Distance Sampling Simulations

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Centre for Research into Ecological and Environmental Modelling

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Overview

- Why simulate?
- How it works
- Automated survey design
  - Coverage probability
  - Which design?
  - Design trade-offs
- Defining the population
  - Population description
  - Detectability
- Example Simulations

Why Simulate?

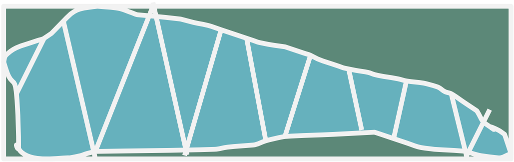
- Surveys are expensive, we want to get them right! *(simulations cheap)*
- Test different survey designs
- Test survey protocols
- Investigate violation of assumptions
- Investigate analysis properties

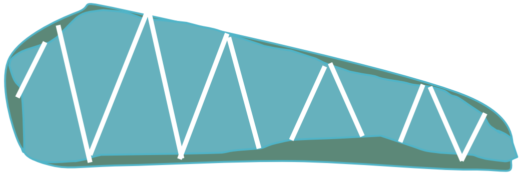
Why Simulate?

I have a fairly long and narrow study region, are edge effects likely to be a problem?

Why Simulate?

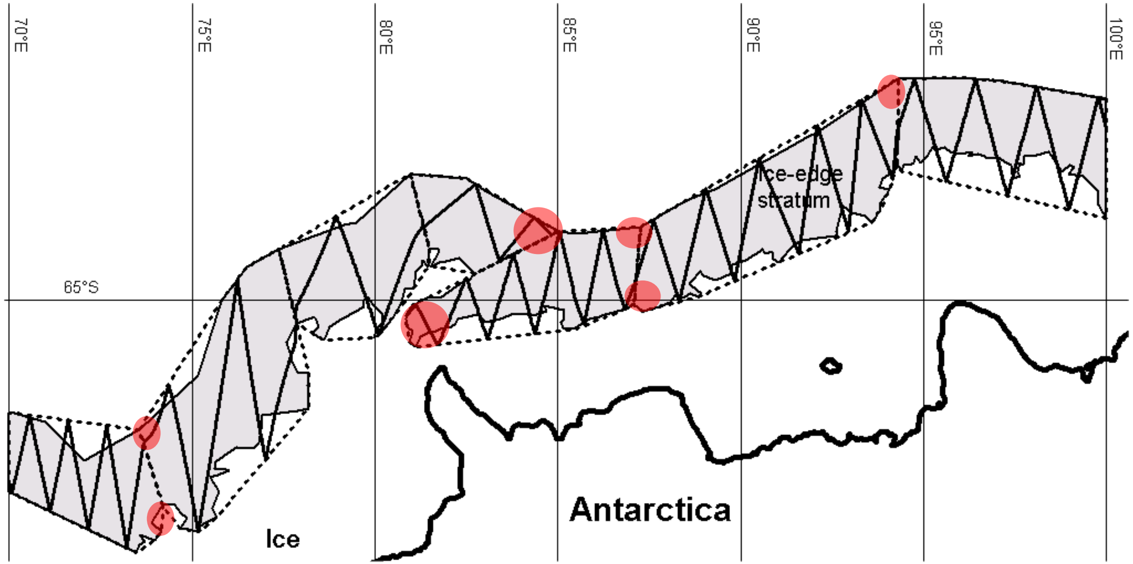
Generating my equal spaced zig zag design in a convex hull gives better efficiency (less off effort transit time) but is this likely to introduce large amounts of bias due to non uniform coverage probability?





Why Simulate?

What is the potential bias in this stratification technique?



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Why Simulate?

From pilot study trials I know that there can be multiplicative error on recorded distances

This error has a ~15% CV when collecting data in 3 bins or ~30% CV when attempting to collect exact distances… which is preferable (if we cannot improve accuracy or correct the measurements)?

Why Simulate?

We suspect that the current survey design is less than ideal and may be introducing bias but people are reluctant to change…

Simulate the current situation to get an idea of how bad things could be

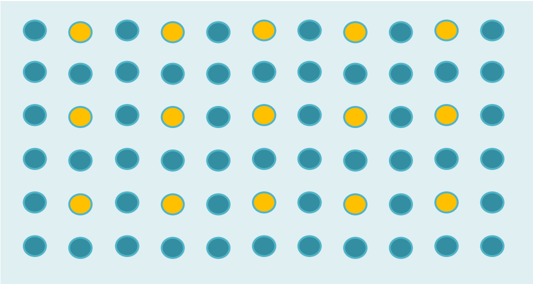
Simulate a new design to show how things could be improved

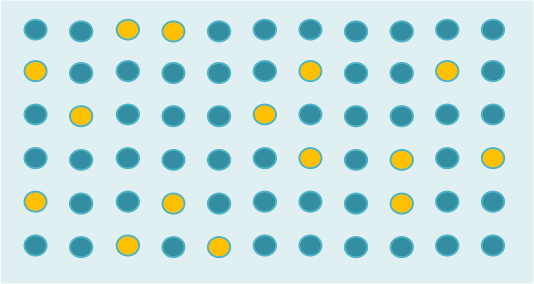
Why Simulate?

I want to do an acoustic survey with two types of detectors.

- The first records distances as per standard distance sampling requirements (standard detectors).
- The second only records the presence of a sound (simple nodes).

How many standard nodes do I need and how should I distribute them?





