Distance Sampling Simulations

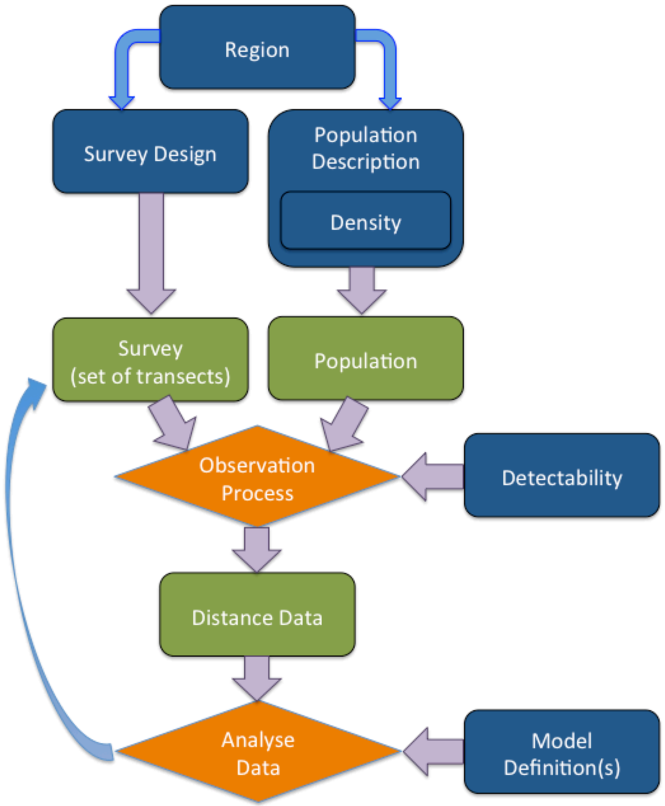
Overview

- 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?

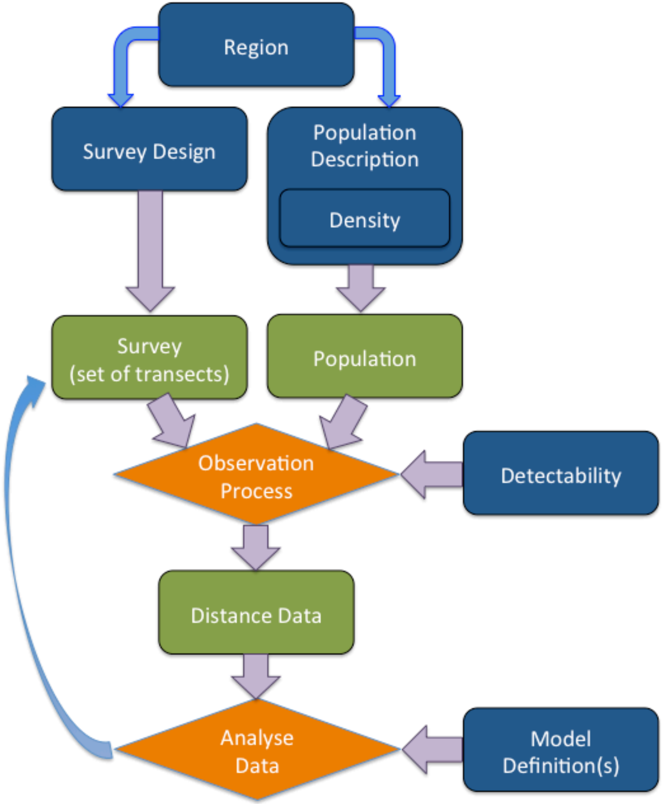
- Surveys expensive, simulations cheap!
- Test different survey designs
- Test survey protocols
- Investigate analysis properties
- Investigate violation of assumptions

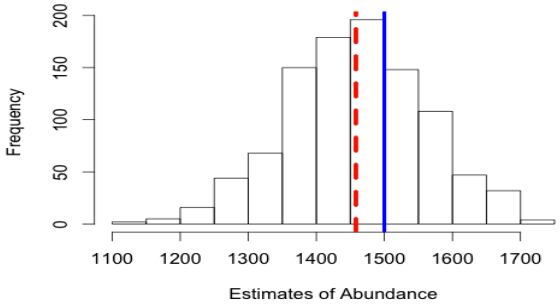
How it works



- 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.

How it works





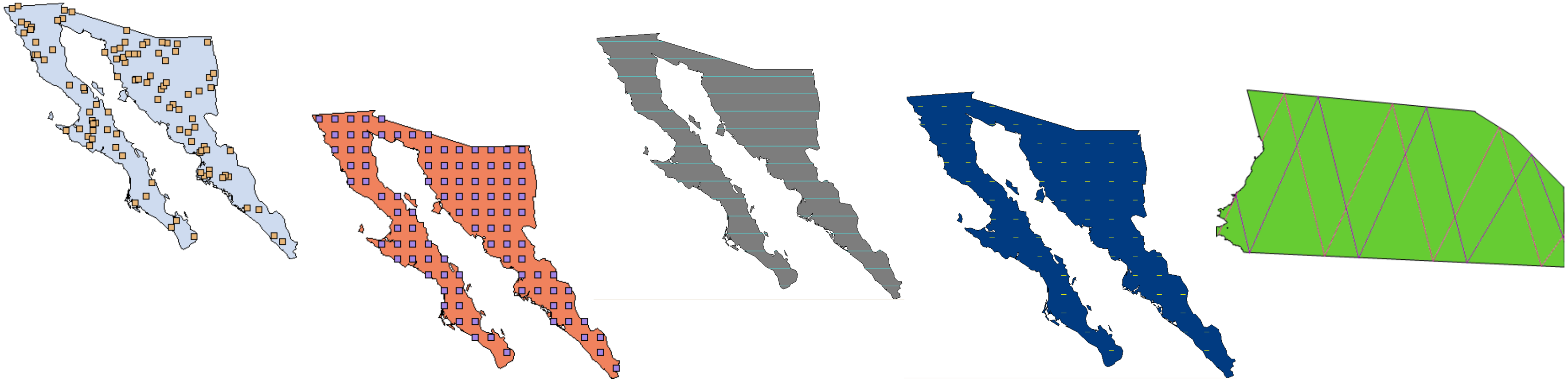
Assess:

- Bias
- Precision
- CI coverage

Across different designs/ scenarios

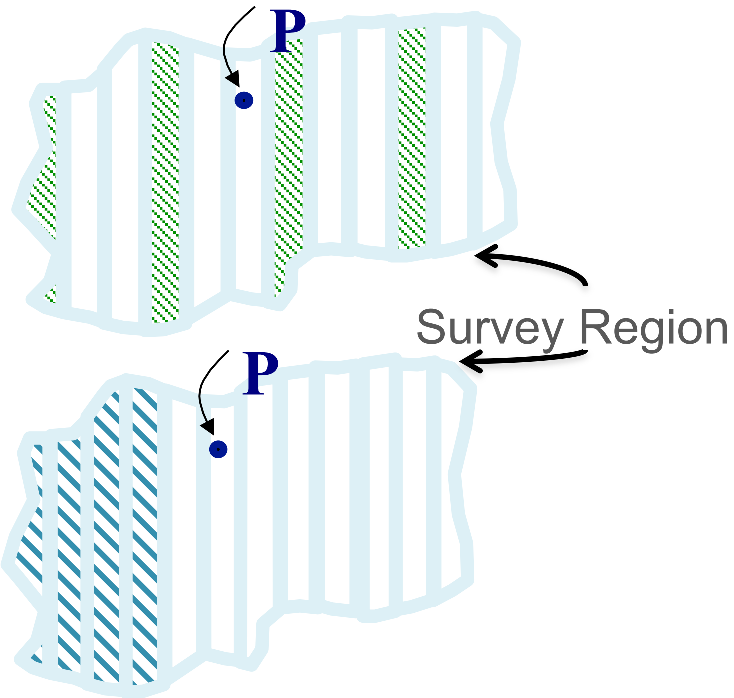
Automated Survey Design

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



Automated Survey Design

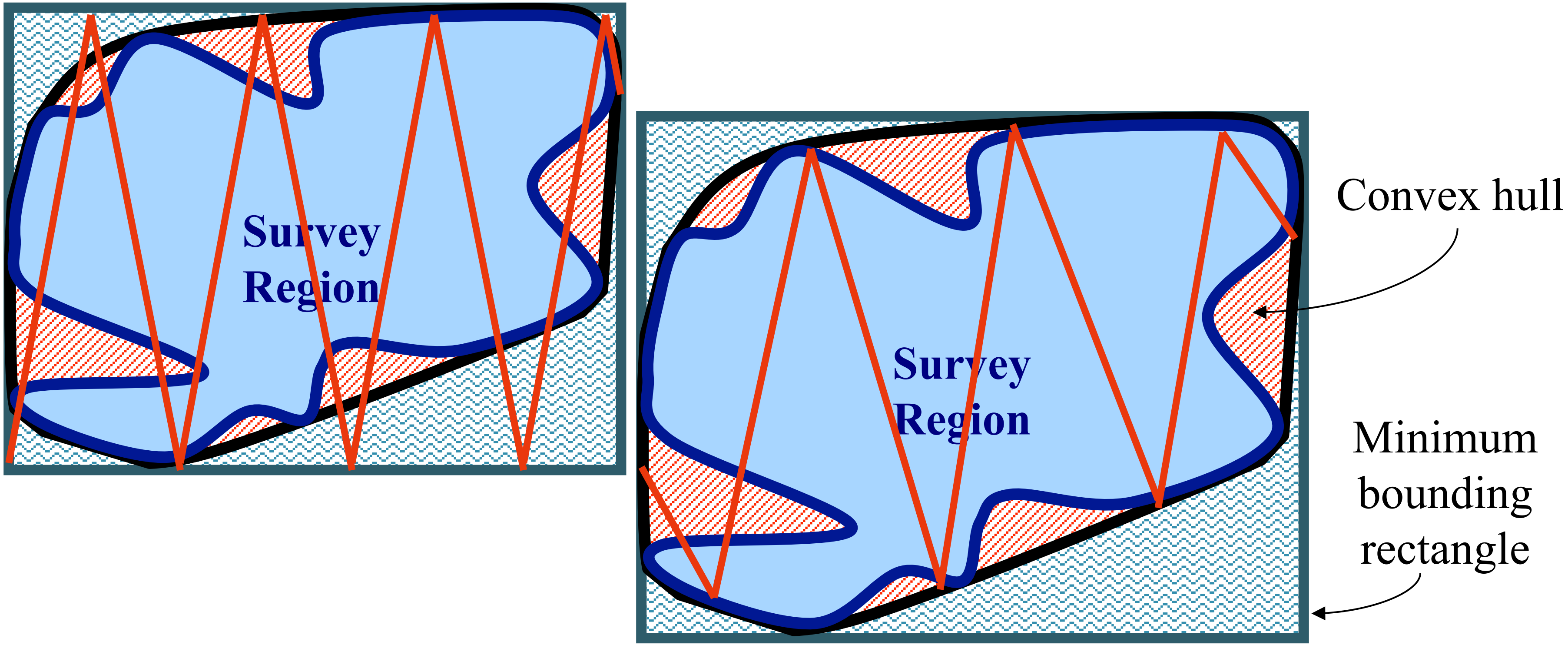
- Coverage Probability
  - Uniform coverage probability, π = 1/3
  - Uniform coverage probability, π = 1/3
  - Uneven coverage for any given realisation



