Design and Analysis of Distance Sampling Studies

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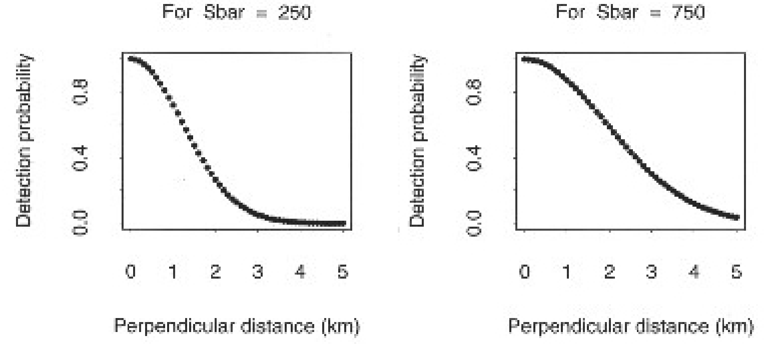
Part 2
Multiple Covariate Distance Sampling - Analysis

MCDS - Multiple Covariate Distance Sampling

MCDS - Intro

Multiple Covariate Distance Sampling:

- Similar to post-stratification where detection function can be modified by covariates (e.g. rainfall, observer, habitat type, etc.)
- Influences the *scale* of Detection function, but NOT its shape.
- Covariates affect rate at which detection function declines with distance, but not shape.



E.g. Half-normal detection function with larger scale (σ).

Covariates vs. post-stratification

- Post-stratification is very coarse; covariates are finer adjustments but need more data
- Need more contrast and more evenly distributed samples across covariate values.
- Post-stratification can have completely different detection functions; covariates only influence *scale* of detection function.

Key assumption about covariates:

- Covariates should be independent of distance
  - E.g. of failure - record habitat but only certain habitats are visible near the line (small shrubs) while other habitats are visible at large distances (tall trees).
- Avoid covariates that are correlated among themselves (e.g. height and mass of object).
- Covariates should act on *scale* parameter only.

MCDS - Intro

Covariates added as more fields to data set and imported in the usual way.

Covariates can be continuous (e.g. temperature) or categorical (e.g. observer)

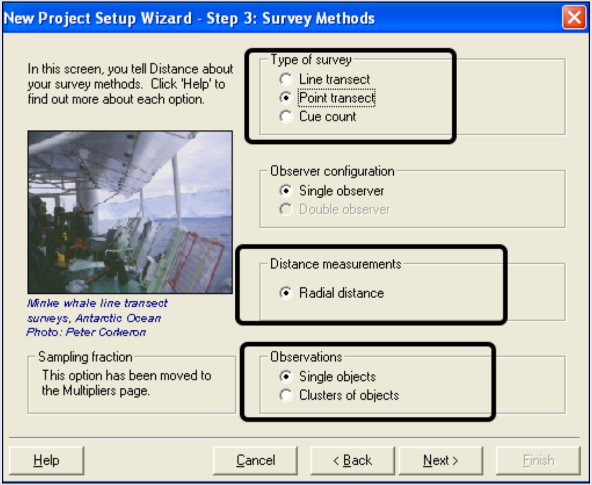
MCDS - Example

Amakihi on island of Hawaiian chain.

- collected as part of a larger study to assess a translocation experiment on the island of Hawaii
- Multi-species point- transect surveys at seven survey periods between July 1992 and April 1995.
- There were 41 point-count stations,
- Counted Hawaii Amakihi (*Hemignathus virens*), a generalist Hawaiian honeycreeper.
- Survey periods = strata.
- Covariates are Observer (OBS), minutes after sunrise (MAS), or hours after sunrise (HAS)
- Distances in meters.

MCDS - Example - Amakihi

Import the data in the usual way.



MCDS - Example - Amakihi

. . . giving . . . .

Data layers

- Study area
  - Region
    - Point transect
      - Observation

Contents of Observation layer 'Observation' and all fields from higher layers

Study area		Region			Point transect			Observation				
ID	Label	ID	Label	Area	ID	Label	Survey effort	ID	Radial distance	OBS	MAS	HAS
ID	Label	ID	Label	Decimal	ID	Label	Decimal	ID	Decimal	Text	Decimal	Text
n/a	n/a	n/a	n/a	ha	n/a	n/a	[None]	n/a	m	n/a	[None]	n/a
Int	Int	Int	Int	Int	Int	Int	Int	Int	Int	Int	Int	Int
								1	40	TJS	50	1
								2	60	TJS	50	1
								3	45	TJS	50	1
					1	1	1	4	100	TJS	50	1
								5	125	TJS	50	1
								6	120	TJS	50	1
								7	140	TJS	50	1

Covariates affect the *scale* of the detection function, e.g. a factor covariate (categorical) with two levels:

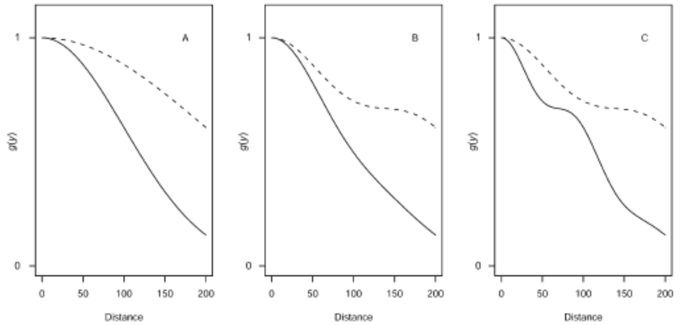


FIG. 2. Illustration of the effect of a factor covariate with two levels ($z = 1, 2$) on the key function (half-normal) with or without adjustment. (A) Key function without adjustment, with a scale term σ incorporating covariates: $\sigma = \exp[\log(50) + z \log(100/50)]$. (B) Key function with one cosine adjustment ($a_2 = 0.1$) in which distances are scaled by truncation distance ($y_s = y/w$). In this case, shape of overall detection function changes depending on covariate values. (C) Key function and one adjustment term as in (B) but with distances in adjustment term scaled by covariate scale parameter ($y_s = y/\sigma$). In this case, shape of overall composite detection-function is constant at all covariate values and only the scale varies.

