19th Biennial Conference on the Biology of Marine Mammals

Workshop: New developments in cetacean survey methods

Sunday November 27th 2011

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New developments in cetacean survey methods
Room #14 Tampa Convention Center
Sunday Nov 27, 1pm-5pm

Schedule

12:45-1:00	Register (i.e. sign attendance sheet)
1:00-1:05	Welcome.
1:05-1:35	Passive Acoustic Density Estimation. Presented by Len Thomas, University of St Andrews
1:35-2:05	Dealing with g(0)<1: Perception Bias. Presented by Steve Buckland, University of St Andrews
2:05-2:35	Dealing with g(0)<1: Availability Bias Presented by Hans Skaug, University of Bergen
2:35-3:00	Questions & Discussion
3:00-3:30	Coffee Break
3:30-4:00	Dealing with Measurement Error Presented by David Borchers, University of St Andrews
4:00-4:30	Density Surface Modelling Presented by Jay Barlow, Southwest Fisheries Science Center
4:30-5:00	Questions, Discussion & Wrap-up

Workshop: New Developments in Cetacean Survey Methods

Passive Acoustic Density Estimation

Len Thomas and Tiago Marques
University of St Andrews

27th November 2011 – SMM Biennial Conference, Tampa

Goals of talk

- Briefly review the issues involved in estimating cetacean density from passive acoustics
- Give an overview of methods for analysis + roadmap
- Motivate the other talks
- Note:
  - Focus is on fixed sensors
  - We'll assume you're familiar with standard methods: mark recapture and distance sampling
  - Examples presented are very broad-brush. Due to time constraints some important issues such as variance estimation are hardly mentioned.

Thanks to…

DECAF

2007-2011

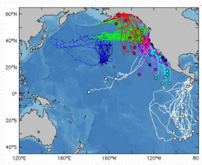
Density Estimation for Cetaceans from passive Acoustic Fixed sensors

www.creem.st-and.ac.uk/decaf/

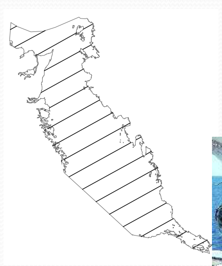
- Tiago Marques, David Borchers, Catriona Harris, Danielle Harris, David Borchers , Len Thomas (University of St Andrews)
- Dave Moretti, Jessica Ward, Nancy DiMarzio, Ron Morrissey, Susan Jarvis, Paul Baggenstoss (Navy Undersea Warfare Center)
- Steve Martin (Space and Naval Warfare Systems Command)
- Dave Mellinger, Elizabeth Küsel (Oregon State University)
- Peter Tyack (Woods Hole Oceanographic Institution)
- Steering group: Steve Buckland, Jay Barlow, Walter Zimmer.

Density estimation for cetaceans: traditional methods

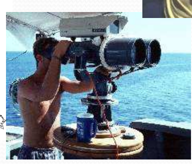
- Mark recapture
  - Photo-ID or Tagging studies
- Visual line transect surveys
  - Animal or Cue based



www.topp.org



Mick Baines



Tim Gerrodette

Rob Williams

Steve Dawson

Outstanding issues with visual surveys

- Some species do not make obvious, discrete cues
  - $g(0)<1$ even for cues (see talks by Hans Skaug and Steve Buckland)
  - detection ranges short (so very low sample sizes)
  - weather dependent
- Visual surveys can only operate in the day (in good conditions)
- Vessel-based surveys can be expensive, or impossible in some places/seasons

The potential of passive acoustics – estimating density via sounds produced

- Some species that are hard to see are very easy to hear
- Can work at night, and less weather dependent
- Sounds can be recorded onto hard drives, so may not require trained marine mammal observers on boat (but require much more processing afterwards)
- For some species, sample sizes per unit effort are much larger
- Many "platforms of opportunity" are available (i.e., hydrophones deployed for other reasons): SOSUS, CTBT, OBSs, etc.