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



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

- Distance needs:
  - shape and scale parameters on the natural scale
  - covariate parameters on the log scale

Detectability

- Golftees project

exp(0.268179) = 1.307581

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

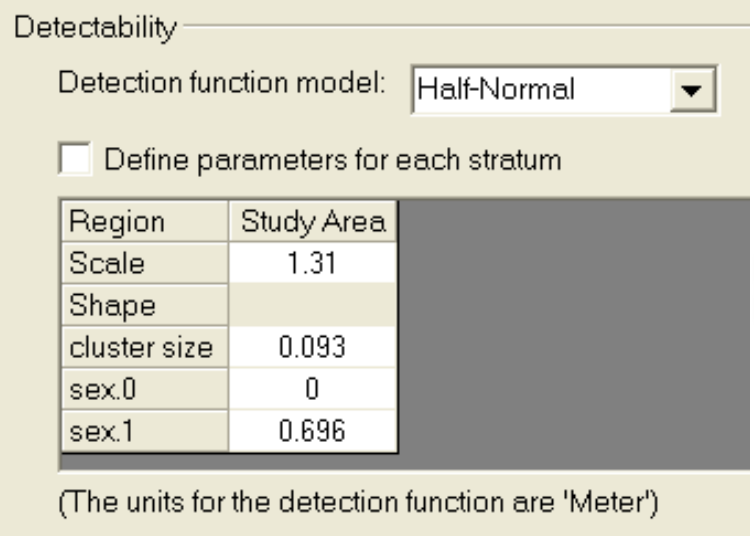
Log scale

Detection Fct/Summary (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:


Detectability

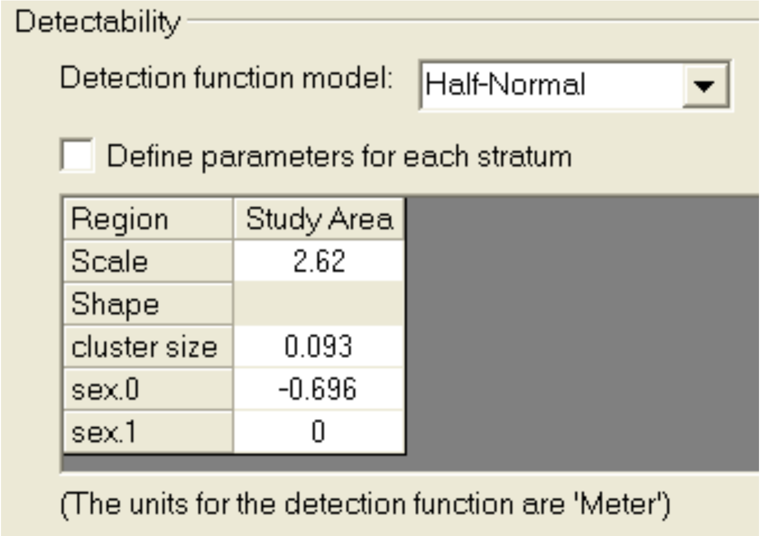
Detection function model: Half-Normal

Define parameters for each stratum

Region	Study Area
Scale	1.31
Shape	
cluster size	0.093
sex.0	0
sex.1	0.696

(The units for the detection function are 'Meter')