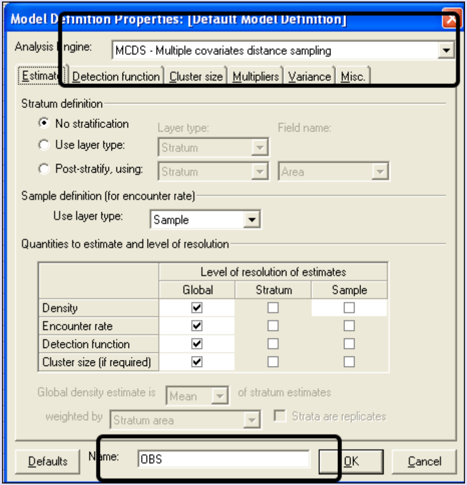
MCDS - Example - Amakihi

Model fitting advice:

- Start small, i.e. incremental add covariates.
- Start small, i.e. few factor levels (group in advance).
- Start with no series adjustments; if this converges try adding one level of adjustment
- Small probability event (i.e. extreme distances) have great effect on stability of estimates – truncate heavily, especially observations with probability of detection < 0.1.
- Truncate at fixed width or radius value.

MCDS - Example - Amakihi

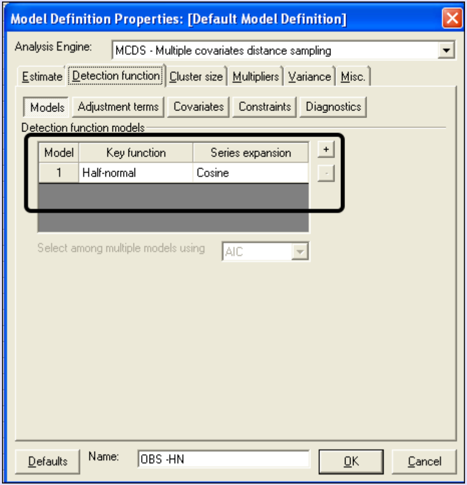
Fit a model with Observer (OBS) as a factor covariate.



Note specification of MCDS.

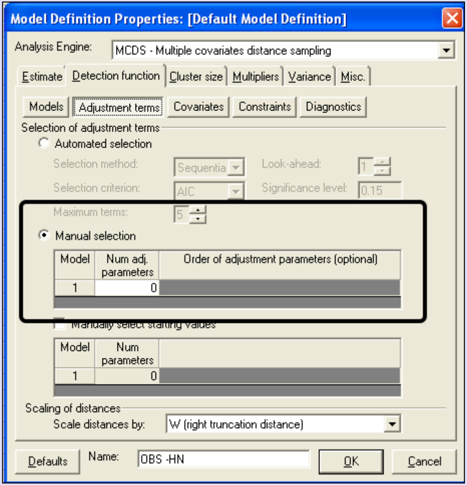
MCDS - Example - Amakihi

... Fit a model with Observer (OBS) as a factor covariate ...



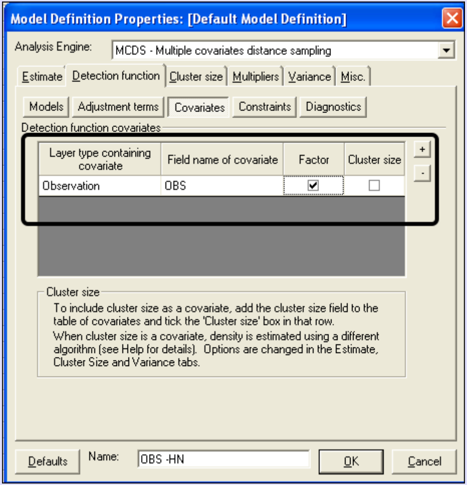
MCDS - Example - Amakihi

. . . Fit a model with Observer (OBS) as a factor covariate . . .

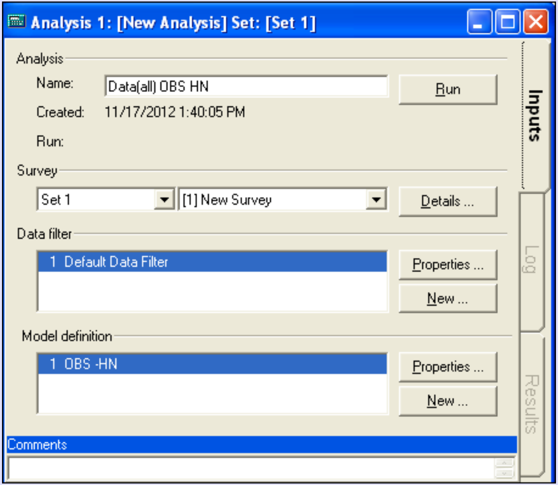


MCDS - Example - Amakihi

... Fit a model with Observer (OBS) as a factor covariate ...



