

Introduction to Mark-Recapture Distance Sampling (MRDS)

- The “g(0) problem”: missing animals on the transect line
- Intuitive introduction to mark-recapture distance sampling (MRDS)
- Full independence and point independence models
- Double observer configurations
- Assumptions and conclusions

For more information, see:

- Laake et al. (2004) – chapter in Advanced Distance Sampling book first describing the methods
- Burt et al. (2014) – accessible introduction to MRDS

Conventional distance sampling

E.g., line transects

animals detected

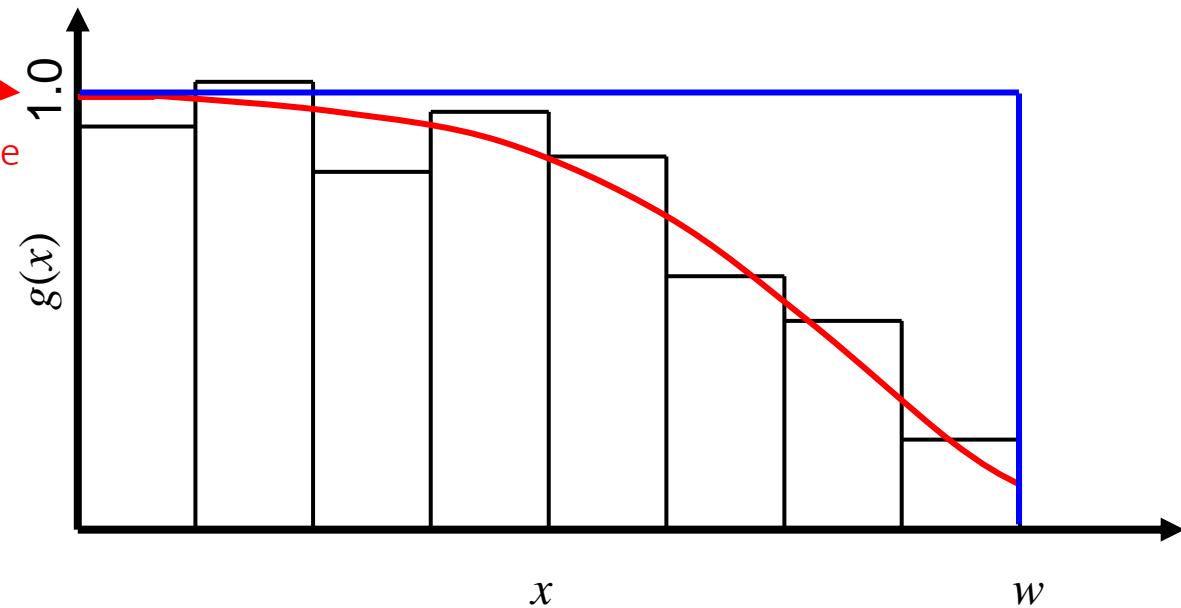
$$\hat{N} = \frac{n}{\hat{P}_a} \times \frac{A}{2wL}$$

detection probability

proportion of study area surveyed

$$\hat{P}_a = \frac{\text{area under curve}}{\text{area under rectangle}} = \frac{\int_0^w \hat{g}(x) dx}{1 \times w}$$

We assume $g(0) = 1$



Fundamental assumption: every animal on the transect line is detected – i.e., $g(0) = 1$

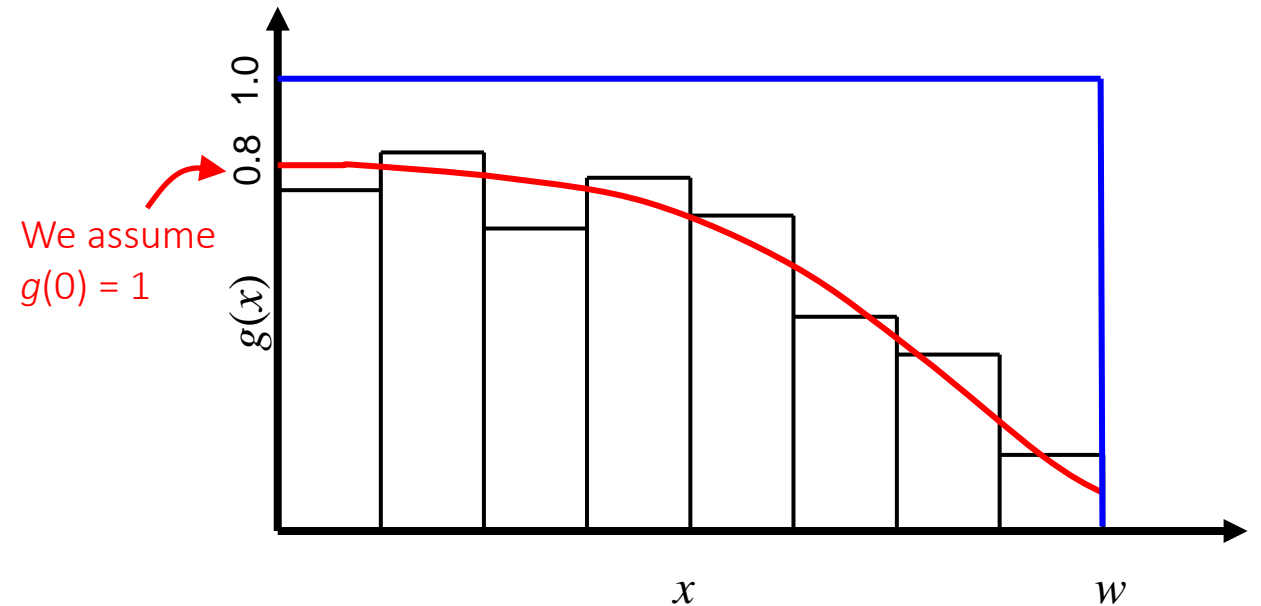
What if $g(0) < 1$?