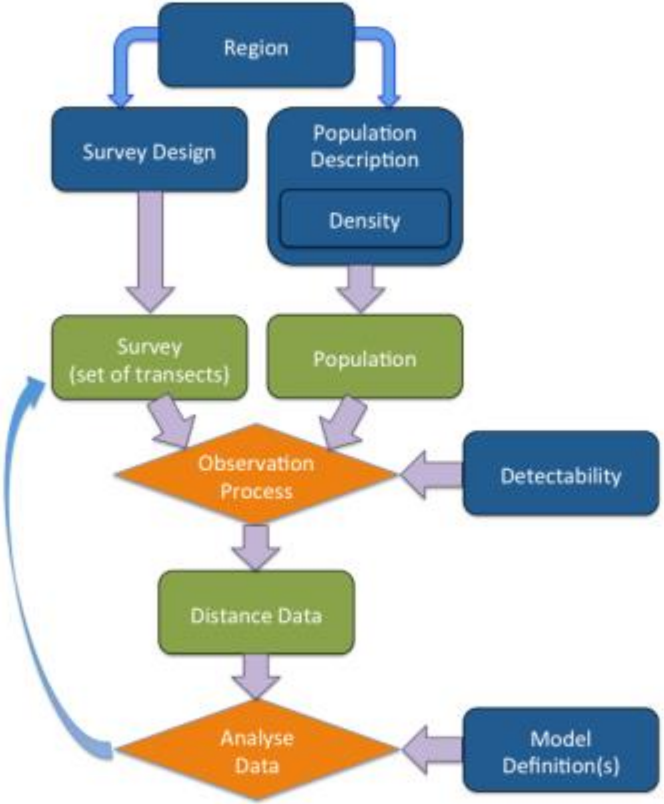
Why Simulate?

I would like to use my data to generate both design (standard distance sampling) and model based (density surface model) estimates of density… which design will work best for my study?

Hopefully coming soon to DSsim…

Some example simulations can be found here:
https://github.com/DistanceDevelopment/DSsim/wiki

How it works



Blue rectangles indicate information supplied by the user.

Green rectangles are objects created by DSsim in the simulation process.

Orange diamonds indicate the processes carried out by DSsim.

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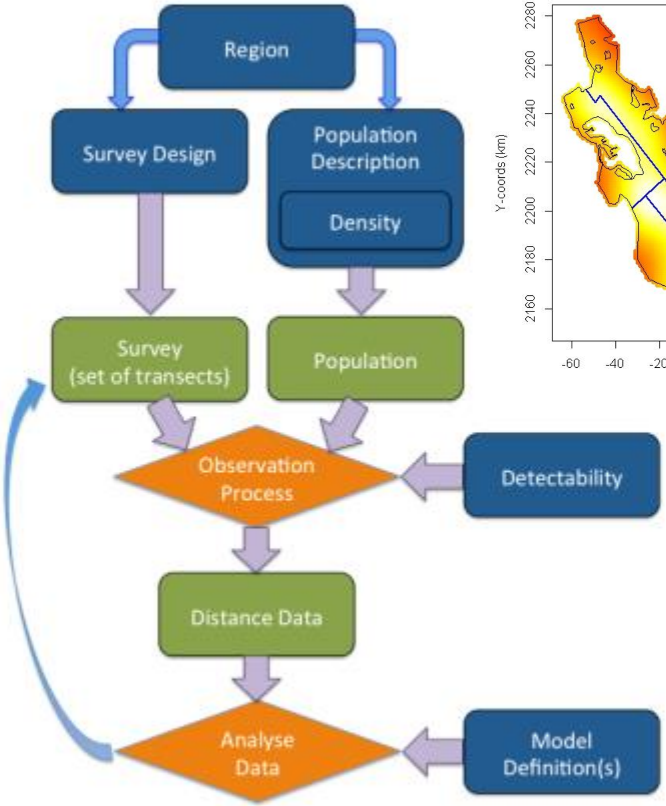
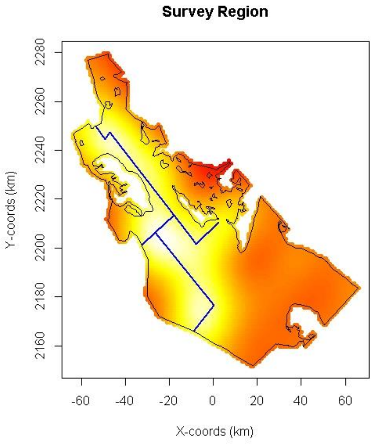
How it works





Population Description

- Population size or density
- Density surface
- Clusters?
- Covariates affecting?

Survey Design:

- Zig zag design
- Equal Spaced
- Spacing = 10km
- Minus sampling

AIC = 2747

AIC = 2748

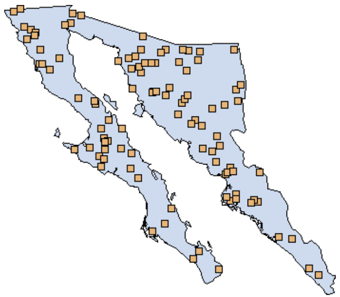
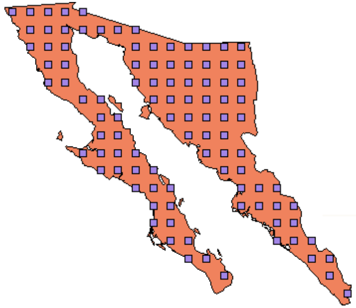
Assess:

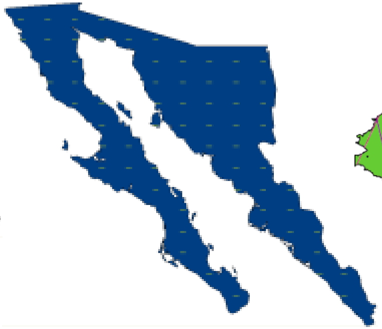
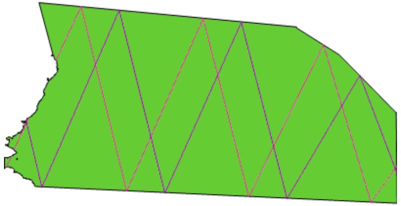
- Bias
- Precision
- CI coverage

Across different designs/scenarios

Automated Survey Design

Generate random sets of transects according to an algorithm
- Assess design properties
- Generate multiple transect sets for simulations