Issues with passive acoustics

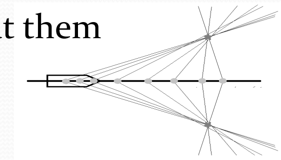
- Will only work for some species
  - Animals have to breathe but they do not have to vocalize!
    - Ecolocation clicks associated with foraging
    - Social sounds (breeding, contact, etc)
    - Potential "availibility bias" (see Hans Skaug talk)
- Post-processing recorded sounds raises issues usually ignored with visual surveys:
  - automated detection and classification systems make mistakes
  - localization measurement error (see David Borchers talk)

Issues with passive acoustics II

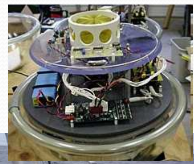
- Even with human operators, we know much less about what animals sound like than what they look like
  - So there is lots of research focus on
    - verifying sounds; associating with sightings
    - development of reliable automated detection and classification systems
- Even for species where we do know what they sound like, we may not know much about their acoustic ecology
  - What proportion of the population vocalize and when; vocalization rates; etc.
- Platform of opportunity data are (usually) not located according to a survey design involving randomization
  - Model-based methods required to extrapolate from local density to density in study area of interest – See Jay Barlow talk

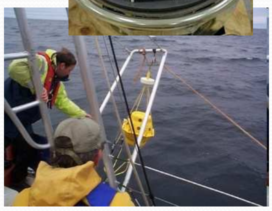
Options for density estimation depend on…

- Target species and what's known about them
- Type of acoustic system
  - Towed vs fixed (vs floating)
  - Capability of sensors:
    - frequencies sensed
    - ability to sense direction
  - Autonomous vs cabled
  - Single sensor or sparse array vs dense array (will depend on species)
- Type of acoustic environment
  - (e.g., may allow ranging)
- What auxiliary information is available



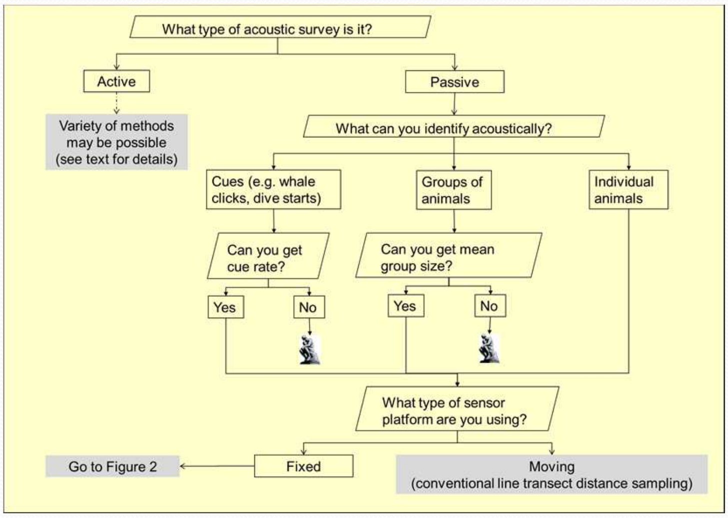
Cornell Laboratory of Ornithology





Doug Gillespie

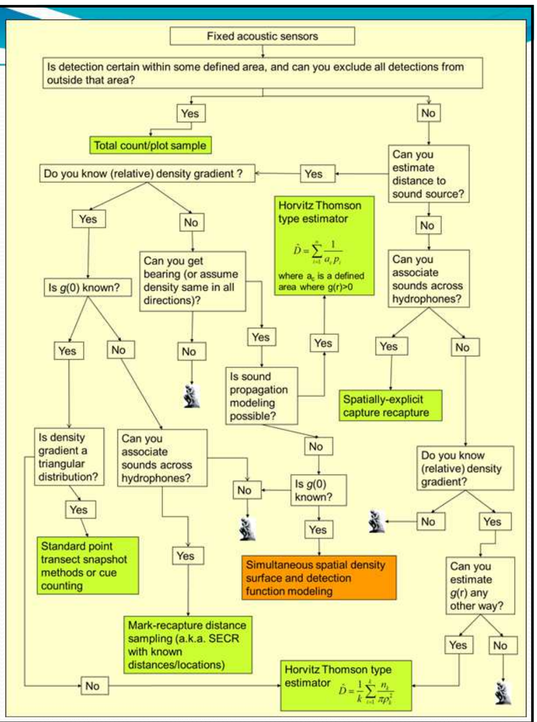
Deciding which method: Roadmap, Part 1



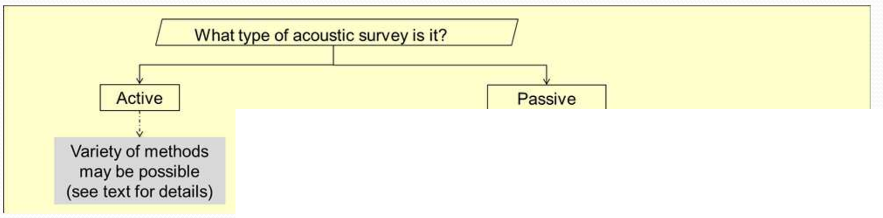
Marques et al. (in prep)