If $g(0) < 1$ we get a negative bias in estimates of N (and D)

E.g., if $g(0) = 0.8$ then estimates of N and D are 80% of true value on average

Nothing in the perpendicular distance data to tell us $g(0) < 1$

Additional data are needed.
This talk is about one approach for what data to collect and how to analyse it.



$$\hat{P}_a = \frac{\int_0^w \hat{g}(x) dx}{1 \times w}$$

$$\hat{N} = \frac{n}{\hat{P}_a} \times \frac{A}{2wL}$$

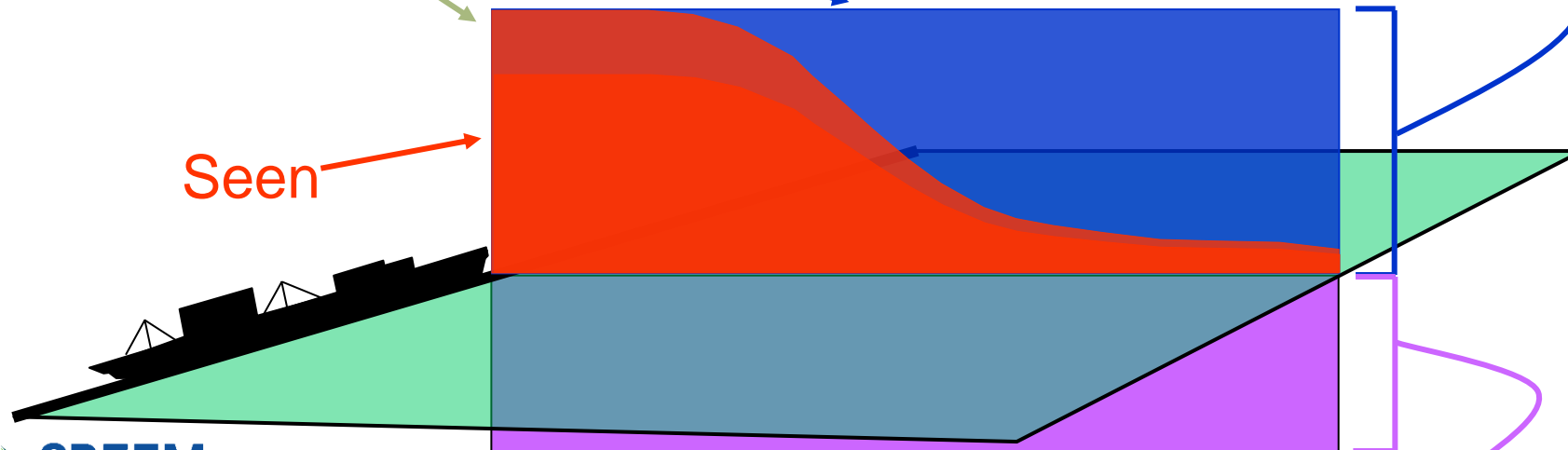
Availability and perception bias

- “**Availability Bias**”: When animals are unavailable for detection.
- “**Perception Bias**”: When observers fail to detect animals **at distance 0** although they are available