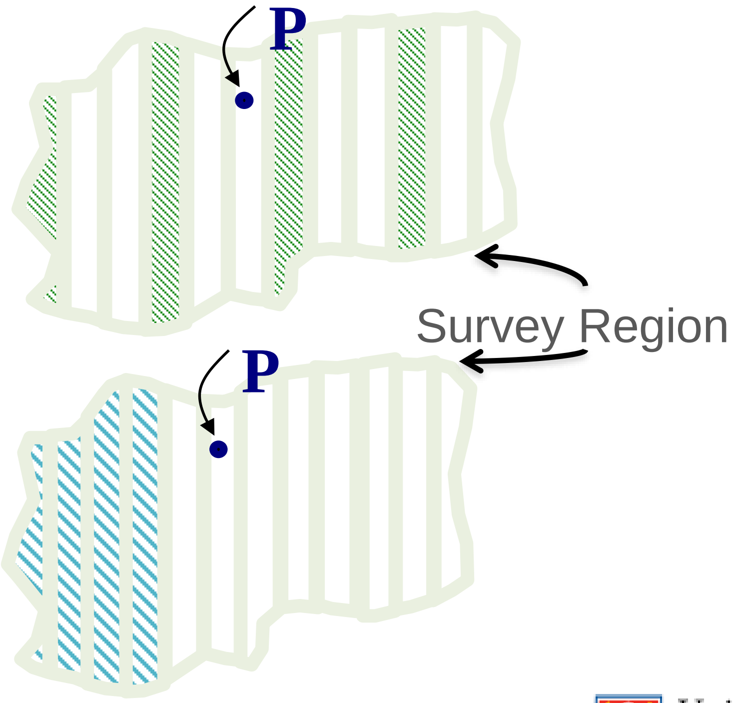



Automated Survey Design

Coverage Probability

- Uniform coverage, π = 1/3
- Even coverage for any given realisation

- Uniform coverage, π = 1/3
- Uneven coverage for any given realisation



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Which Design?

Uniformity of coverage probability

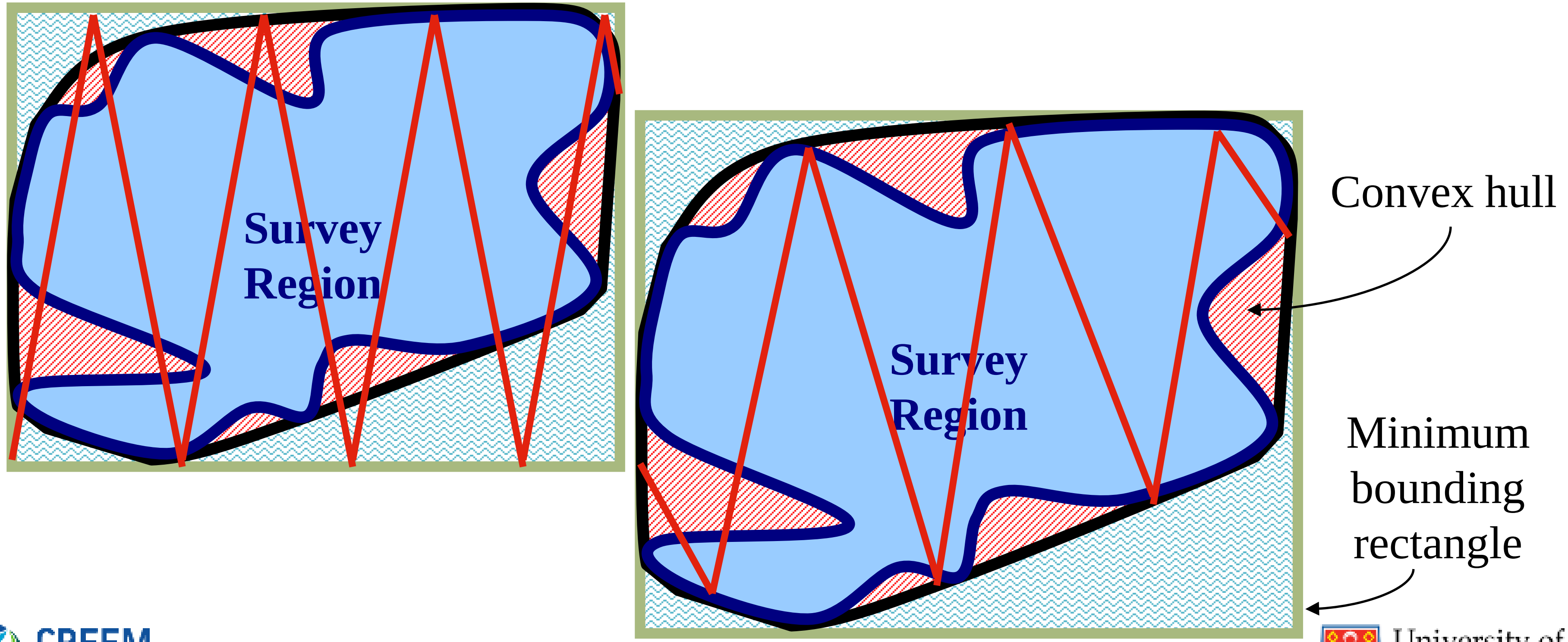
Even-ness of coverage within any given realisation

Overlap of samplers

Cost of travel between samplers

Efficiency when density varies within the region

Design Trade-Offs



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Population Definition

True population size?

Occur as individuals or clusters?

Covariates which will affect detectability?

How is the population distributed within the study region?

