beavers and Ramsey, 1998, J. Wildl. Manage. 63: 948-957

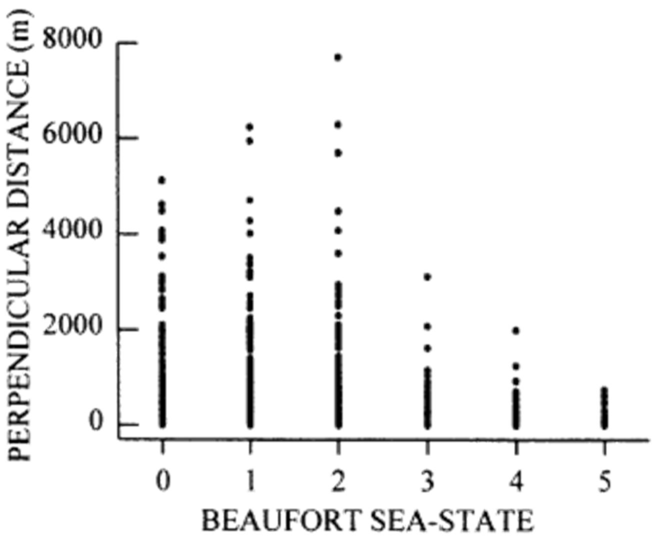


Fig. 2. Covariates of air temperature, sea surface temperature, and Beaufort sea-state plotted against unadjusted, ungrouped perpendicular sighting distances (m) of sea turtles in the eastern tropical Pacific, 1989–90.

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Examples of heterogeneity 3

Effect of cluster size on beer cans. Otto and Pollock, 1990, Biometrics 46: 239-245

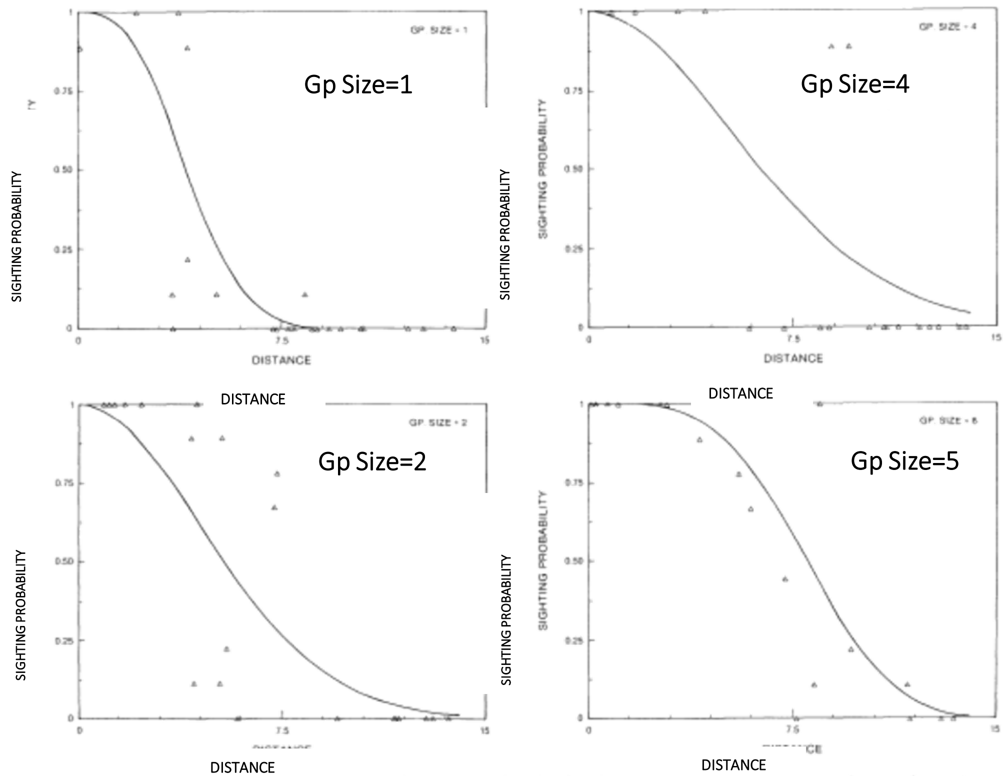

Figure 1. Otto beer can data plot of empirical exponential power series sighting function versus perpendicular distance for each group size on transect 1. The Δs give the proportion of observers who sighted each object.