Animals available for detection

Missed

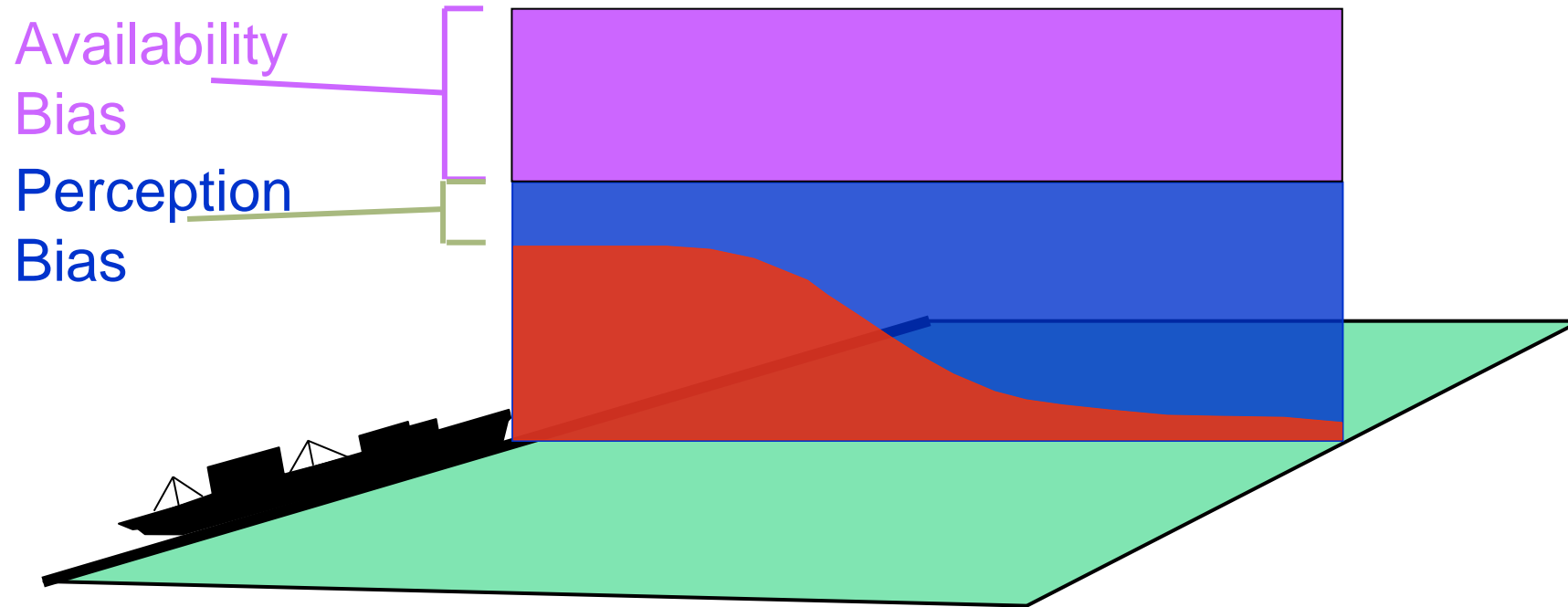
Seen



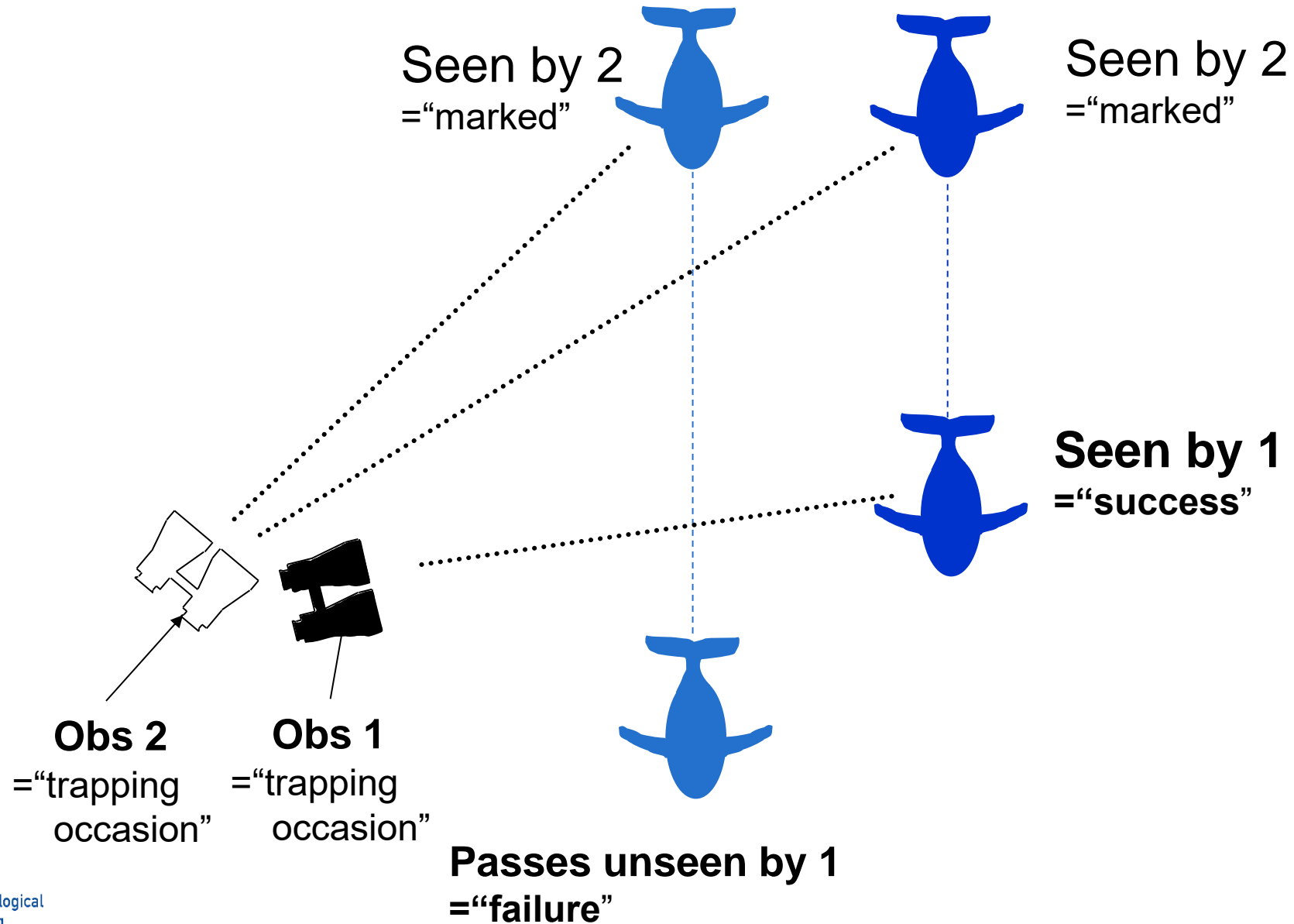
Animals UNavailable for detection

“**Availability Bias**”: When animals are unavailable for detection.

“**Perception Bias**”: When observers fail to detect animals **on the transect** although they are available



Visual Mark-Recapture



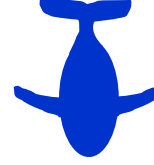
Visual Mark-Recapture

Seen by 2
="marked"



Passes unseen by 1
="failure"

Seen by 2
="marked"



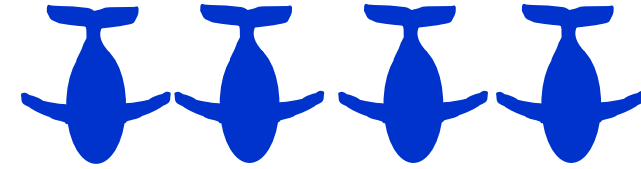
Seen by 1
="success"

- We know 2 animals passed (because Obs 2 saw them)

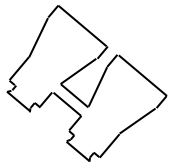
- Of these, Obs 1 saw 1

- So **estimate:**
$$\Pr(\text{Obs 1 sees}) = \hat{p}_1 = \frac{1}{2} = \frac{n_{12}}{n_2} = \frac{\text{number "duplicates"}}{\text{number seen by 2}}$$

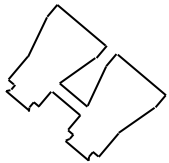
Simulated data example



Simulated 2000 animals between 0 and 1000m, with two observation platforms and detectability a function of distance from transect line and “visibility”.



$$n_2 = 831$$



$$n_{12} = 520$$

$$\hat{p}_1 = \frac{n_{12}}{n_2} = \frac{520}{831} = 0.626$$



$$n_1 = 835$$

$$\hat{N} = \frac{n_1}{\hat{p}_1} \times \frac{A}{2wL} = \frac{835}{0.626} \times 1 = 1334$$

Why didn't it work?