- Ideally have a previously fitted density surface otherwise test over a range of plausible distributions

Detectability

DSsim needs:

shape and scale parameters on the natural scale

and covariate parameters on the log scale

Detectability

Golftees project

Detection Fct/Global/Parameter Estimates (MCDS)

```
Effort        :    210.0000
# samples     :      1
Width         :    4.000000
# observations:   162

Model
   Half-normal key, k(y) = Exp(-y**2/(2*s**2))

   s = A(1) * Exp(fcn(A(2)) + fcn(A(3)))
   Parameter A(1) is the intercept of the scale parameter s.
   Parameter A(2) is the coefficient of covariate CLUSTER SIZE.
   Parameter A(3) is the coefficient of level 0 of factor covariate SEX.


             Point        Standard     Percent Coef.       95 Percent
 Parameter   Estimate       Error      of Variation    Confidence Interval
 ---------  -----------  -----------  --------------  ----------------------
   A( 1)      2.622        0.8370
   A( 2)     0.9294E-01   0.8172E-01
   A( 3)    -0.6951       0.2937
   f(0)     0.36330      0.17850E-01       4.91       0.32972       0.40030
   p        0.68814      0.33810E-01       4.91       0.62454       0.75821
   ESW      2.7525       0.13524           4.91       2.4981        3.0329
 ---------  -----------  -----------  --------------  ----------------------
```

Natural scale

Log scale

exp(0.268179) = 1.307581

(MRDS)

```
Summary for ds object
Number of observations :  162
Distance range         :  0  -  4
AIC                    :  428.572

Detection function:
 Half-normal key function

Detection function parameters
Scale coefficient(s):
             estimate          se
(Intercept) 0.26817900 0.27140001
size        0.09314751 0.08176431
sex1        0.69600047 0.29401571

                          Estimate          SE         CV
Average p                0.6882835  0.05258548 0.07640090
N in covered region 235.3681131 21.00939868 0.08926187
```

Detectability

In simulation:

```
cov.param <- list()
cov.param$size <- 0.093
cov.param$sex <- data.frame(level = c(0,1),
                            param = c(-0.696, 0))

detect <- make.detectability(key.function = "hn",
                           scale.param = 2.62,
                           cov.param = cov.param,
                           truncation = 4)
```

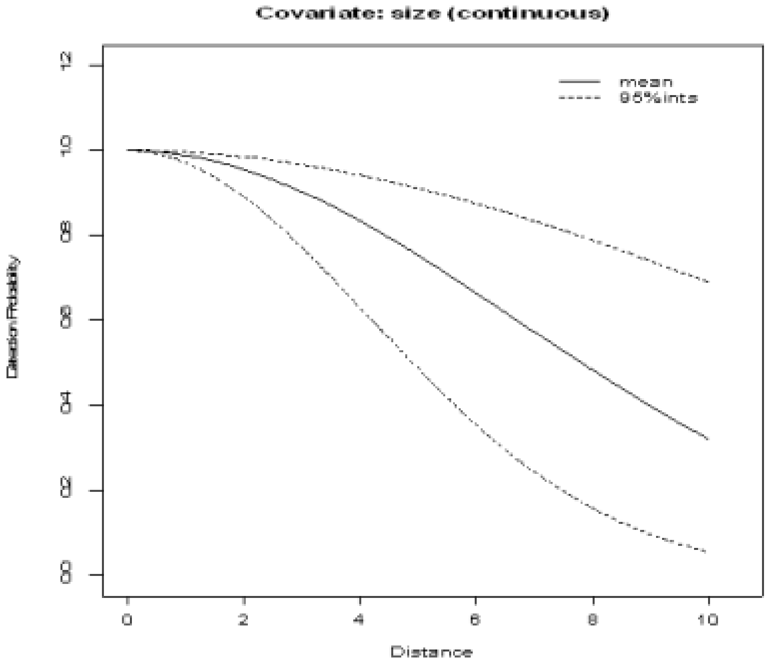
=

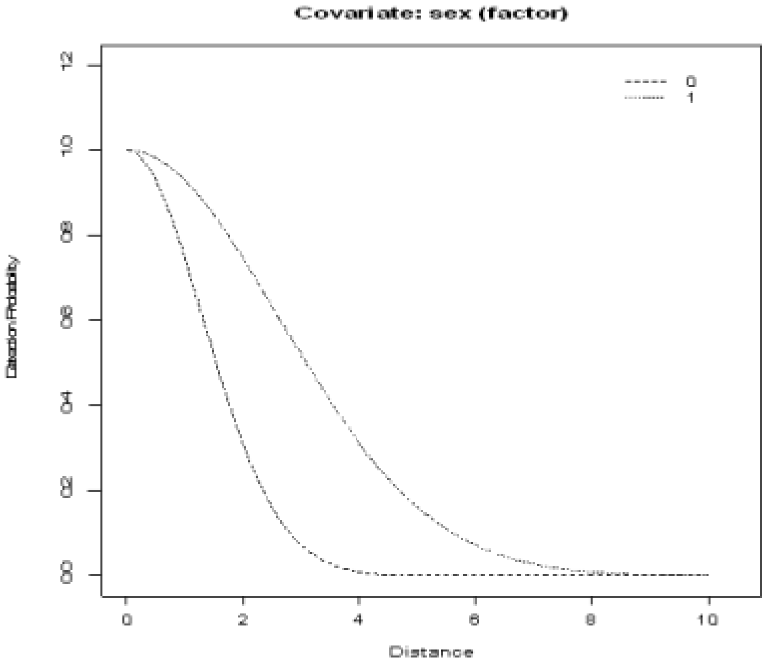
```
cov.param <- list()
cov.param$size <- 0.093
cov.param$sex <- data.frame(level = c(0,1),
                            param = c(0,0.696))

detect <- make.detectability(key.function = "hn",
                           scale.param = 1.31,
                           cov.param = cov.param,
                           truncation = 4)
```

exp(log(1.307581)+0.696) = 2.622633

exp(log(2.622)-0.696) = 1.307265

Detectability





Example Simulations

To bin or not to bin?

- It is better to collect binned data accurately than attempt to collect exact distances and introduce measurement error!

Testing pooling robustness in relation to truncation distance.

- Demonstrating why you shouldn't be scared to truncate distance sampling data

Comparison of subjective and random designs.

- How wrong can you go with a subjective design?
- Comparing zig zag and parallel designs.

To Bin or Not to Bin?