... Fit a model with Observer (OBS) as a factor covariate ...



MCDS - Example - Amakihi

... wait while the model is fit ...

Uses conditional MLE followed by a Horvitz-Thompson adjustment (which is slow).

Variance estimates are computed by bootstrapping (which is slow)

MCDS - Example - Amakihi

Results:

```
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 level SGF of factor covariate OBS.
   Parameter A(3) is the coefficient of level TJS of factor covariate OBS.
      A( 1) bounds = ( 2.5000      , 0.10000E+07 )
```

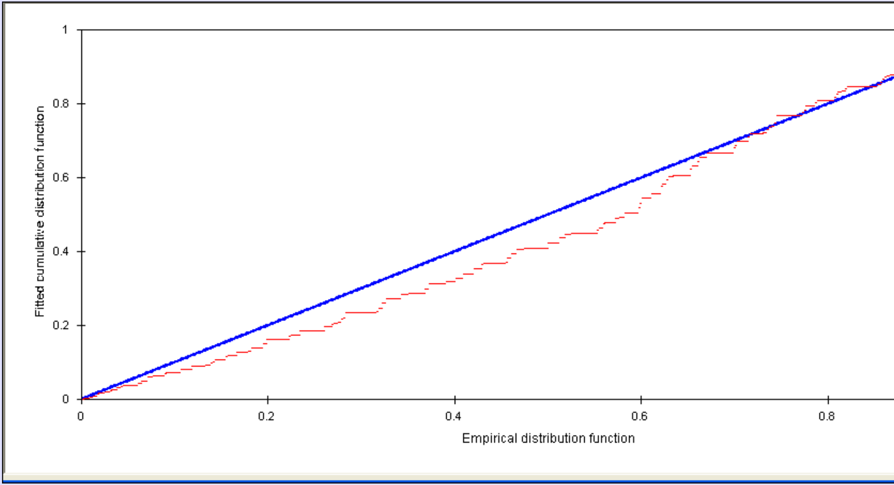
Factor covariates operate on scale and are offsets from base level (observer TKP)

Looks like strong observer effect:

Parameter	Point Estimate	Standard Error	Percent Coef. of Variation	95 Percent Confidence Interval	
A(1)	36.79	0.4172			
A(2)	-0.6990E-01	0.4936E-01			
A(3)	0.1761	0.4233E-01			
h(0)	0.58128E-03	0.15026E-04	2.58	0.55255E-03	0.61151E-03
p	0.55051E-01	0.14231E-02	2.58	0.52329E-01	0.57914E-01
EDR	58.657	0.75814	1.29	57.189	60.163

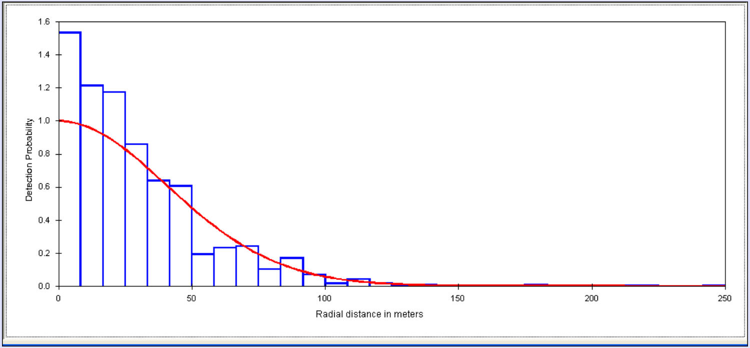
MCDS - Example - Amakihi

Results:



Hmmm ... good evidence of lack of fit. KS/CM GOF tests fail.

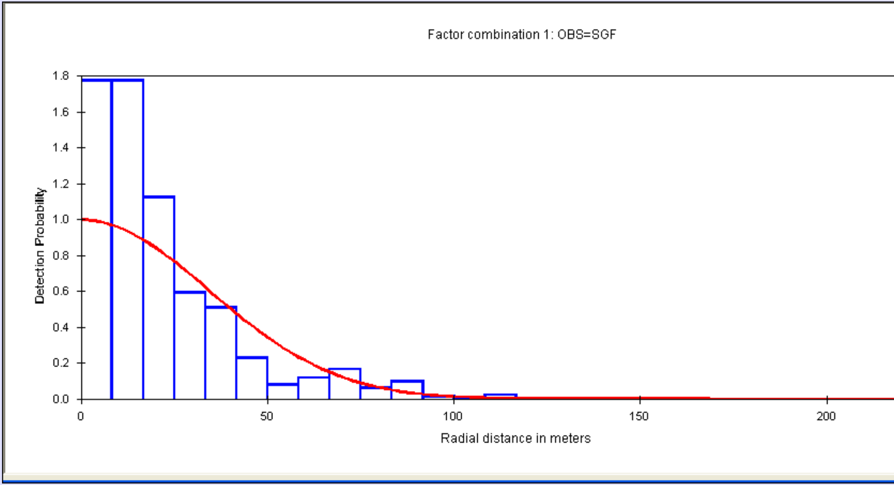
Results:



Hmmm ... good evidence of lack of fit. χ^2 GOF fail.