Unmodelled heterogeneity in detection probability!

Just in the surveyed transect strip

Effect of heterogeneity - illustration

	N	p	$E(n_2)$	$E(n_{12})$	$E(n_1)$
Big animals	1000	0.9	900	810	900
Small animals	1000	0.1	100	10	100
Total	2000	0.5	1000	820	1000

Using the totals:

$$\hat{p}_1 = \frac{n_{12}}{n_2} = \frac{820}{1000} = 0.82 \quad \hat{N} = \frac{n_1}{\hat{p}_1} = \frac{1000}{0.82} = 1220$$

Effect of heterogeneity - illustration

	N	p	$E(n_2)$	$E(n_{12})$	$E(n_1)$
Big animals	1000	0.9	900	810	900
Small animals	1000	0.1	100	10	100
Total	2000	0.5	1000	820	1000

Using the different types of animal:

$$\hat{p}_{1,Big} = \frac{n_{12,Big}}{n_{2,Big}} = \frac{810}{900} = 0.9 \quad \hat{N}_{Big} = \frac{n_{1,Big}}{\hat{p}_{1,Big}} = \frac{900}{0.9} = 1000$$

$$\hat{p}_{1,Small} = \frac{n_{12,Small}}{n_{2,Small}} = \frac{10}{100} = 0.1 \quad \hat{N}_{Small} = \frac{n_{1,Small}}{\hat{p}_{1,Small}} = \frac{100}{0.1} = 1000$$

$$\hat{N} = \hat{N}_{Big} + \hat{N}_{Small} = 1000 + 1000 = 2000$$

General formulation:
$$\hat{N} = \sum_{\text{groups } k} \frac{n_k}{\hat{p}_k} = \sum_{\text{individuals } i} \frac{1}{\hat{p}_i}$$

Effect of heterogeneity - conclusion

Unmodelled heterogeneity in detectability with mark-recapture type data causes

Positive bias in estimation of p

Negative bias in estimation of N

If you can model it correctly, the bias disappears

Sources of heterogeneity

Many! E.g.,

Animals

Behaviour, Intrinsic visibility, Cluster size, Distance from the transect

Environment

Habitat, Environmental conditions (mist, glare, sea state...)

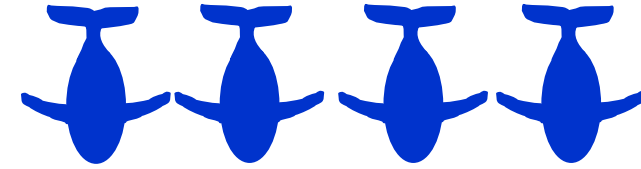
Observers

Observer abilities, Observation platform (height, visibility, ...)

...

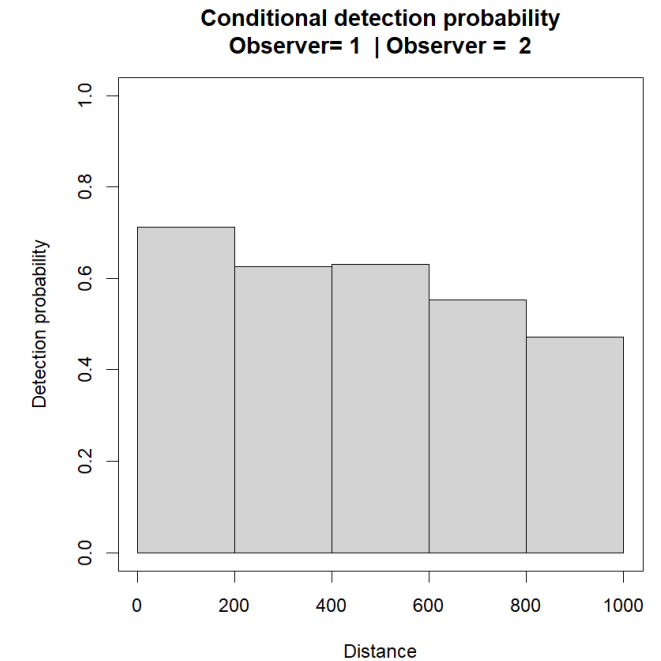


Simulated data example Revisited



Incorporate distance from transect line into the analysis

Distance	n_2	n_{12}	\hat{p}_1	n_1	\hat{N}
0-200m	281	200	0.711	283	398
200-400m	174	109	0.626	184	294
400-600m	149	94	0.631	144	228
600-800m	123	68	0.553	119	215
800-1000m	104	49	0.471	105	223