=


Detectability

Detection function model: Half-Normal

Define parameters for each stratum

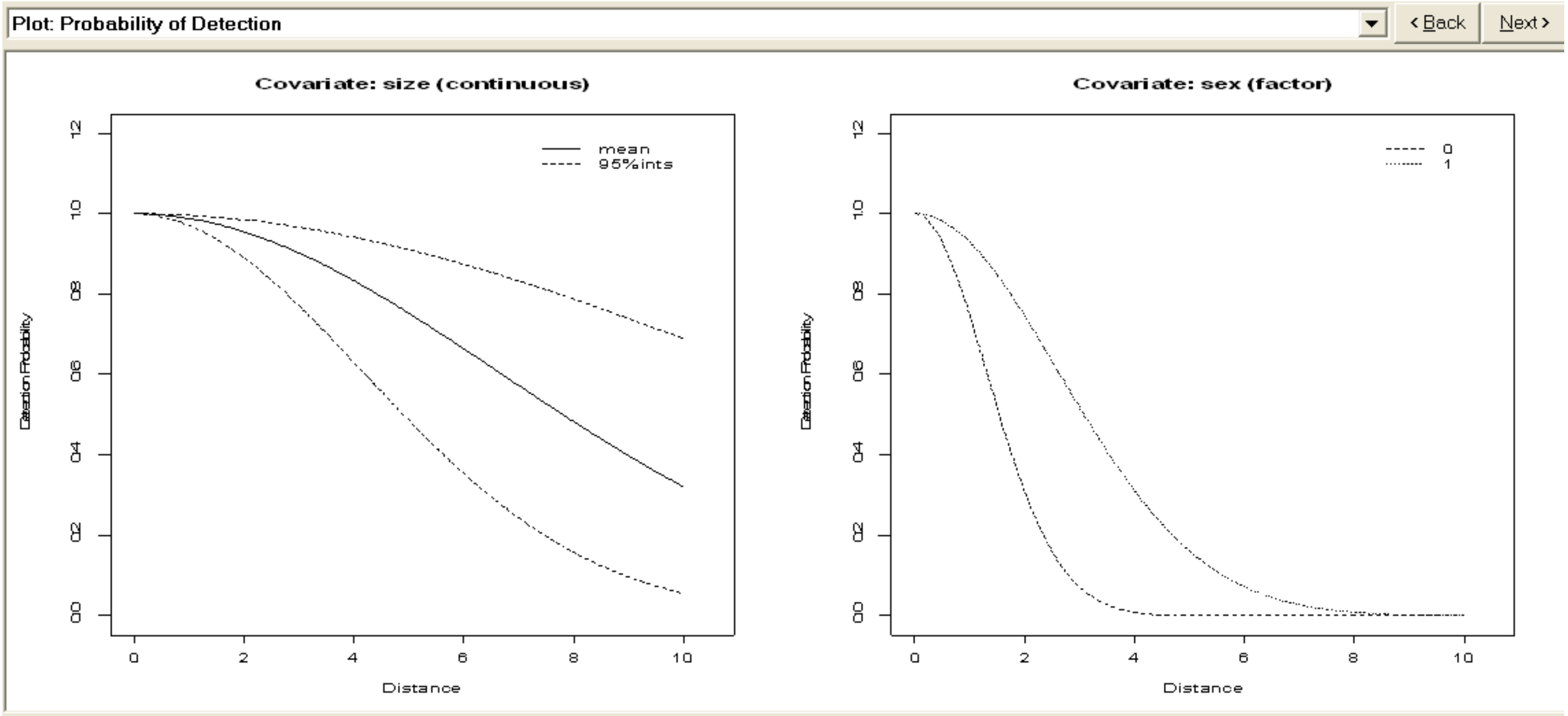
Region	Study Area
Scale	2.62
Shape	
cluster size	0.093
sex.0	-0.696
sex.1	0

(The units for the detection function are 'Meter')

exp(log(1.307581)+0.696) = 2.622633

exp(log(2.622)-0.696) = 1.307265

Detectability



Analysis

- **Data Filter** must specify a right truncation distance
- **Model Definition** must be either MRDS or MA
  - MRDS – for fitting a specific model
  - MA – for model selection (Note: MA model definitions require the creation of analyses)

Any questions so far...

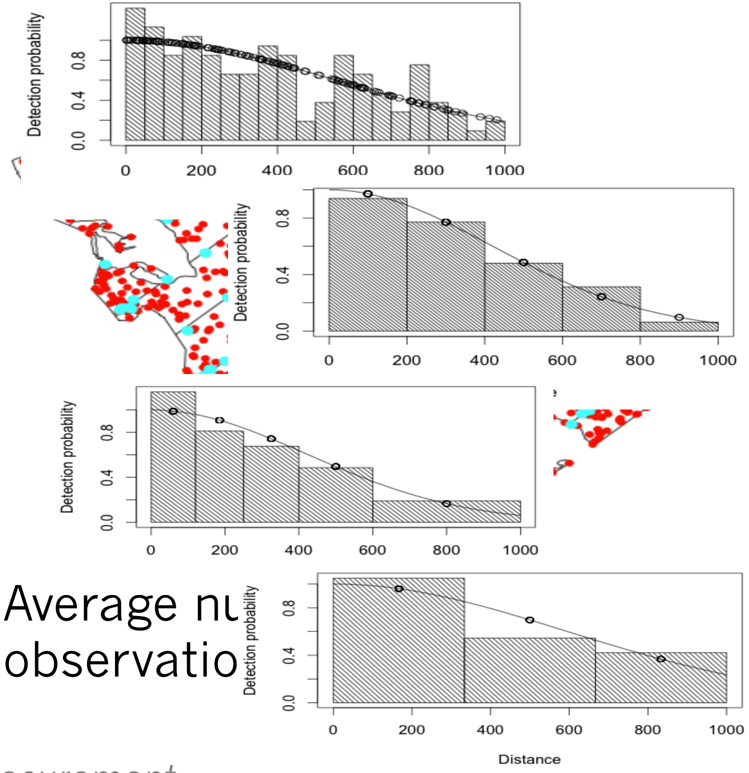
Example Simulations

- To bin or not to bin?
- Testing pooling robustness in relation to truncation distance.
- Comparison of subjective and random 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