Roadmap Part 2 – Fixed acoustic sensors

(slightly out of date)

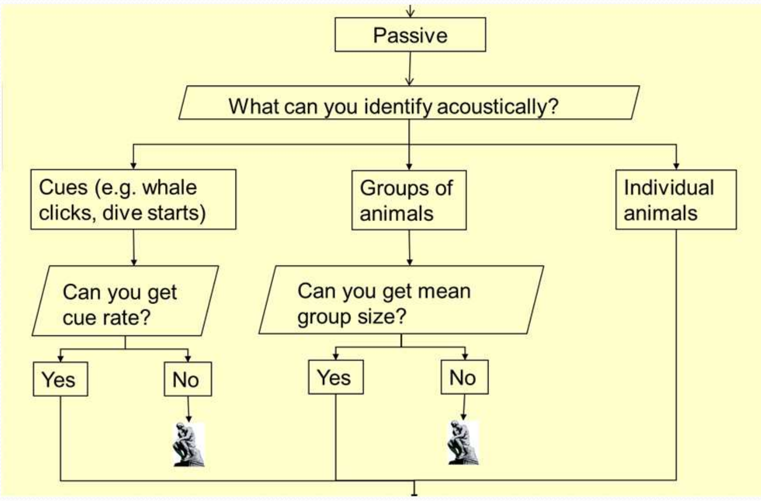


Type of acoustic survey



- Active methods allow animals to be detected when they are not vocalizing
- Ranging is often feasible
- Can use standard distance sampling methods
- But:
  - Animals may respond to the sound (assumption violation)
  - Possible welfare issues
- Active acoustics will not be our focus here

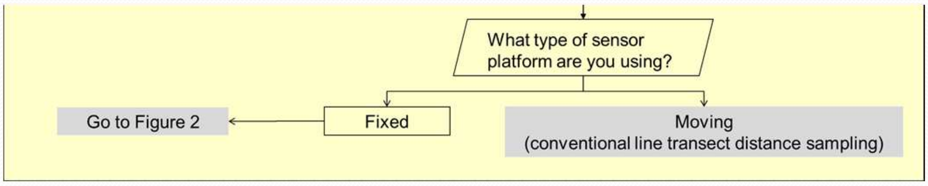
What can you count?



Counting cues, counting groups

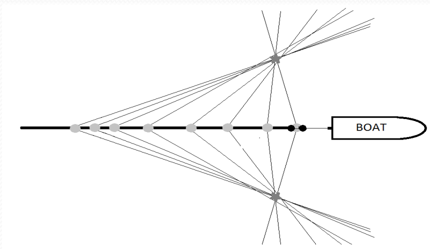
- If you can count individuals acoustically, then you can (potentially) estimate the density of individuals
- More commonly, however, one can only count groups, or cues (or it may be better to do so) – indirect methods
- Then, you can estimate the density of groups or cues.
- Need a multiplier to convert to density of individuals: group size or mean cue rate
- Need auxiliary data to get these
  - Often the Achilles heel of indirect methods
  - Better to get them from a representative sample taken at the time and place of the main survey

Type of sensor platform



Moving platforms

- I assume a multi-sensor towed (or bow mounted) array
- Obtain bearing to individuals (or groups)
- Multiple bearings give position

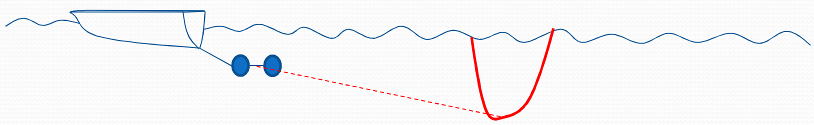


- Analogous to a standard line transect survey
- Examples: Hastie et al. 2003; Barlow and Taylor 2005; Lewis et al. 2007

Moving platforms - issues

- In some cases, count groups rather than individuals
  - Then need (somehow) to get an estimate of mean group size (e.g., visually)
- Detection not certain at zero distance
  - Can be corrected for if you know vocalisation pattern
  - Availability bias: see talk by Hans Skaug
- Inaccurate localization causes measurement error in perpendicular distances
  - Usually not a major problem
  - Methods exist for dealing with measurement error if you know the error distribution: see talk by David Borchers

Moving platforms – issues (contd.)