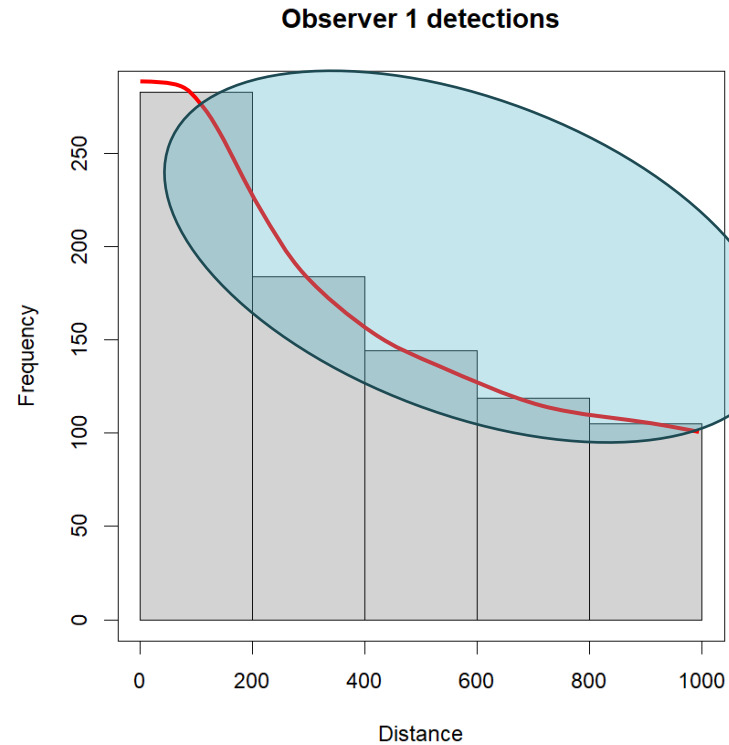
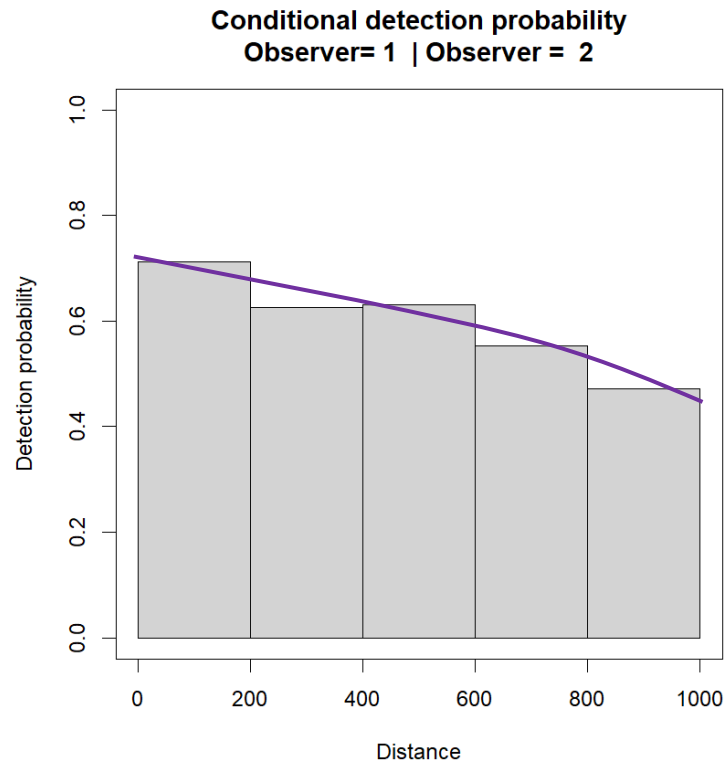


Summing across distance bands: $\hat{N} = 1358$

Bit better than previous estimate (1334)

but not close to true value of 2000!

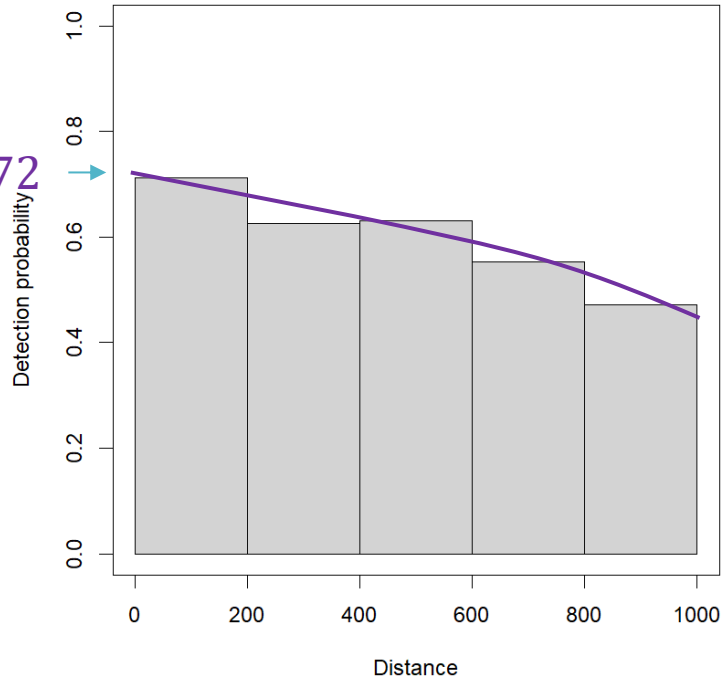
Evidence still unmodelled heterogeneity



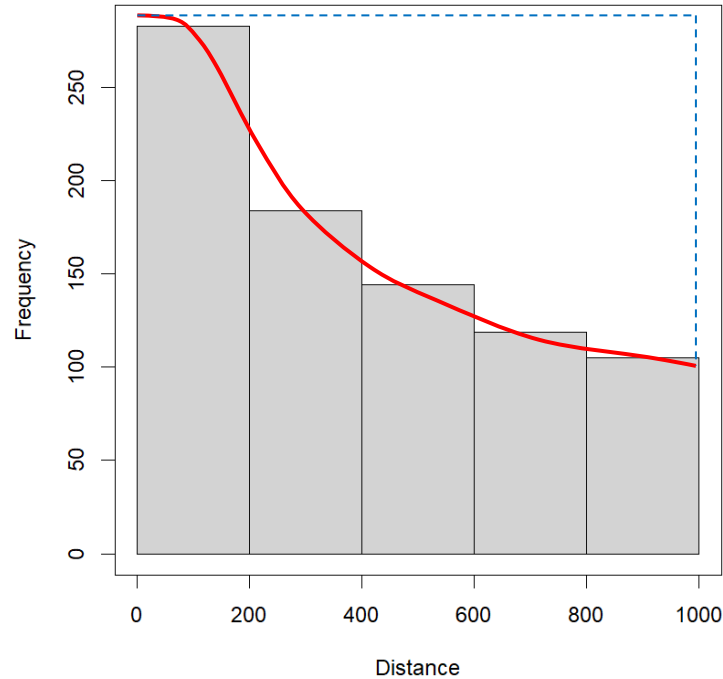
Unmodelled heterogeneity here

Dealing with unmodelled heterogeneity

Conditional detection probability
Observer= 1 | Observer = 2



Observer 1 detections



$$\hat{P}_{a,1}^* = \frac{\text{area under curve}}{\text{area under rectangle}}$$

$$\approx \frac{835}{283 \times 5} = 0.59$$

$$\hat{N} = \frac{n_1}{\hat{g}_1(0) \times \hat{P}_{a,1}^*} = \frac{835}{0.72 \times 0.59} = 1966$$