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Why worry about heterogeneity?

In CDS, we use models that are pooling robust, so why worry about heterogeneity?

- Pooling robustness works for all but extreme levels of heterogeneity
- Potential bias if density is estimated at a ‘lower level’ than detection function (e.g. density by geographic region, detection function global)
- Could potentially increase precision of detection function estimate
- Interest in sources of heterogeneity in their own right (e.g. group size)

Dealing with heterogeneity

Stratification

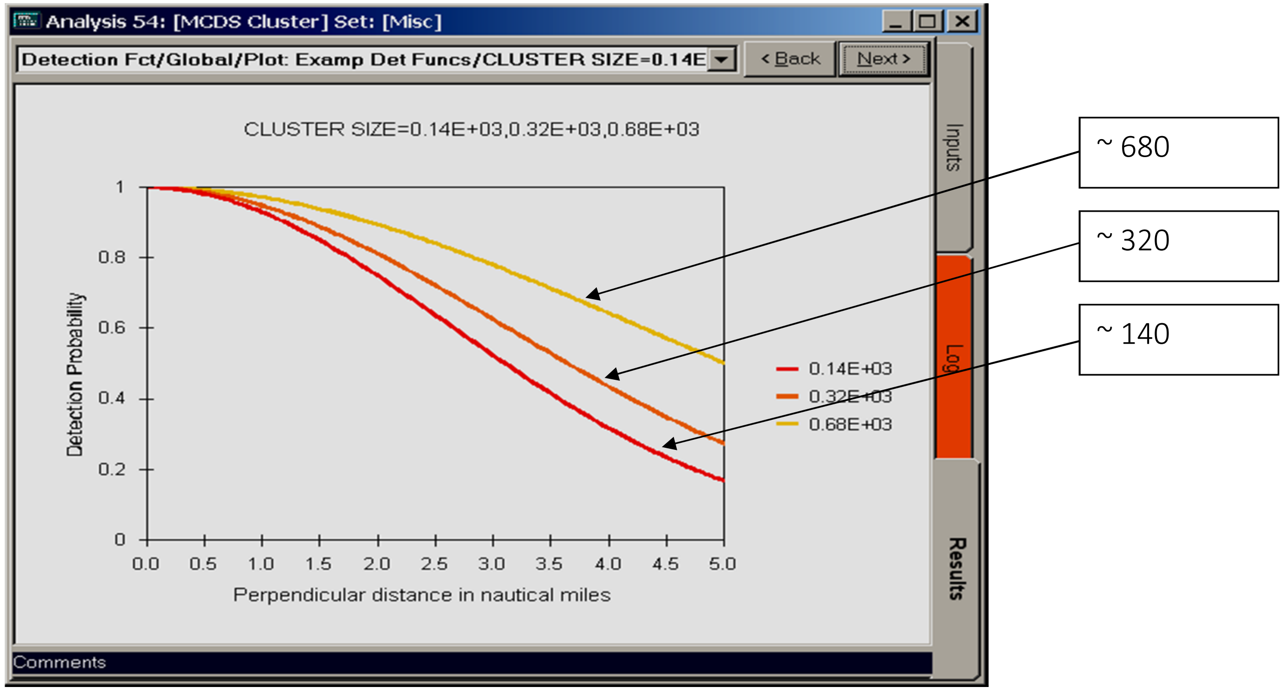
Requires estimating separate detection function parameters for each stratum, so often not possible due to lack of data

Model as covariates in detection function

Allows a more parsimonious approach:

- can model effect of numerical covariates

- can 'share information' about detection function *shape* between covariate levels