Simulation:

Generated 999 datasets

Added multiplicative measurement error

Distance = True Distance * R

R = (U + 0.5), where U~Beta(θ, θ)[1]

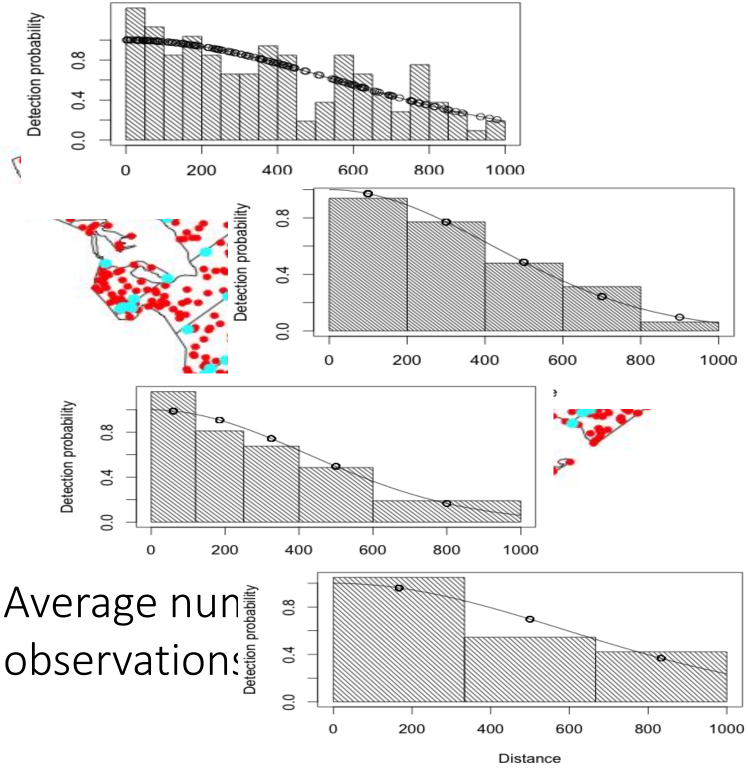
No error, ~15% CV (θ = 5), ~30% CV (θ = 1)

Analysed them in difference ways

Exact distances, 5 Equal bins, 5 Unequal bins, 3 Equal bins

Model selection on minimum AIC

Half-normal v Hazard rate



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[1]*Marques T. (2004) Predicting and correcting bias caused by measurement error in line transect sampling using multiplicative error models Biometrics* **60***:757--763*

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To Bin or Not to Bin Results

	Exact Distances	5 Equal Bins	5 Unequal Bins	3 Equal Bins
No Error	-1.16% bias 210 SE	-1.11% bias 217 SE	-0.16% bias 221 SE	-0.19% bias 255 SE
15% CV	0.48% bias 214 SE	o.5% bias 221 SE	1.36% bias 221 SE	1.72%bias 264 SE
30% CV	6.66% bias 237 SE	6.61% bias 250 SE	7.43% bias 262 SE	8.20% bias 338 SE

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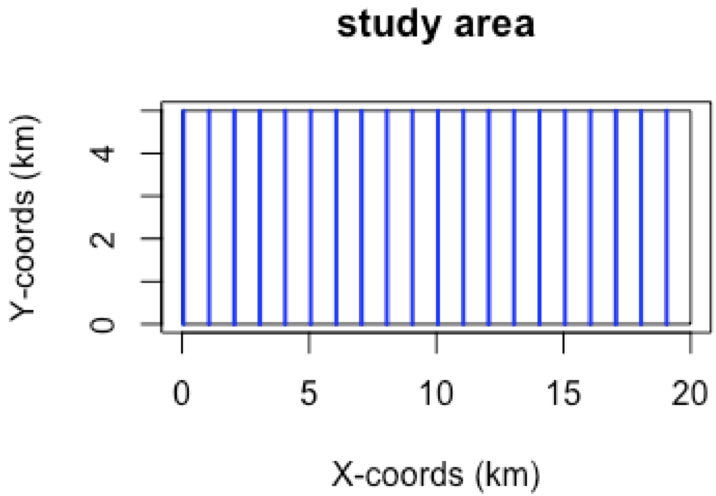
Pooling Robustness and Truncation

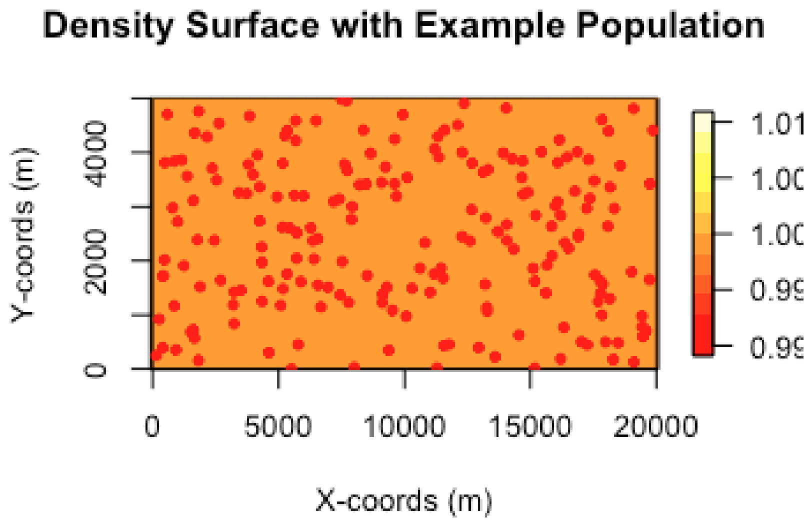
DSsim vignette



- Rectangular study region
- Systematic parallel transects with a spacing of 1000m