Full vs point independence models

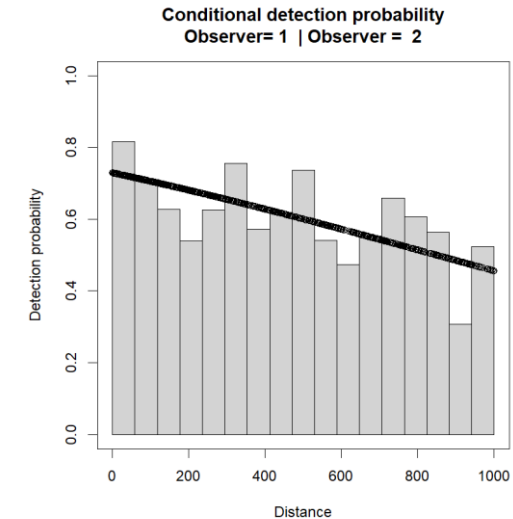
Full independence model

Uses detections from one observer as “trials” to obtain detection probability for the other

Detection function model is a binary regression with logit link function (a.k.a. logistic regression) – “*mark-recapture model*”

Assumes probability of detection by the observer setting up the trial is independent of the probability of detection by the other observer at *all distances*, given covariates – “*full independence*”

```
mrmodel = ~glm(~distance)
```



	Estimate	SE	CV
Average p	0.5978057	0.01834089	0.03068034
Average primary p(0)	0.7293052	0.02213859	0.03035572
N in covered region	1396.7747929	52.02831290	0.03724889

Full vs point independence models

Point independence model

Uses *mark-recapture model* to get $g(0)$ (called $p(0)$ in some literature)

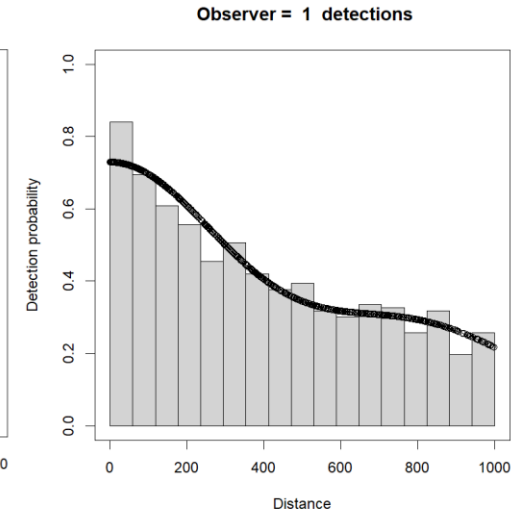
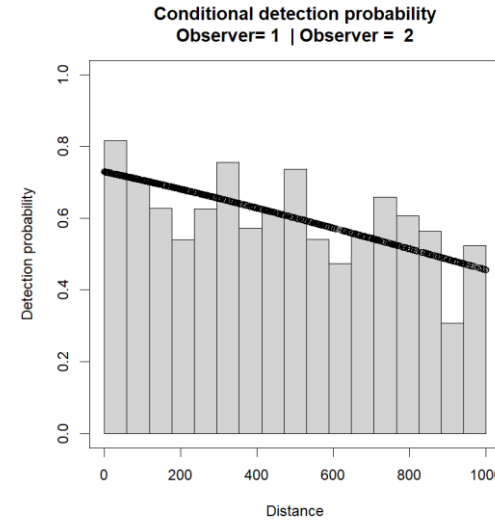
Uses standard *distance sampling model* to get \hat{P}_a^*

Combines them to estimate overall average detection prob

Assumes probability of detection by the observer setting up the trial is independent of the probability of detection by the other observer at *0 distance only*, given covariates – “*point independence*”

```
mrmodel =  
  ~glm(~distance)
```

```
dsmodel =  
  ~mcds(key = "hn",  
  adj.series = "cos",
```



	Estimate	SE	CV
Average p	0.4210556	0.02526106	0.05999459
N in covered region	1983.1109662	129.93081451	0.06551868

Full vs point independence models

Full independence model

Sensitive to unmodelled heterogeneity
– negative bias.

Assumption of uniform animal
distribution not required – so useful for
responsive movement.

Don't use unless you have to!

Point independence model

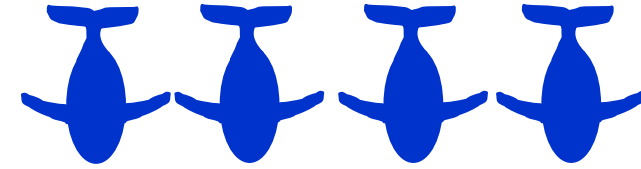
Less sensitive to unmodelled heterogeneity.

Assumption of uniform animal distribution
required for ds model – so no good if there
is responsive movement.

Use unless there is responsive movement.