- Unknown depth means horizontal perpendicular distance is unknown
  - Only a problem for deep-diving species
  - Ignoring the problem tends to overestimate distances, and so underestimate density
  - Can be corrected for if you know the distribution of depths for vocalizing animals (treat like measurement error)
  - See talk by David Borchers

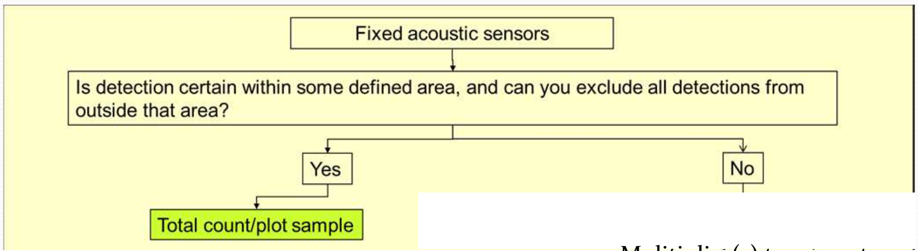
Moving platforms – issues (contd.)

- Object mis-classification
  - Treat separately for each species:
    - False positives need to be accounted for
    - Often use manual analysis of a sample of data to "ground truth" an automated detector - need to be careful with sampling design (systematic random sample is best)
    - Obtain estimate of proportion of detections that are false positives – can use as a multiplier
    - False negatives may not be a problem (if there are none on the trackline) – otherwise also need accounted for (example of perception bias – see Steve Buckland talk)
  - A more coherent approach is to deal with mis-classification for all species together (Caillat in prep PhD thesis)

Fixed sensors

- Advantages over towed systems:
  - Often cheaper to deploy (although gliders)
  - Can make use of existing systems
  - Better temporal coverage
- Disadvantages over towed systems:
  - Possibly poor spatial coverage
  - Need to account for animal movement
  - More difficult to do ranging
- (Note: floating sensors and gliders may be more like fixed sensors if they move slowly compared with animal speed)

Total count methods



Count of things detected

Area surveyed

$$\hat{D} = \frac{n}{a} \times C$$

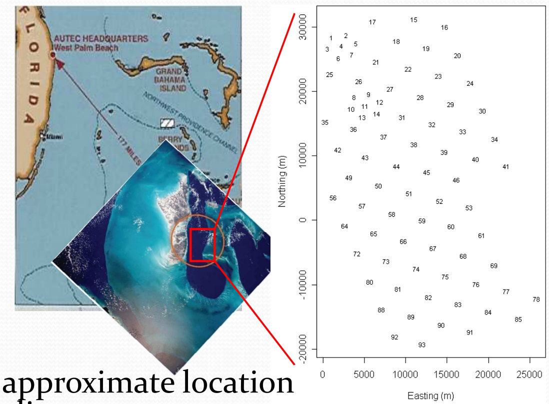
Mulitiplier(s) to convert number of things detected to number of individuals – e.g., group size, if detections are groups

- Simple, no modelling required: good if you can do it, but often not feasible (e.g., needs lots of sensors)

Example: Dive counting for beaked whales at AUTEC

Image: Diane Claridge

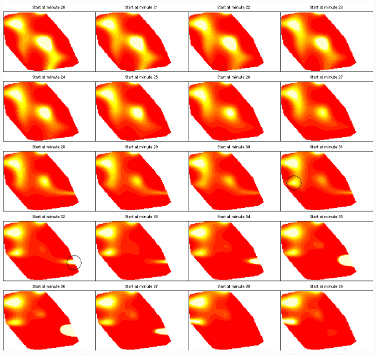
Fig. from http://seagrant.mit.edu/cfer/acoustics/exsum/jarvis/extended.html Thanks to D. Moretti.