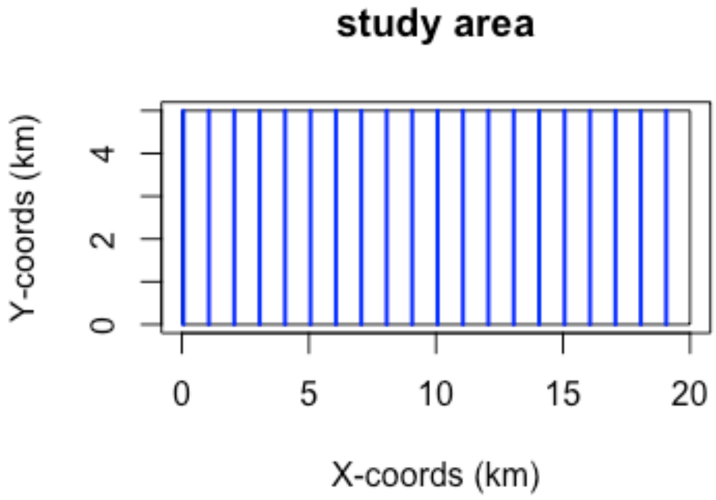
[1] *Marques T. (2004) Predicting and correcting bias caused by measurement error in line transect sampling using multiplicative error models Biometrics 60:757--763*