Simulated data example

Model selection

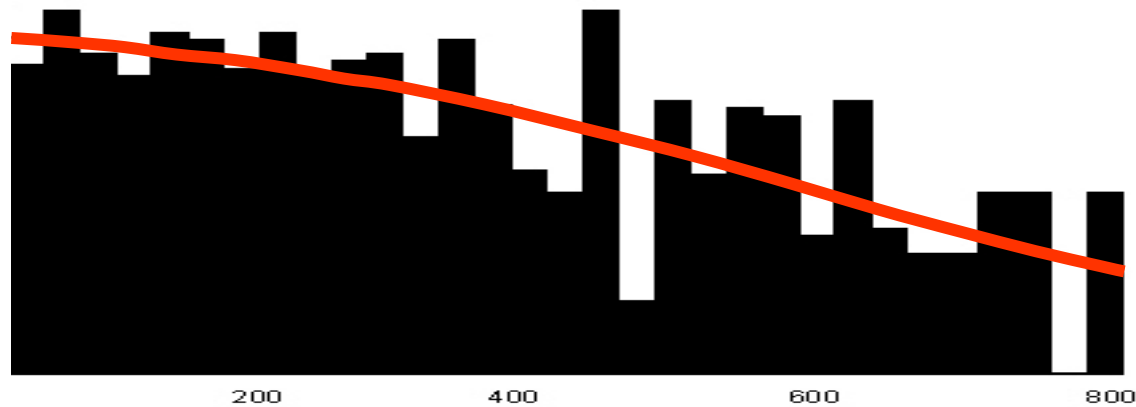


Model type	MR model	DS model	AIC	\hat{N}
Full independence	~ 1	-	12636.83	1334
Full independence	$\sim \text{distance}$	-	12552.17	1396
Point independence	$\sim \text{distance}$	$\sim \text{hn} + \cos(2)$	12506.41	1983
Full independence	$\sim \text{distance} + \text{visibility}$	-	12430.23	1540
Full independence	$\sim \text{distance} \times \text{visibility}$	-	12269.08	1917

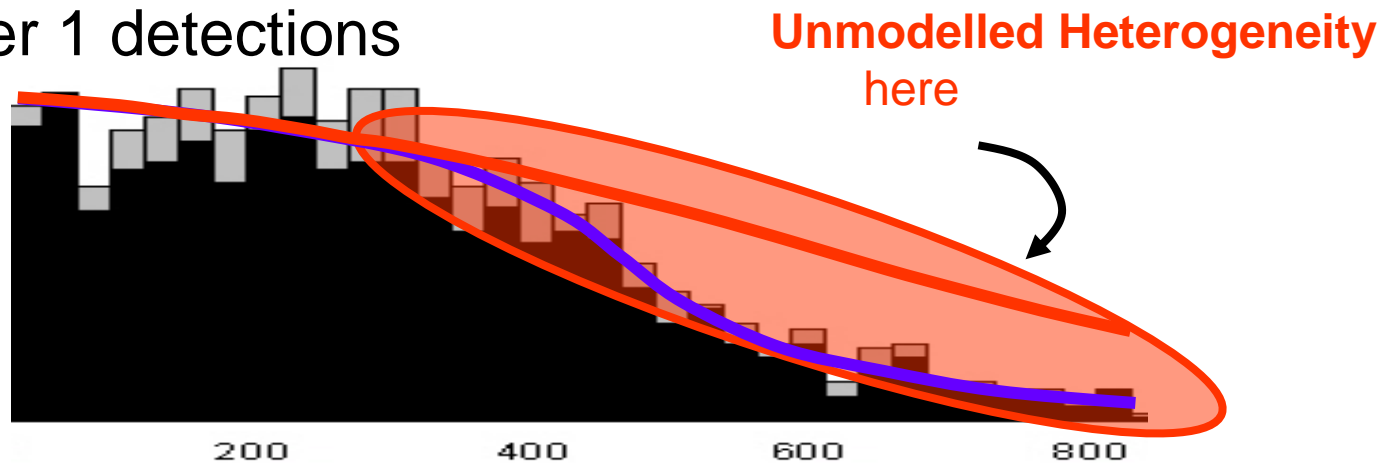
General class of models are known as “Mark-Recapture Distance Sampling” (MRDS)

Real data example: pack-ice seals

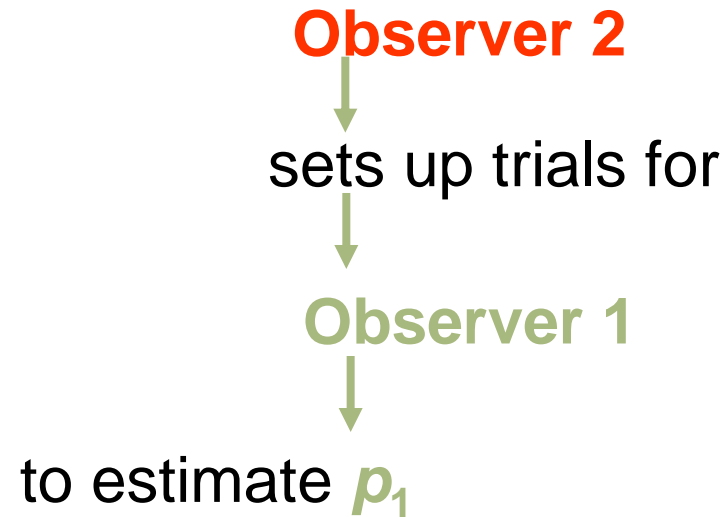
Proportion of Observer 2 detections seen by Observer 1