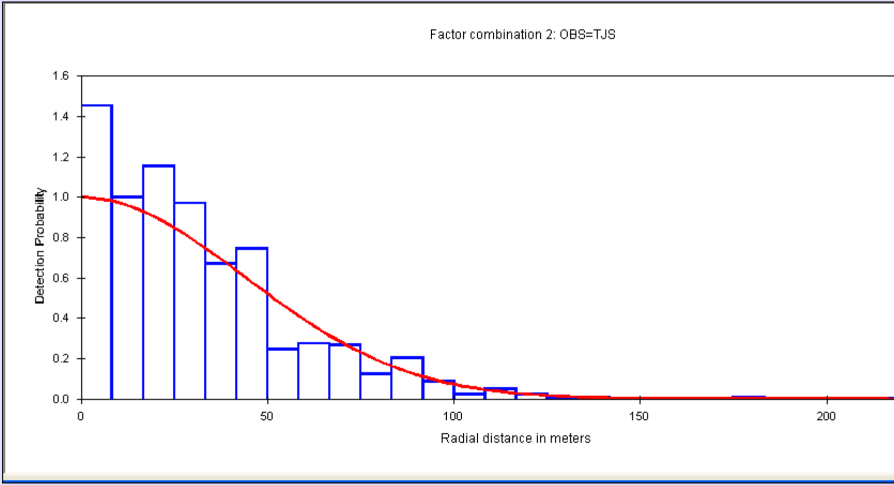
MCDS - Example - Amakihi

Results - look at individual observers



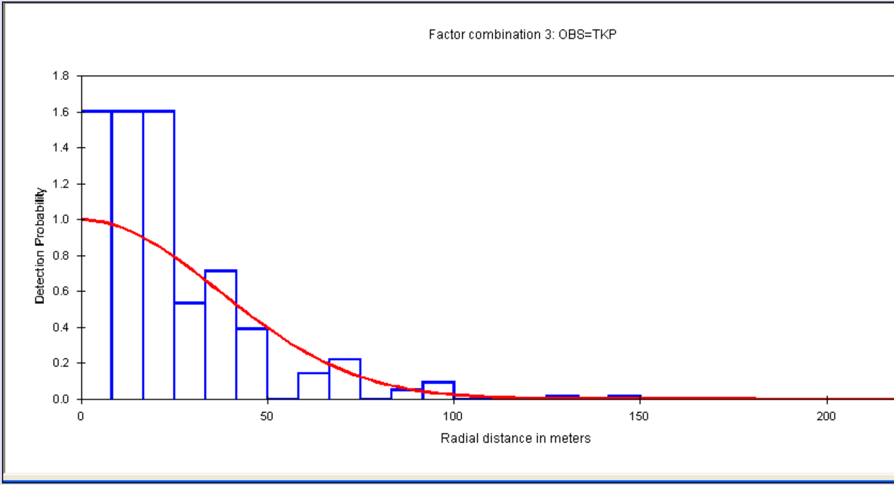
MCDS - Example - Amakihi

Results - look at individual observers



MCDS - Example - Amakihi

Results - look at individual observers



MCDS - Example - Amakihi

Results - look at final estimates

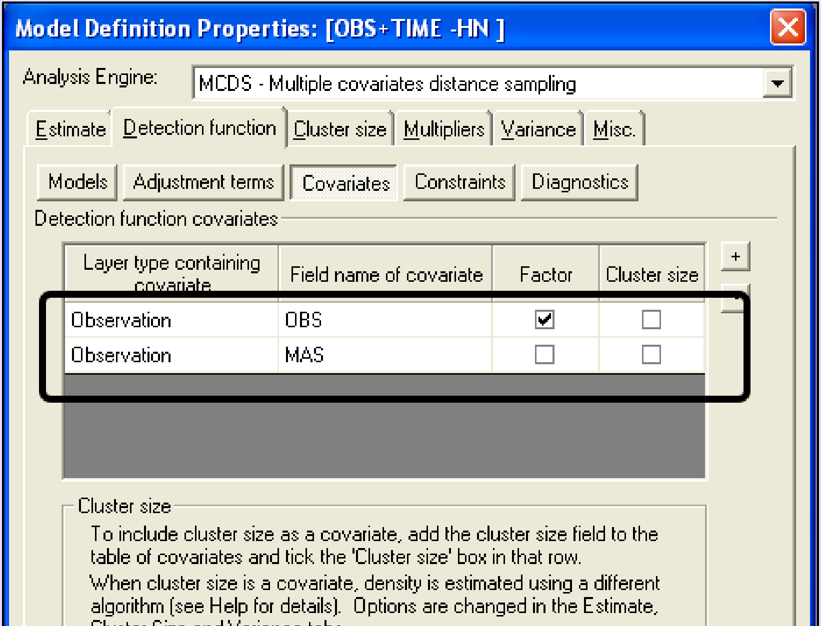
Parameter	Point Estimate	Standard Error	Percent Coef. of Variation	95% Percent Confidence Interval	
h(0)	0.58128E-03	0.15026E-04	2.58	0.55255E-03	0.61151E-03
p	0.55051E-01	0.14231E-02	2.58	0.52329E-01	0.57914E-01
EDR	58.657	0.75814	1.29	57.189	60.163
n/K	5.5618	0.19427E-01	0.35	5.5237	5.6002
D	5.1454	0.13422	2.61	4.8888	5.4155

```
Measurement Units
---------------------------------
Density: Numbers/hectares
    EDR: meters

Component Percentages of Var(D)
-------------------------------
Detection probability    :  98.2
Encounter rate           :   1.8
```

MCDS - Example - Amakihi

Add *MAS* as a continuous covariate along with *OBS* and refit.