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

Pooling Robustness and Truncation

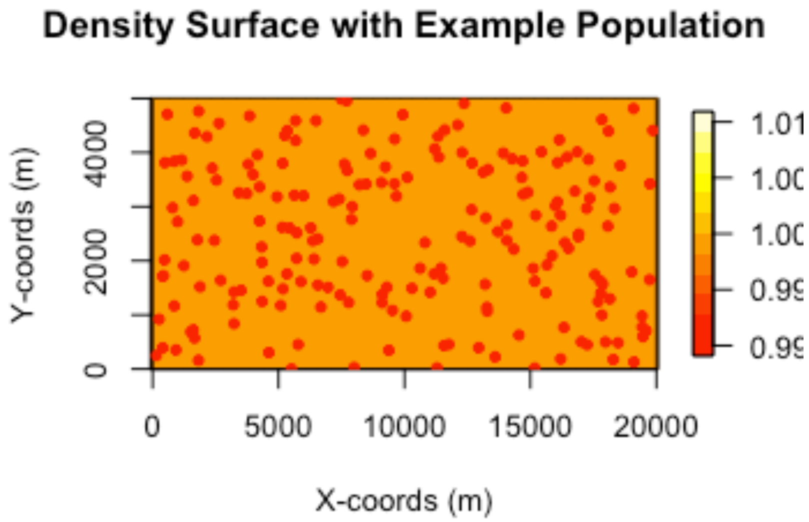
- DSsim vignette



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

Pooling Robustness and Truncation

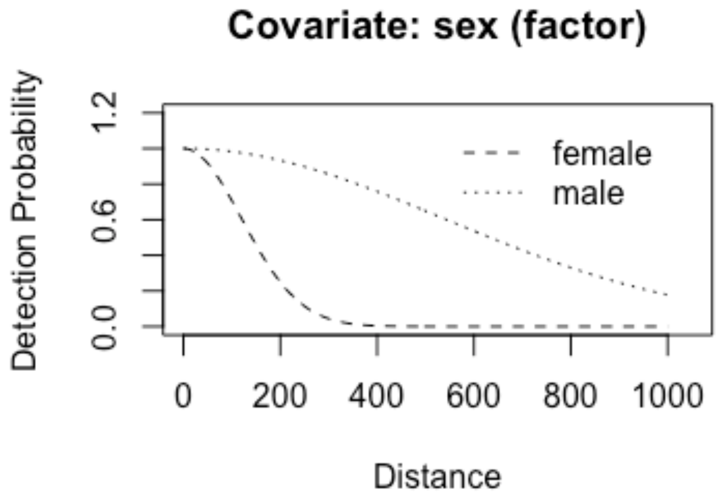
- DSsim vignette



- 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

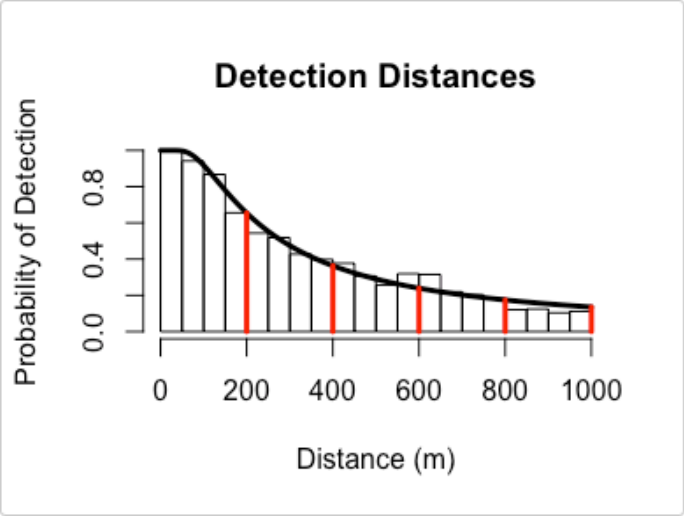
```
# Create the covariate parameter list
cov.params <- list()
# Note the covariate parameters are supplied on the log scale
cov.params$sex = data.frame(level = c("female", "male"),