Pooling Robustness and Truncation

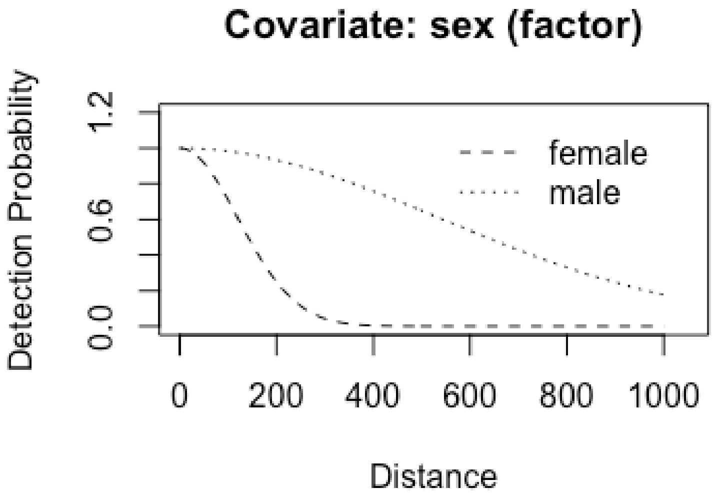
DSsim vignette



- Uniform density surface
- Population size of 200
- 50% male, 50% female

Pooling Robustness and Truncation

DSsim vignette



- Half-normal shape for detectability
- Scale parameter of 120 for the females
- Scale parameter of ~540 for the males

Pooling Robustness and Truncation

DSsim vignette

```
# Create the covariate parameter list
cov.params <- list()
# Note the covariate parameters are supplied on the log scale
cov.params$sex = data.frame(level = c("female", "male"),
                            param = c(0, 1.5))

detect.cov <- make.detectability(key.function = "hn" ,
                                 scale.param = 120,
                                 cov.param = cov.params,
                                 truncation = 1000)
```

- Half-normal shape for detectability
- Scale parameter of 120 for the females
- Scale parameter of ~540 for the males

exp(log(120)+1.5) = 537.8

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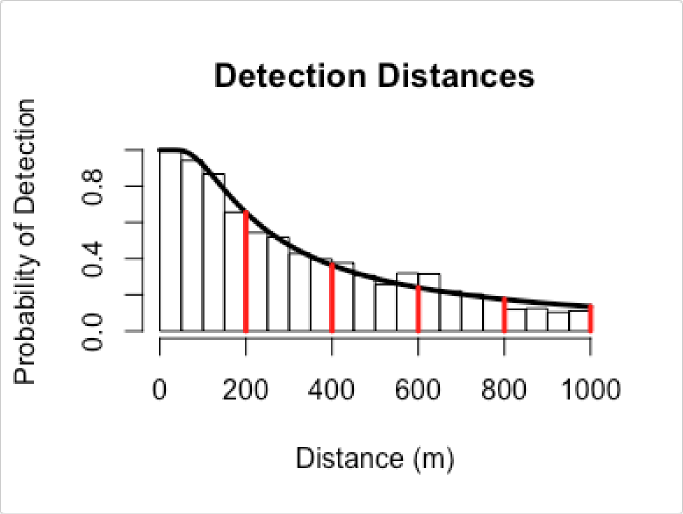
Pooling Robustness and Truncation

DSsim vignette



Histogram of data from covariate simulation with manually selected candidate truncation distances.

- Two types of analyses:
  - **hn v hr**
  - hn ~ sex
- Selection criteria: AIC

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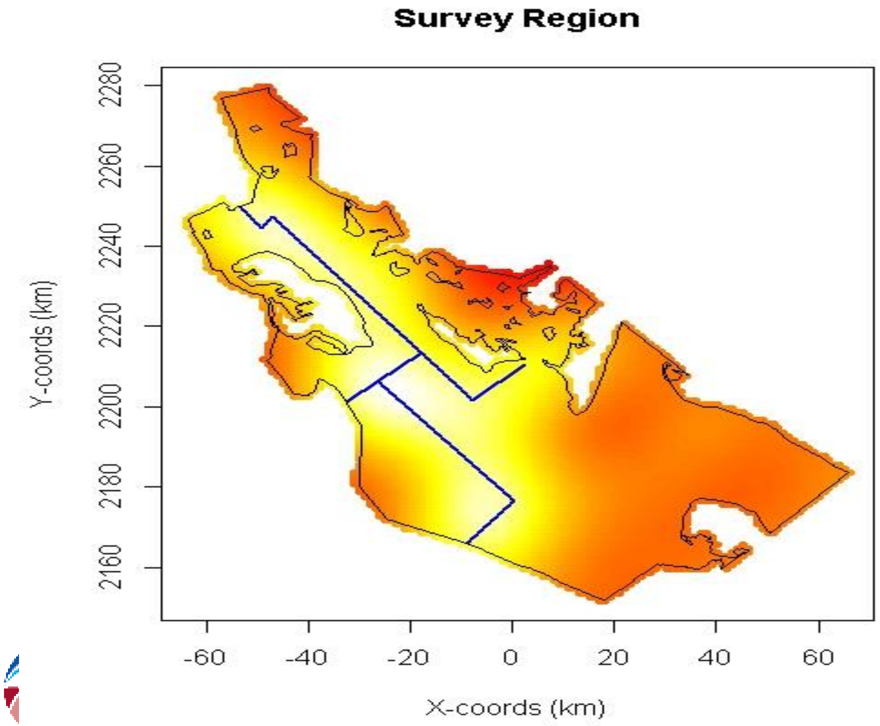
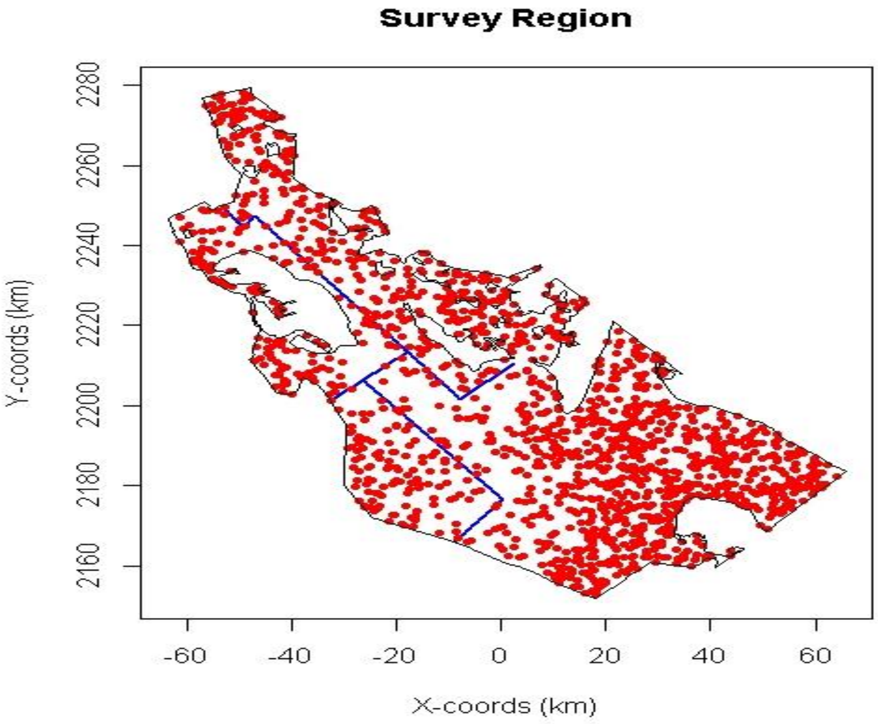
Pooling Robustness and Truncation