MCDS - Example - Amakihi

Data(all) OBS + MAS HN/cos(0) form of detection function:

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

   s = A(1) * Exp(fcn(A(2)) + fcn(A(3)) + fcn(A(4)))
   Parameter A(1) is the intercept of the scale parameter s.
   Parameter A(2) is the coefficient of level SGF of factor covariate OBS.
   Parameter A(3) is the coefficient of level TJS of factor covariate OBS.
   Parameter A(4) is the coefficient of covariate MAS.
```

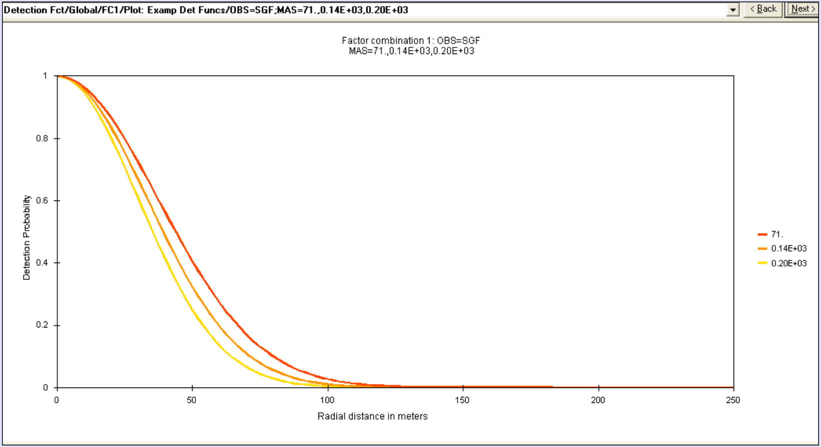
MCDS - Example - Amakihi

Data(all) OBS + MAS HN/cos(0) - evidence of an effect of time

Parameter	Point Estimate	Standard Error	Percent Coef. of Variation	95 Percent Confidence Interval	
A(1)	48.37	0.6143			
A(2)	-0.1412	0.5086E-01			
A(3)	0.1254	0.4481E-01			
A(4)	-0.1699E-02	0.1477E-03			
h(0)	0.62202E-03	0.16661E-04	2.68	0.59019E-03	0.65557E-03
p	0.51445E-01	0.13780E-02	2.68	0.48813E-01	0.54220E-01
EDR	56.704	0.75942	1.34	55.234	58.213

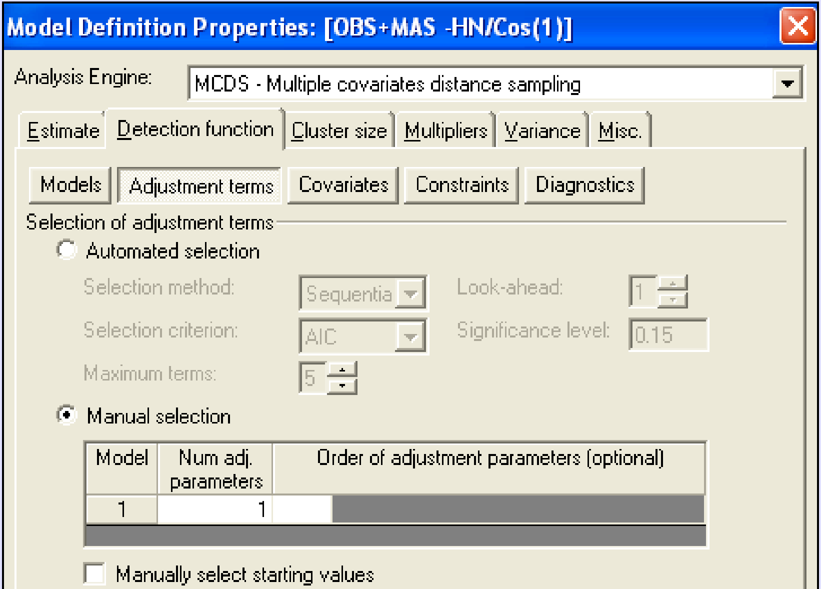
MCDS - Example - Amakihi

Data(all) OBS + MAS HN/cos(0)- fit has improved but not that great and only minor effect of time



MCDS - Example - Amakihi

Try and add cosine series adjustment term to detection function:
Data(all) OBS + MAS HN/cos(1)



MCDS - Example - Amakihi

Data(all) OBS + MAS HN/cos(1) - Results . . ...