Moretti et al. (2010)
Monitoring period:
10 days around time of a Navy exercise

- Identify time and approximate location of start of a group dive
- Assume certain detectability
- Assume can tell whether inside or out of survey area
- Assume no mis-classification

Example: Dive counting beaked whales at AUTEC range



number of dive starts

mean group size from separate visual surveys

$$\hat{D} = \frac{n}{a} \times \frac{\hat{s}}{T\hat{r}}$$

area monitored

time spent monitoring

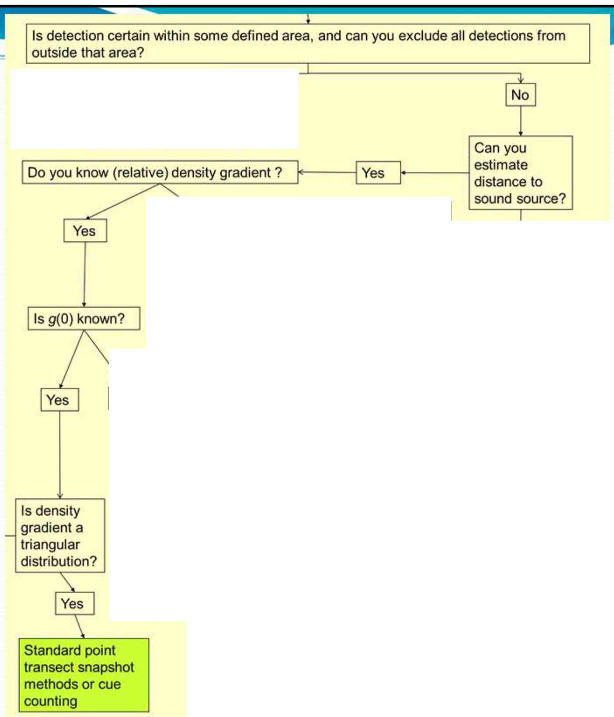
mean dive rate taken from a sample of tagged whales

- Issues:
  - *s* and *r* come from different time and small samples
  - dive counting hard to automate
  - groups diving close together

Example: Sperm whales at AUTEC

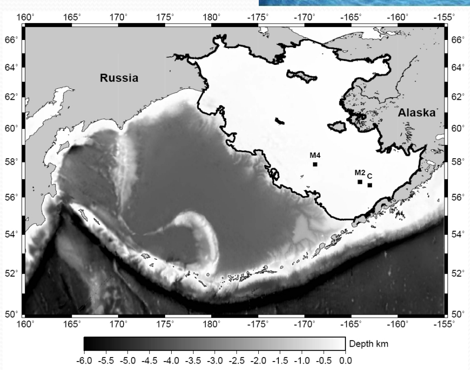
- Ward et al. (in press)
- Sophisticated acoustic processing let us count all sperm whales on the range in a sample of 50 10-minute periods
- Treat time periods as "snapshots"
- To convert to density, needed to account for availability: proportion of 10 minute periods an animal will vocalize
  - Estimated using a separate dataset of tagged animals (from same place but different time)
- Other complications – see Ward et al. paper

Distance sampling methods



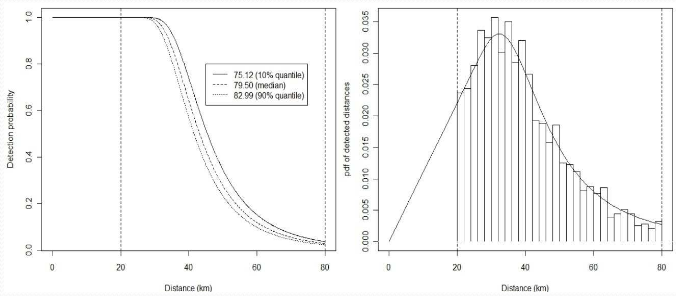
Example: North pacific right whales in the Bering sea

- Marques et al. (2011)
- Example of cue count method
- 3 autonomous sensors over May-Oct, approx. 370 days of recordings
- Data processed to obtain distances to right whale up calls
- Treated as point transect cue count – cue is up call
- Cue rate obtained from recordings of known groups



Example: North pacific right whales in the Bering sea

- Fitted detection function



- Assuming a triangular distribution of animals about the hydrophones, $\hat{p} = 0.29$ (CV 1.8%)