                            param = c(0, 1.5))

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

exp(log(120)+1.5) = 537.8

- 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



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

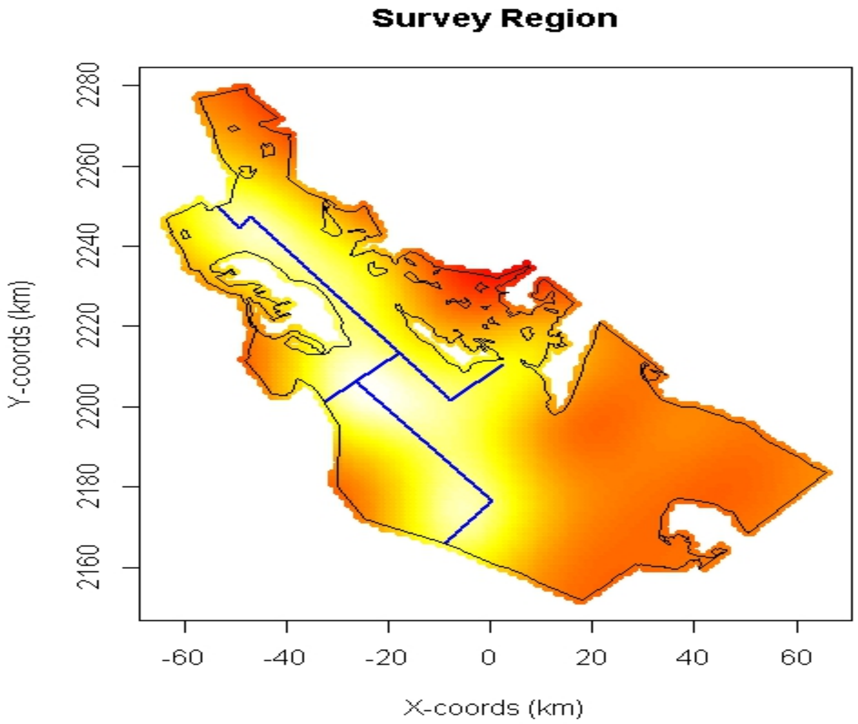
- Two types of analyses:
  - **hn v hr**
  - hn ~ sex
- Selection criteria: AIC

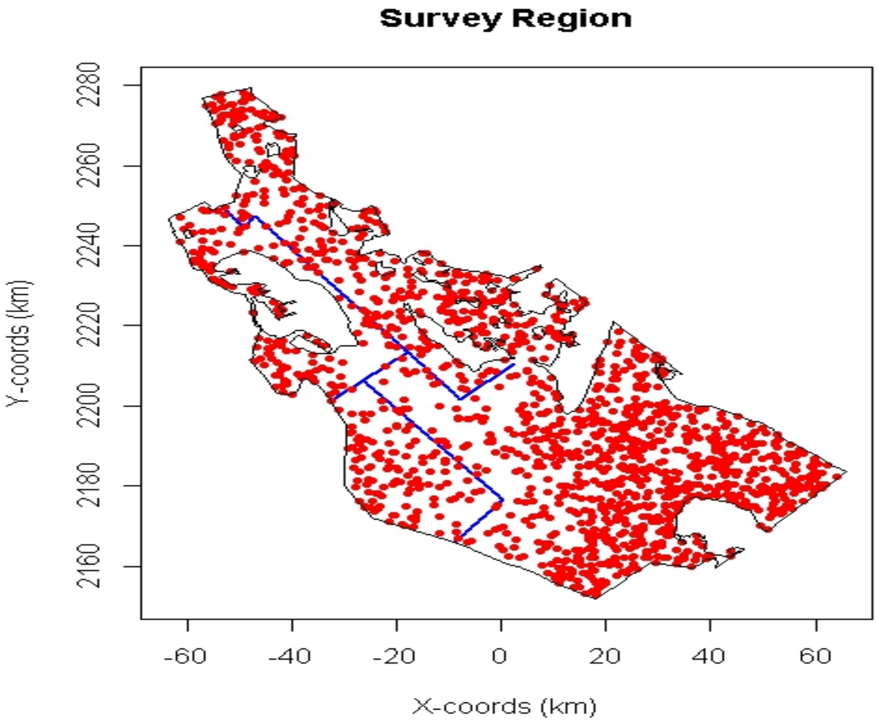
Pooling Robustness and Truncation

- Results HN v HR:

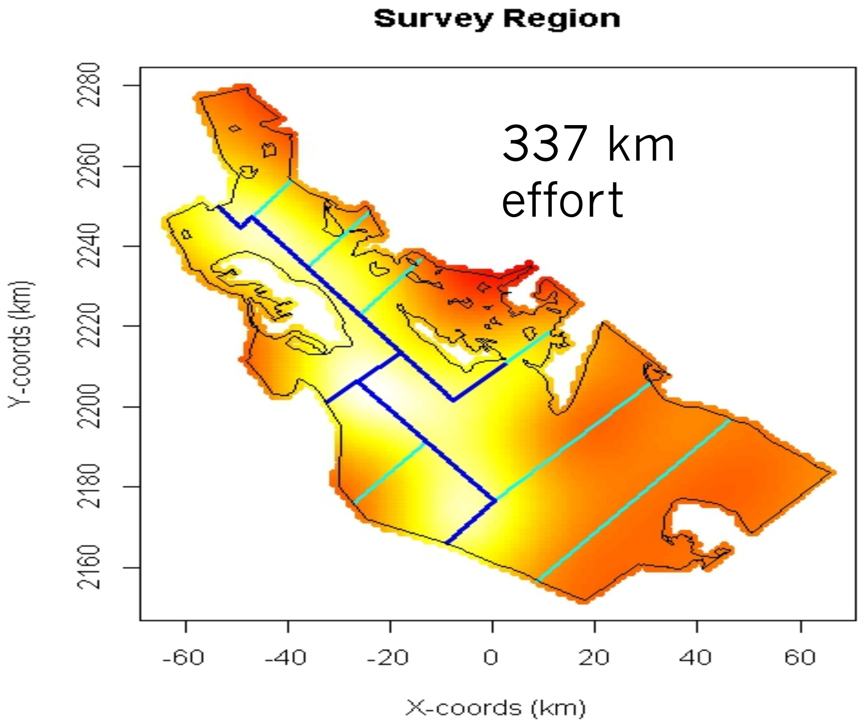
Truncation	*mean n*	*mean* $\hat{N}$	*mean se*	$SD(\hat{N})$	*%Bias*	*RMSE*	*% CI Coverage*