MCDS - Example - Amakihi

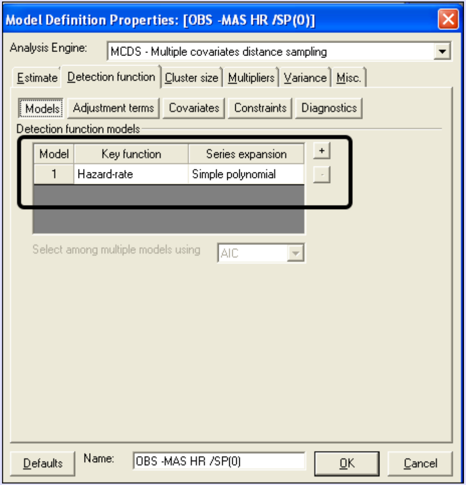
Original paper results . . .

Key	Adjustment terms	Covariates	Number of parameters	ΔAIC
		CDS $f(0)$ pooled		
HN	Cos	–	5	21.40
Uni	Cos	–	2	25.11
HR	SP (0)	–	2	29.90
		CDS $f(0)$ by strata (survey period)		
Uni	Cos	–	12	13.50
HR	SP (0)	–	14	18.59
HN	Cos	–	15	22.87
		MCDS		
HR	SP (0)	OBS TIME	5	0.00
HR	SP (0)	OBS	4	1.73
HN	Cos	OBS HOUR	10	3.61
HN	Cos	OBS TIME	6	5.53
HR	SP (0)	OBS HOUR	9	5.62
HN	Cos	OBS	6	7.12
HN	Cos	TIME	4	24.56
HN	Cos	HOUR	8	24.57
HR	SP (0)	TIME	3	29.18
HR	SP (0)	HOUR	7	31.62

Fit the top MCDS model... (truncation at 82.5 m), TIME=MAS

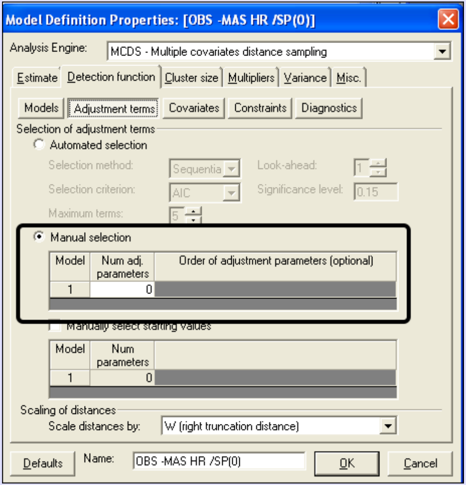
MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0)



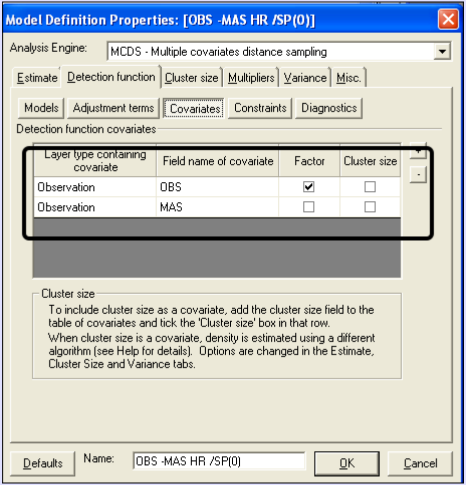
MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0)



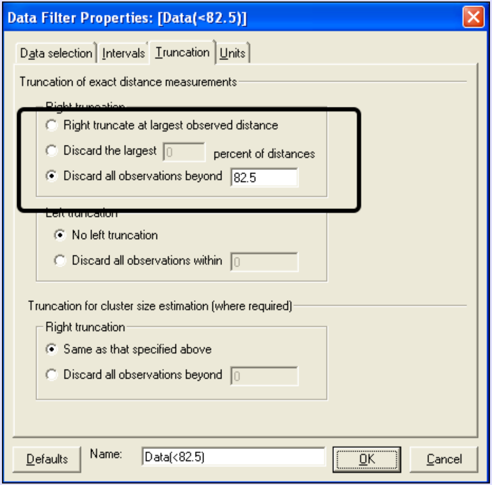
MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0)



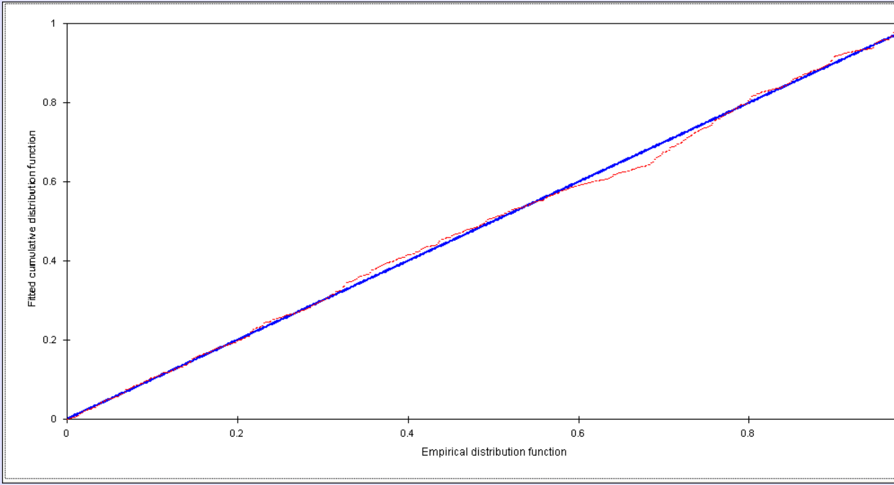
MCDS - Example - Amakihi

Data($<$ 82.5) OBS + MAS HR/SP(0)



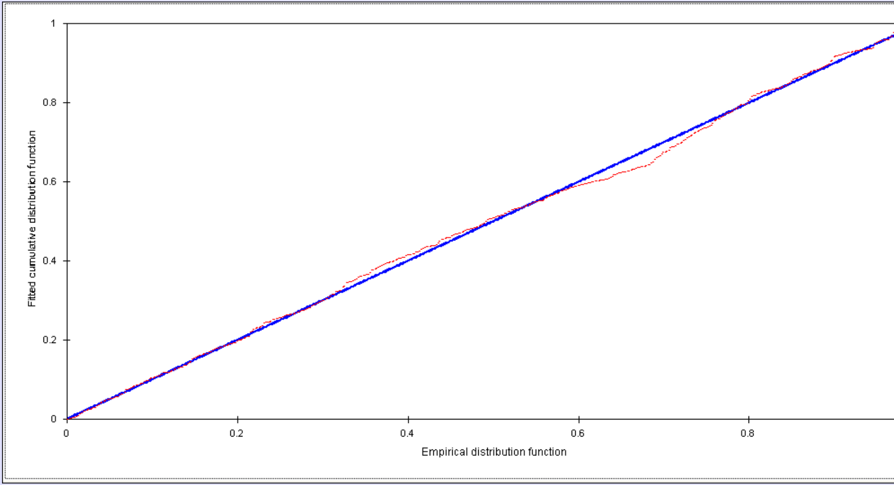
MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0): Results ...



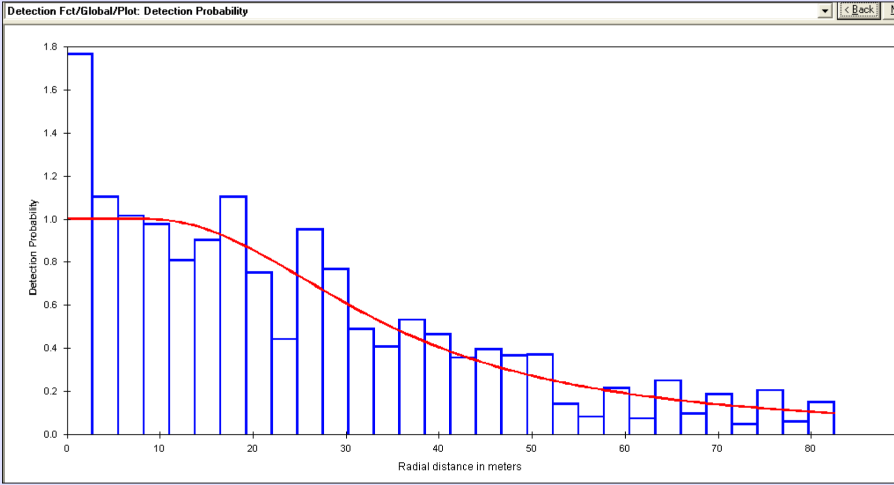
MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0): Results ...