Example: North pacific right whales in the Bering sea

- Cue count method (with allowance for mis-classification)

number of cues (up-calls) detected

estimated proportion of false positives (from a manually processed sample)

$$\hat{D} = \frac{n}{a\hat{p}} \times \frac{(1-\hat{c})}{T_k \hat{r}}$$

area monitored $= \pi w^2$

estimated cue rate

time spent monitoring (summed over the k sensors)

estimated average detection probability of an up-call within the area monitored

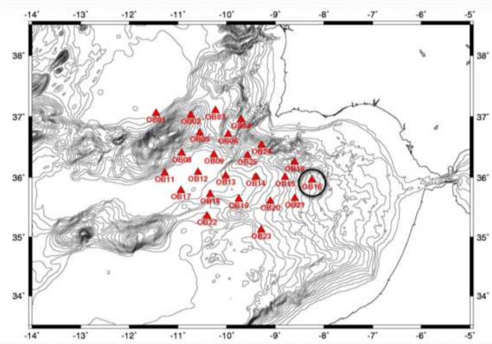
truncation distance

Example: North pacific right whales in the Bering sea

- Issues:
  - Only 3 sensors, non-randomly placed, so assumption that true distribution of call distances is triangular is tenuous
  - With only 3 sensors, variance estimation is problematic
  - Call rates used may not be representative (obtained from groups found because they were vocalizing?)
  - (For other issues, see Marques et al. 2011)

Example: Fin whales in the Gulf of Cadiz

- Harris (In prep – PhD thesis)
- Data from OBS: 24 points, each with 4 sensors – can get distances.
- Better example because there are more points! Assumption of triangular distribution of call distances is better justified.



Example: Fin whales (contd.)

- Could treat as a cue count – methods would be just the same as the right whale example
- Alternatively, if you could track individuals within range of each sensor, could use a snapshot approach
- Assuming all individuals can be tracked at zero distance, you get:

number of individuals detected

estimated proportion of false positives

$$\hat{D} = \frac{n(1-\hat{c})}{at\hat{p}}$$

area monitored $= k\pi w^2$

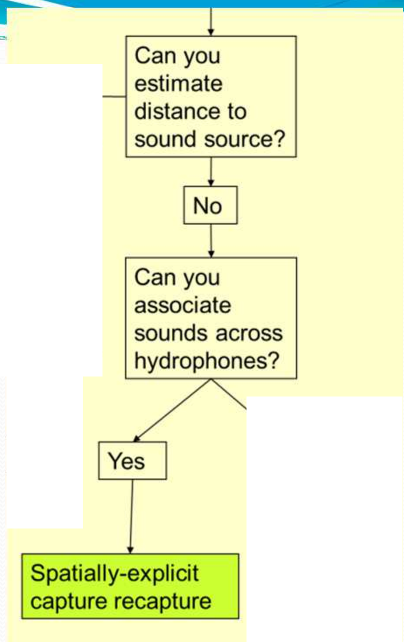
number of snapshots

estimated average detection probability of an individual at a snapshot moment (from standard detection function modelling)

Cue counting vs snapshots

- Cue counting pros
  - Easy to identify cue
  - Occurs at an instant so no need to worry about movement
- Cue counting cons
  - Need cue rate multiplier
  - Detection of cues may not be independent
- Snapshot pros
  - No need for cue rate mulitplier
- Snapshot cons
  - Need to be able to count individuals
  - What snapshot interval/spacing to use: arbitrary
  - Need to be careful with variance estimation
  - Ad hoc
- Would be better to have methods that explicitly incorporate animal movement – under development (e.g., DiTraglia 2007; Cheap DECAF project)

Density without distances: SECR



Spatially Explicit Capture Recapture

- Borchers & Efford 2008
- Borchers in press

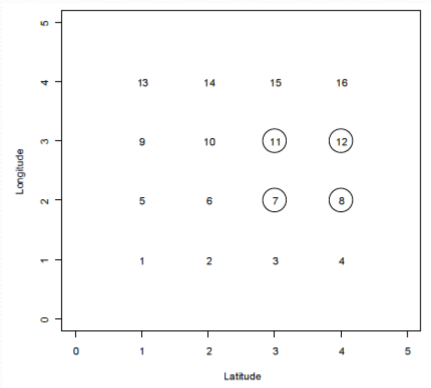
An animal's capture history tells us something

(0,0,1,1,0,1,1,0,0)

But it can tell us more, it has a spatial component usually ignored

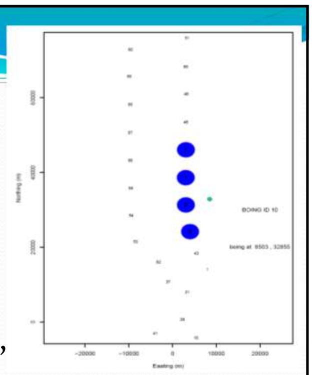
(0,0,8,12,0,11,7,0,0)