Multiple covariate models Recap of CDS models

$g(x)$ = Pr[animal at distance x is detected]

$$= k(x)\left[1+\sum_{j=1}^{m} a_j p_j(x_s)\right]/c$$

Key function

Scaling constant to ensure $g(0) = 1$

j^{th} series adjustment term

CDS models continued

Key functions

Shape parameter

Hazard rate $k(x) = 1 - \exp\left[-\left(\frac{x}{\sigma}\right)^{-b}\right]$

Half-normal $k(x) = \exp\left(\frac{-x^2}{2\sigma^2}\right)$

Neg. exp. $k(x) = \exp\left(\frac{-x}{\lambda}\right)$

Uniform $k(x) = 1$

Scale parameter

Series adjustments

Cosine $\cos(j\pi x_s)$

Polynomial x_s^j

Hermite poly. $H_j(x_s)$

x_s are scaled distances (see later)

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Modelling with covariates –
ignoring adjustments terms (for now)

$g(x,\mathbf{z})$ = Pr[animal at distance x and covariates $\mathbf{z}$ is detected]

Assume the covariates affect the ***scale*** of the key function, not its ***shape***. So choose key functions with a scale parameter

Let $$\sigma(z) = \exp\left(\beta_0 + \sum_{j=1}^{J} \beta_j z_j\right)$$

e.g. Hazard rate $$k(x,z) = 1 - \exp\left[-\left(\frac{x}{\sigma(z)}\right)^{-b}\right]$$

Half normal $$k(x,z) = \exp\left(\frac{-x^2}{2\sigma(z)^2}\right)$$

k is used here to denote the "key" function

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Modelling with covariates

Example: Dolphin tuna vessel data

Model: half-normal, with no adjustments

Covariate: cluster size, *s*

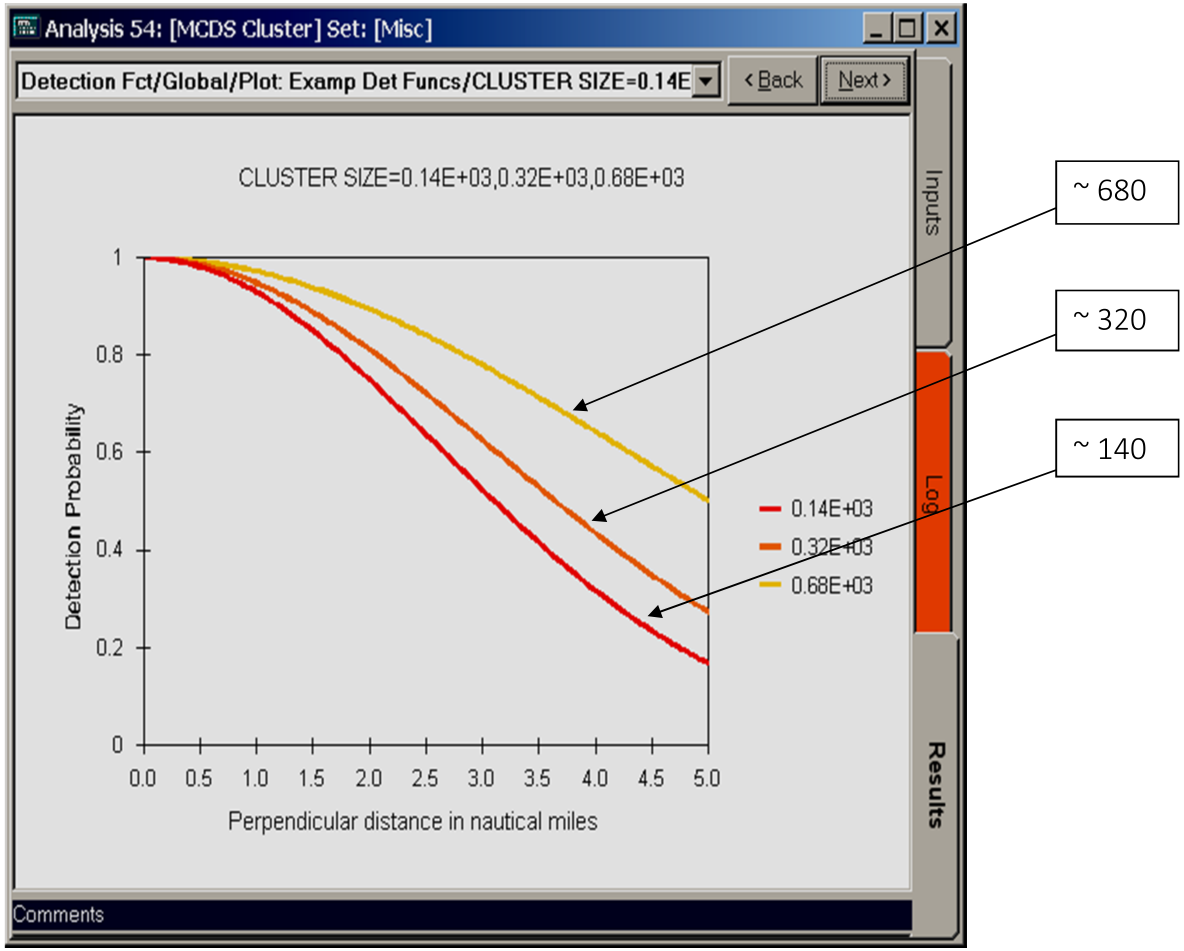
$$g(x,s) = \exp\left(\frac{-x^2}{2\sigma(s)^2}\right)$$