200	66	197	34.27	34.05	-1.32	34.13	97.5
400	102	190	31.06	34.79	-5.13	36.25	87.9
600	128	190	34.04	35.27	-5.24	36.77	81.9
800	144	190	34.31	36.61	-5.10	37.99	77.1
1000	154	184	30.93	39.49	-7.76	42.42	68.1

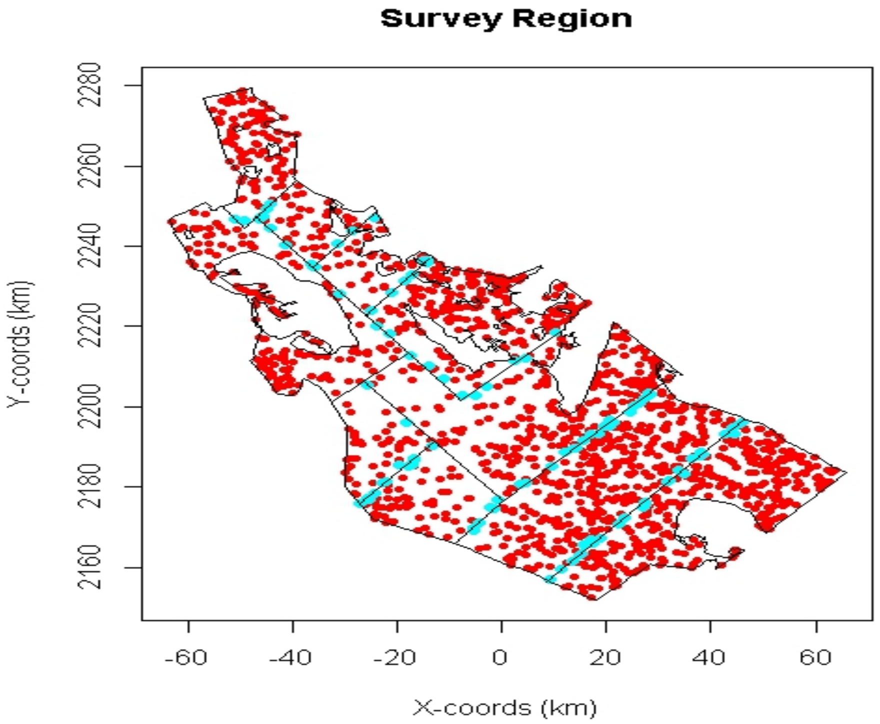
Example Simulation



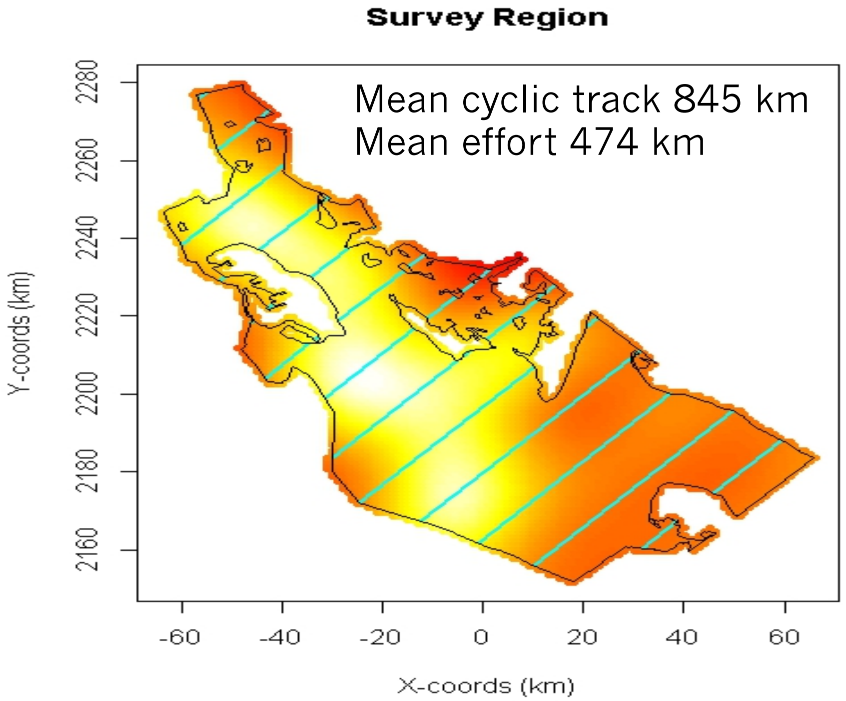


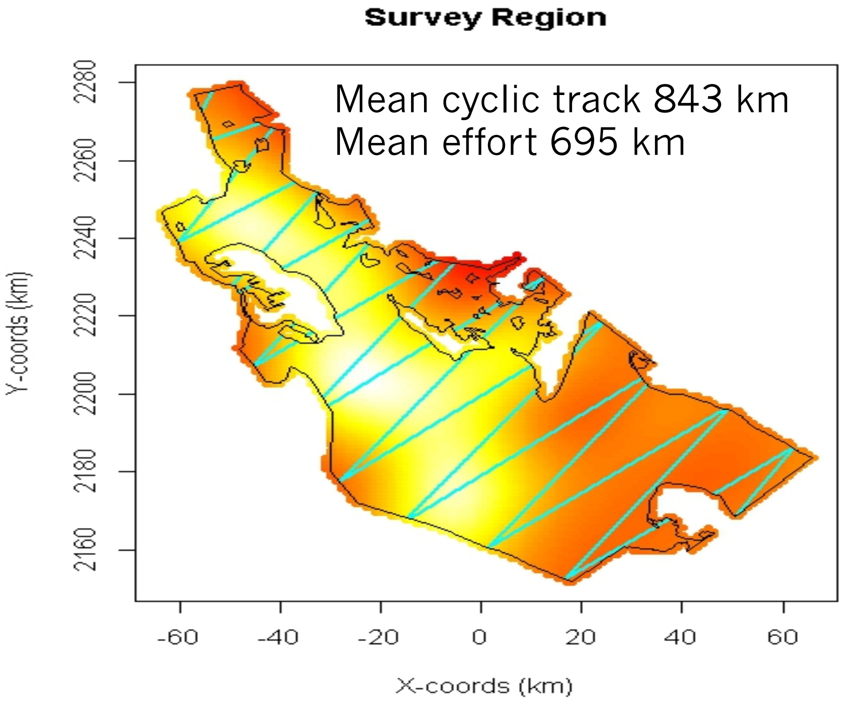
Subjective survey design





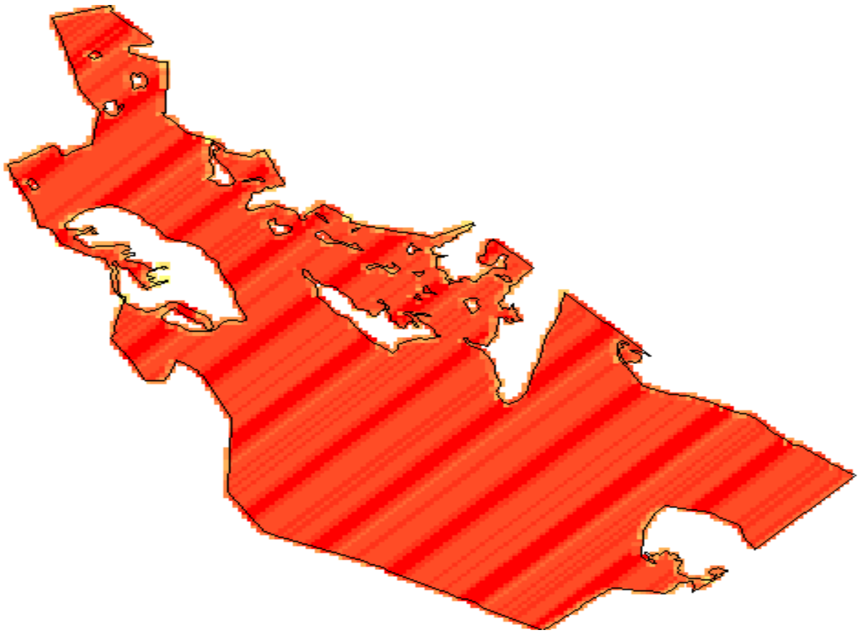
Random Designs



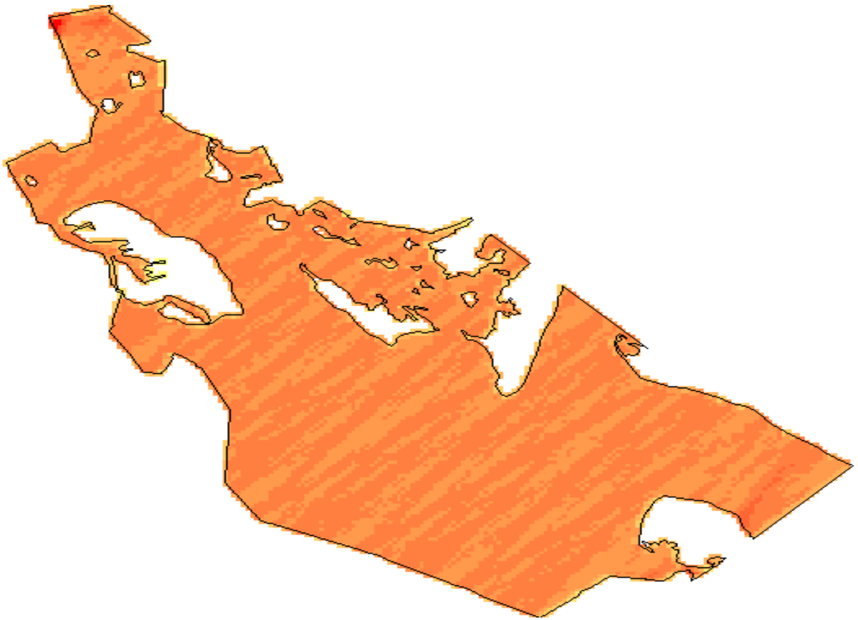


Coverage probability

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.*