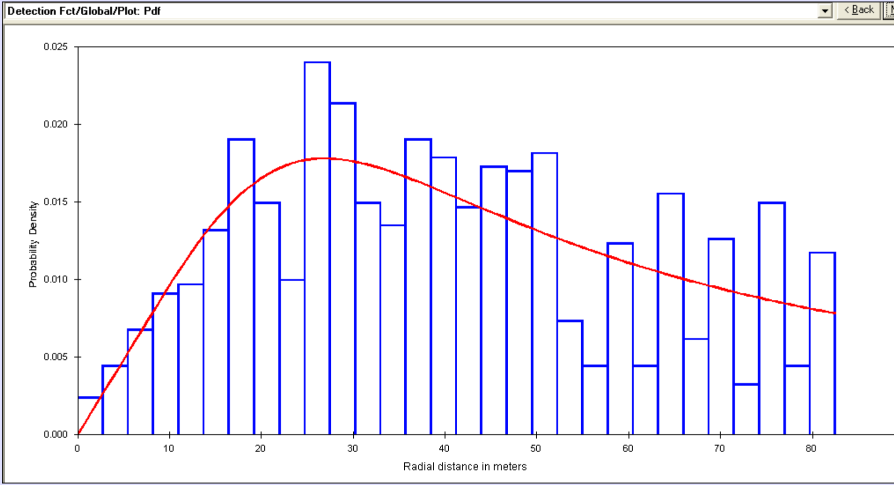
MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0): Results . . .

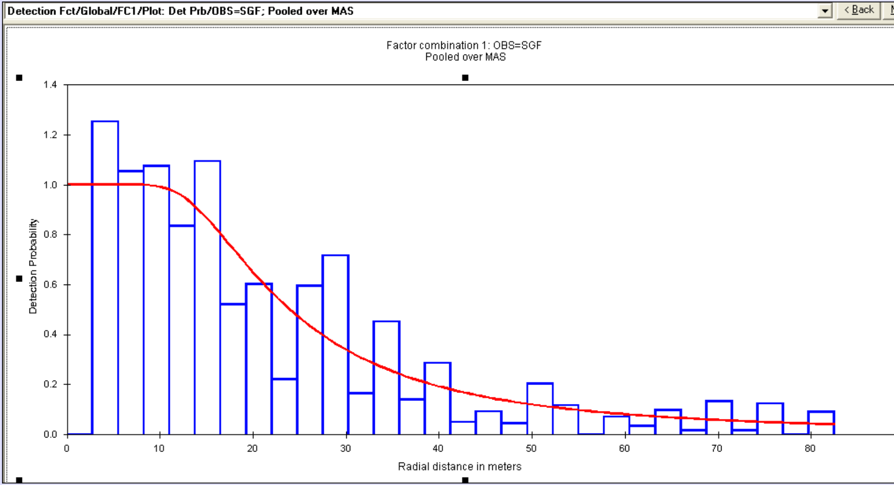


MCDS - Example - Amakihi

Data(<82.5) OBS + MAS HR/SP(0): Results ...

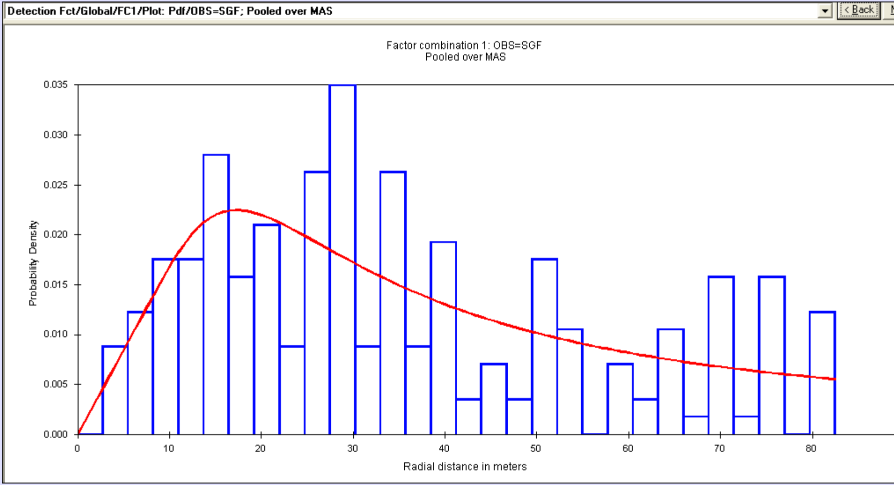


Data(< 82.5) OBS + MAS HR/SP(0): Results ...



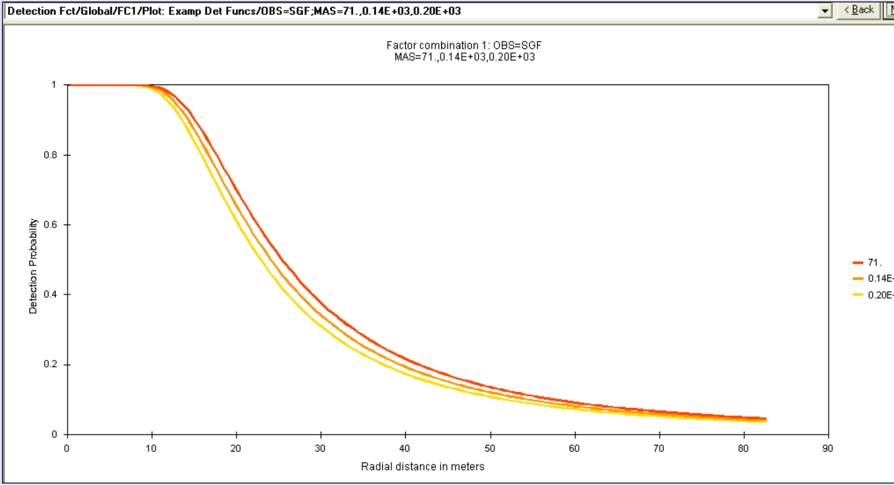
MCDS - Example - Amakihi

Data($<$ 82.5) OBS + MAS HR/SP(0): Results . . .



MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0): Results ...



Compare the different observers detection profile.

MCDS - Example - Amakihi

Data(< 82.5) OBS + MAS HR/SP(0): Final Results ...

Parameter	Point Estimate	Standard Error	Percent Coef. of Variation	95% Percent Confidence Interval	
h(0)	0.96419E-03	0.25533E-04	2.65	0.91538E-03	0.10156E-02
p	0.30476	0.80706E-02	2.65	0.28934	0.32101
EDR	45.544	0.60304	1.32	44.376	46.743
n/K	4.6554	0.18534E-01	0.40	4.6191	4.6921
D	7.1440	0.19131	2.68	6.7784	7.5293

MCDS - Example - Amakihi

Multiple models – notice the difference in estimated Densities by model.

	ID				Name		# params	Delta AIC	AIC	ESW/EDR	D	D LCL	D UCL	D CV
	3	1	1	3	Data(all) OBS +MAS HN/cos(1)	11/17/	5	0.00	14031.48	54.5	5.953	5.649	6.273	0.027
	2	1	1	2	Data(all) OBS +MAS HN	11/17/	4	27.63	14059.11	56.7	5.506	5.222	5.806	0.027