Results HN v HR:

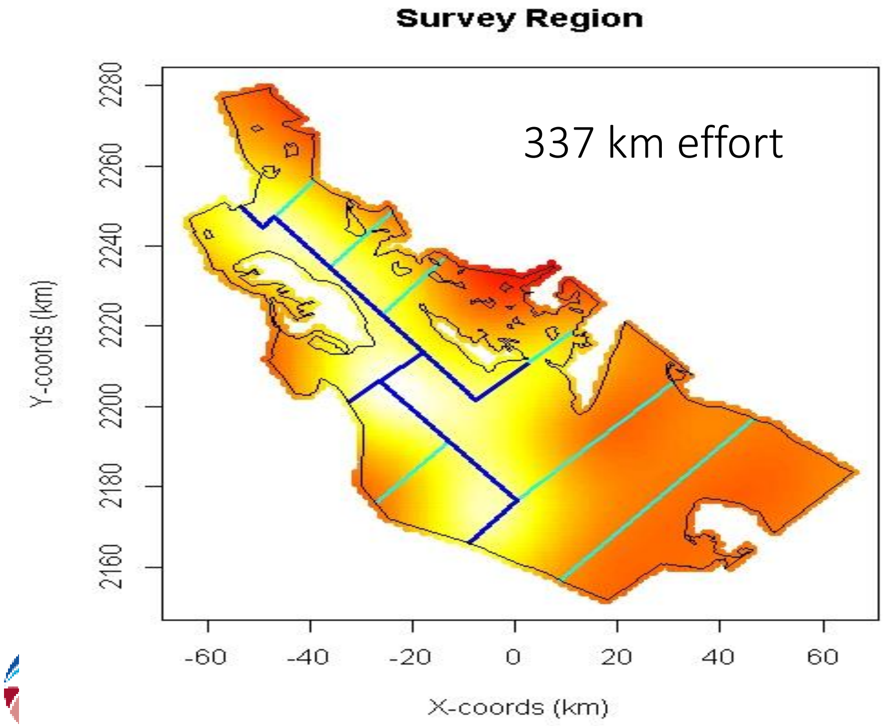
Truncation	*mean n*	*mean $\hat{N}$*	*mean se*	*SD($\hat{N}$)*	*%Bias*	*RMSE*	*% CI Coverage*
200	66	197	34.27	34.05	-1.32	34.13	97.5
400	102	190	31.06	34.79	-5.13	36.25	87.9
600	128	190	34.04	35.27	-5.24	36.77	81.9
800	144	190	34.31	36.61	-5.10	37.99	77.1
1000	154	184	30.93	39.49	-7.76	42.42	68.1