Observer 1 detections

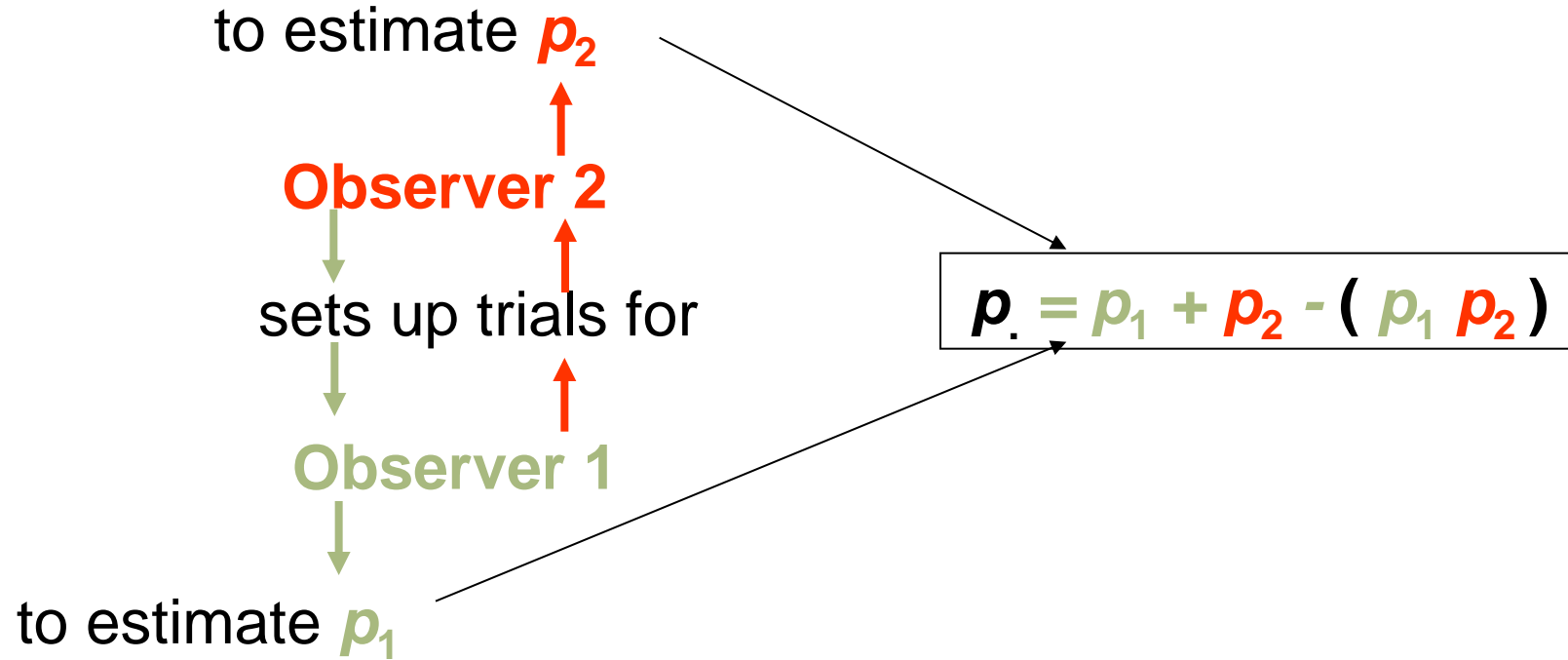


Configuration: Trial



The Observer at the end of an arrow must be independent of the Observer at the start of the arrow

Configuration: Independent Observer



The Observer at the end of an arrow must be independent of the Observer at the start of the arrow

Abundance estimation

Trial

$$\hat{N} = \sum_{\text{seen by } 1} \frac{1}{\hat{p}_1(x_i, \dots)}$$

Independent Observer

$$\hat{N} = \sum_{\text{seen}} \frac{1}{\hat{p}_\cdot(x_i, \dots)}$$

Comparing configurations

Trial

Only requires observer 1 to be isolated from observer 2 (who sets up trials).

Can be robust to responsive movement if observer 2 searches far ahead and their perpendicular distances are the ones used for analysis.

Uses less data – only trials from observer 1.

Independent observer

Requires both observation platforms to be isolated from one another.

Not applicable, as both observers' set up trials, and it is generally better if they search different distances ahead (reduces availability bias).

Uses more data – trials from both observers.

Critical assumptions of MRDS

We have the required level of independence between observers

Trial configuration: one-way independence – observer 1 independent of observer 2

Independent observer configuration: two-way independence

No unmodelled heterogeneity

Full independence models: at all distances

Point independence models: at zero distance

Duplicates (resightings) are known

Duplicate identification

Can use a dedicated “duplicate identifier”

Or for trial configuration, observer 2 (or one observer on that team) can track animals until they go abeam

Record positions and times of sightings as precisely as possible

Allows rule-based duplicate identification after the survey

Record ancillary data – behaviour, etc.

Can record measure of confidence in duplicate identification

Allows analysis using different levels of confidence

Related MRDS models not covered

Limiting independence

Further relaxes assumption about unmodelled heterogeneity – assumes heterogeneity tends to zero as probability of detection approaches 1

No standard software

Buckland et al. (2009)

Point transects

Implemented in standard software

Laake et al. (2011)

Summary & Conclusions

In standard methods we assume $g(0)=1$

But $g(0)$ can be <1 because of availability or perception bias

One approach to combat this is to deploy two (semi-) independent observation platforms, and identify duplicate detections

These data can be analyzed using Mark Recapture Distance Sampling (MRDS) models

Results are sensitive to unmodelled heterogeneity

- Collect relevant covariates

- Consider point- or full-independence models

Thought: given the complications, can you make $g(0)$ close to 1 by altering your field methods?

References

- Borchers, D. L., Laake, J. L., Southwell, C., & Paxton, C. G. M. (2006). Accommodating unmodeled heterogeneity in double-observer distance sampling surveys. *Biometrics*, *62*, 372–378. <https://doi.org/10.1111/j.1541-0420.2005.00493.x>
- Buckland, S. T., Laake, J., & Borchers, D. L. (2010). Double observer line transect methods: Levels of independence. *Biometrics*, *66*, 169–177. <https://doi.org/10.1111/j.1541-0420.2009.01239.x>
- Burt, M. L., Borchers, D. L., Jenkins, K. J., & Marques, T. A. (2014). Using mark-recapture distance sampling methods on line transect surveys. *Methods in Ecology and Evolution*, *5*, 1180–1191. <https://doi.org/10.1111/2041-210X.12294>
- Laake, J. L., & Borchers, D. L. (2004). Methods for incomplete detection at distance zero. In S. T. Buckland, D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, & L. Thomas (Eds.), *Advanced distance sampling* (pp. 127–208). Oxford: Oxford University Press.
- Laake, J. L., Collier, B. A., Morrison, M. L., & Wilkins, R. N. (2011). Point-based mark-recapture distance sampling. *Journal of Agricultural, Biological and Environmental Statistics*, *16*, 389–408. <https://doi.org/doi.org/10.1007/s13253-011-0059-5>
- Southwell, C., Borchers, D., de la Mare, B., Paxton, C. G. M., Burt, L., & de la Mare, W. (2007). Estimation of detection probability on aerial surveys of Antarctic pack-ice seals. *Journal of Agricultural, Biological, and Environmental Statistics*, *12*, 1–14. <https://doi.org/10.1198/108571107X162920>