	1	1	1	1	Data(all) OBS HN	11/17/	3	127.13	14158.61	58.6	5.145	4.889	5.415	0.026
	4	1	1	4	Data(all) OBS +MAS HR/SP(0)	11/17/	5	234.98	14266.46	67.0	3.944	3.753	4.145	0.025
	5	1	2	4	Data(<82.5) OBS +MAS HR/SP(0) 1	11/17/	5	0.00	10777.72	45.5	7.144	6.778	7.529	0.027

Don't compare model AICs with different data filters.

WHEW!

This was a large dataset where very small effects can be detected.

MCDS - Exercise

Go back to Example-Line (first example) and use ClusterSize as a covariate.
Compare to the previous results.

- When cluster size is a covariate, a different fitting procedure is used and you must obtain variance estimates using the bootstrap. Be sure to check the correct boxes.
- Not much evidence of an effect of cluster size on detection (where does it show this?)
- Look at detection function by cluster size – is this sensible?
- Small glitch in reported SE for $\widehat{D}$ but it is in the output. Look carefully for it.

MCDS - Summary

Summary

- Covariates are an alternative to pre- and post-stratification.
- Covariates should be independent of distance.
- Covariate can be factor (categorical) or continuous.
- Covariates work on Detection function only and typically modify the *scale* parameters.
- Start simple and work to more complex models, esp. with series adjustments for key functions.