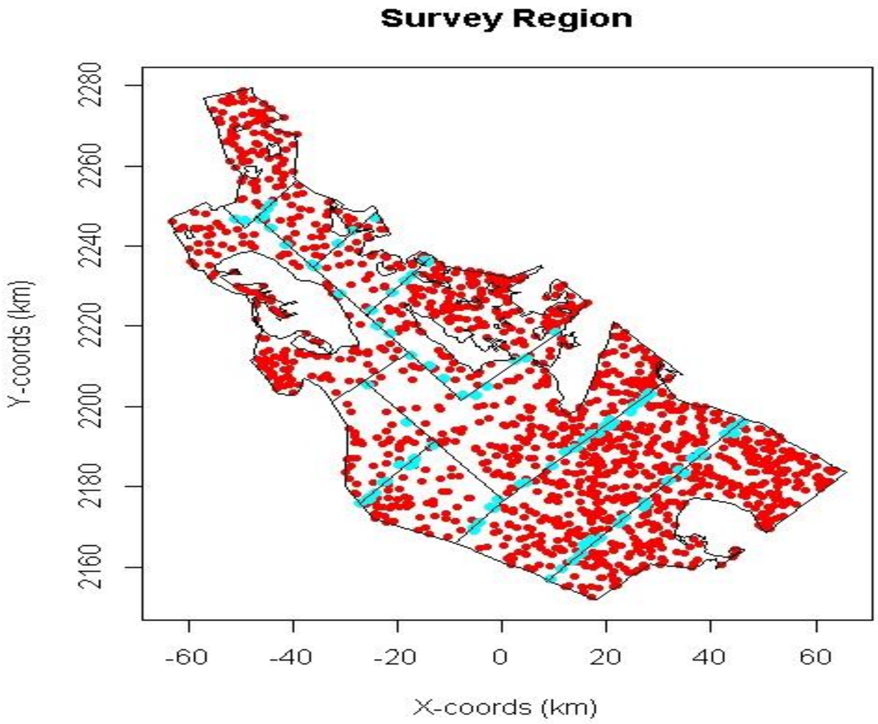
Example Simulation



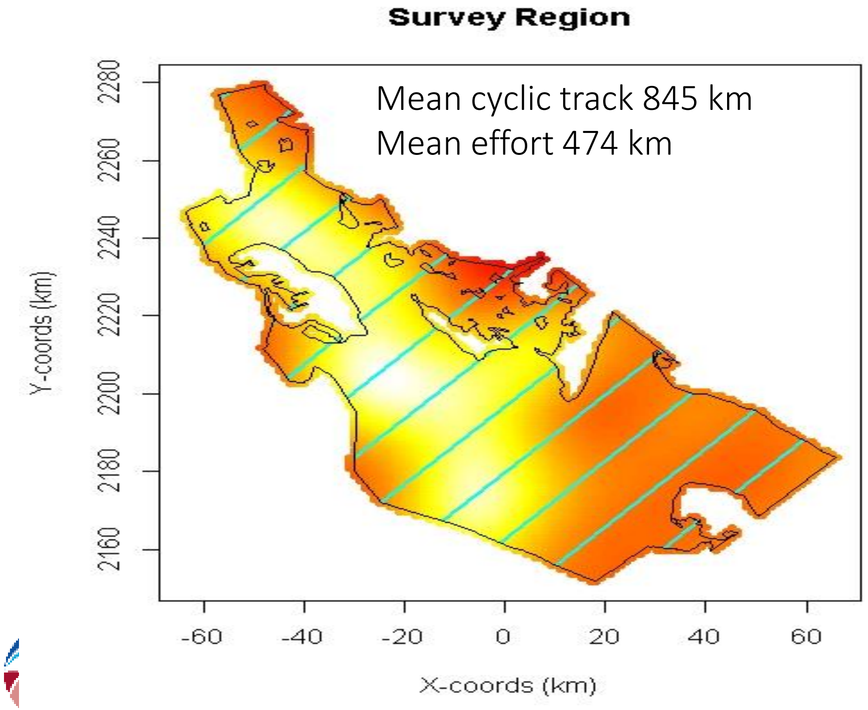


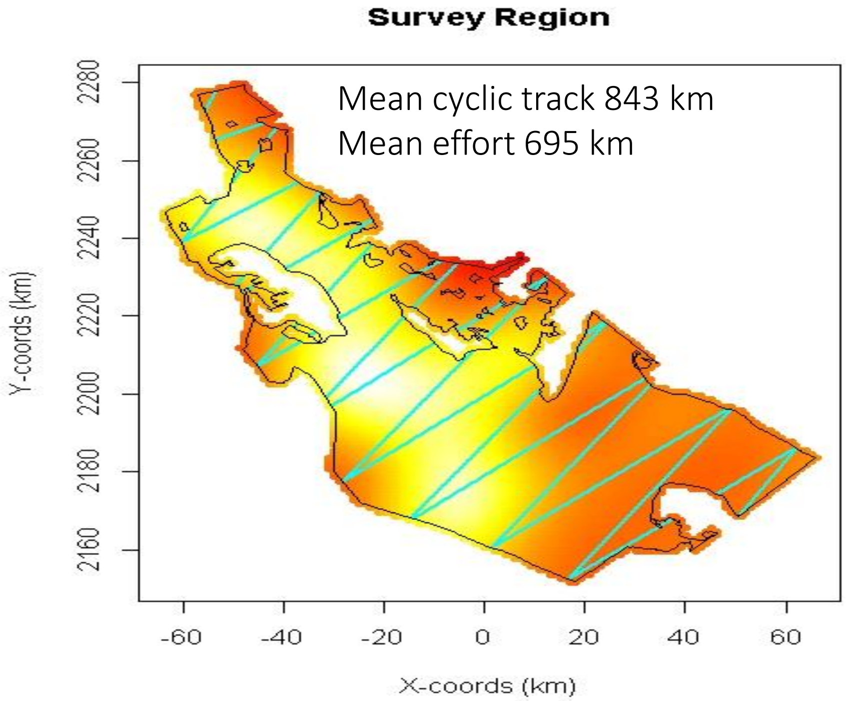
Subjective survey design





Random Designs

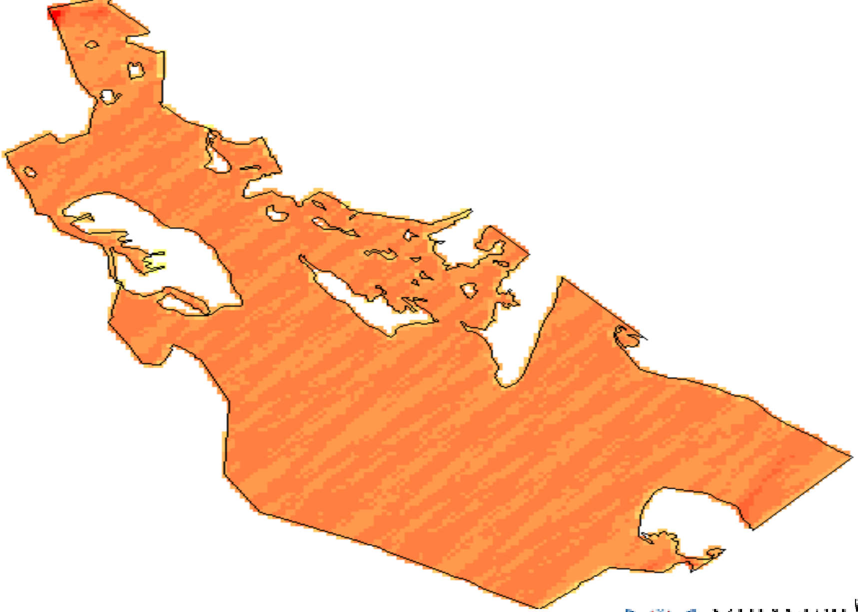




Coverage probability

SYSTEMATIC PARALLEL DESIGN

EQUAL SPACED ZIGZAG DESIGN



Simulation

Generates a realisation of the population based on a fixed N of 1500

Generates a realisation of the design
- Different each time for the random designs
- The same each time for the subjective design

Simulates the detection process

Analyses the results
- Half-normal
- Hazard-rate

Repeats a number of times

Practical

Now attempt the DSsim practical:

R version – subjective design and parallel v zig zag

(Distance version – parallel v zig zag only)

You will need the library *shapefiles.*