$$\begin{aligned}\sigma(s) &= \exp(\beta_0 + \beta_1 s)\\ &= \exp(\beta_0).\exp(\beta_1 s)\\ &= A1.\exp(A2s)\end{aligned}$$

From distance output

$\hat{A}1 = 2.331$

$\hat{A}2 = 0.00895$



Estimating abundance without covariates using Horvitz-Thompson estimator

$$\hat{N} = \sum_{i=1}^{n} \frac{1}{\Pr[animal\ included]} = \sum_{i=1}^{n} \frac{1}{\left[\frac{2L\hat{\mu}}{A}\right]} = \frac{nA}{2L\hat{\mu}}$$

Recall that *f(x)* = pdf of observed *x*'s $= \dfrac{g(x)}{\int g(x)dx} = \dfrac{g(x)}{\mu}$

Because *g*(0)=1 by assumption, then *f*(0) = 1/μ

So $\boxed{\hat{N} = \dfrac{nA}{2L}\hat{f}(0)}$

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Estimating abundance with covariates

$$\hat{N}=\sum_{i=1}^{n}\frac{1}{\Pr\left[\textit{animal included}\right]}=\sum_{i=1}^{n}\frac{1}{\left[\frac{2L\hat{\mu}(z_i)}{A}\right]}=\frac{A}{2L}\sum_{i=1}^{n}\frac{1}{\hat{\mu}(z_i)}$$

Now $$f(x\,|\,\mathbf{z})=\frac{g(x,\mathrm{z})}{\int g(x,\mathrm{z})dx}=\frac{g(x,\mathrm{z})}{\mu(\mathrm{z})}$$

Because $g(0,\mathbf{z})=1$ by assumption, then $f(0\,|\,\mathbf{z})=1/\mu(\mathbf{z})$

So $$\boxed{\hat{N}=\frac{A}{2L}\sum_{i=1}^{n}\hat{f}(0\,|\,\mathbf{z}_i)}$$

Note similarity to CDS estimator

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MCDS in Distance

In Model Definition, choose MCDS analysis engine

See Chapter 9 of online Users Guide

Covariate type:

- Factor covariates classify the data into distinct classes or levels. Can be numerical or text. One parameter per factor level.
- Non-factor (i.e., continuous) covariates must be numerical (integer or decimal). One parameter per covariate + 1 for the intercept.