Example: Small mammal survey
16 traps, 9 capture sessions



Data give information about "home range center" - but also directly about probability of detection (detection function) and density

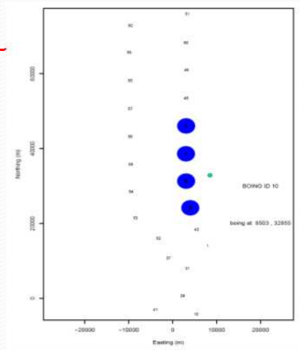
SECR for acoustic data



- You can treat a sound like an animal: it starts from a single location (the "home range center") and radiates out, being detected ("trapped") at various hydrophones ("traps") (Efford et al. 2009; Dawson and Efford 2009)
- You only need one "trapping occasion" as the same sound can be detected at multiple hydrophones

Example: Minke whales at PMRF

Image: Reefteach

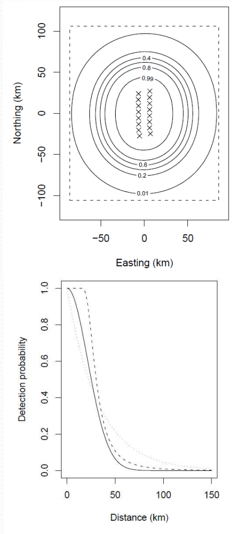


Marques et al. In press; Martin et al. In press

- We used 16 hydrophones at the Pacific Missile Range Facility (PMRF), off Kauaii, Hawaii
- Minke whale "boings" were detected, and TDOA and dominant frequency were used to associate calls across hydrophones

Example: Minke whales at PMRF

- Marques et al. (in press)
- Proof of concept analysis: six 10-minute sample periods were fit using secr package in R (and a Bayesian approach)
- Issues:
  - No accounting for islands (partially rectified in the follow-up paper)
  - Too few time periods (rectified in follow-up)
  - So far, we just assumed that animals are uniformly distributed through the area
  - No cue rate available so only obtain density of cues (preliminary estimate used in follow-up)



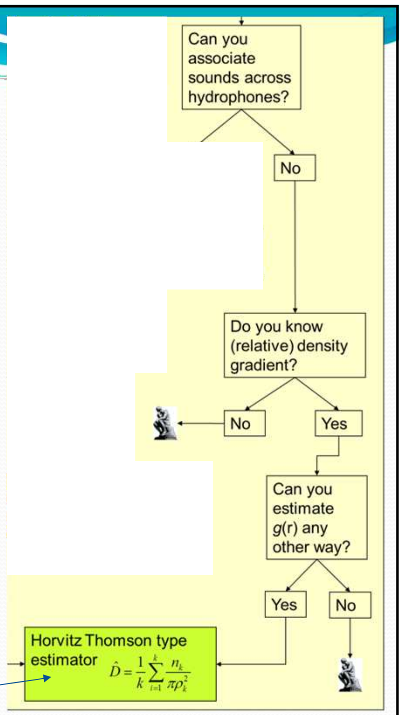
Beyond SECR

- SECR makes use of associations – can think of this as giving information about locations but with measurement error
- But in many cases you have more information about location of sound:
  - Can often localize some sounds
  - Relative received levels may contain information about relative distances.
  - Ditto for frequency components
  - Sometimes you have bearing information
- We are working on methods that use all of this information (Borchers In press; Borchers et al. In prep.)

Density without distances: det. prob. from auxiliary information

- This is a worst-case scenario, as you need to rely on auxiliary information not part of the main survey to get detection probability
- Just as with all multipliers, you need to be careful this information is applicable

See Borchers 2002



Example: Baltic harbour porpoises with auxiliary visual observations

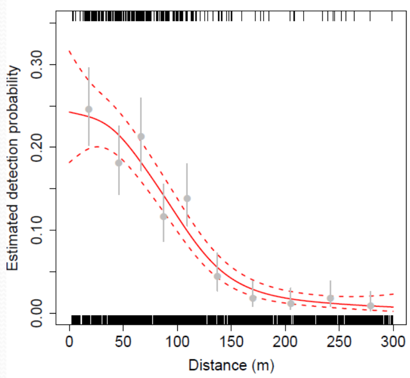
- Kyhn (2010); Kyhn et al. (In press)
- Evaluation of concept: density estimation from T-PODs
- T-PODs are porpoise detectors – record detection of porpoise clicks
- T-PODs were deployed at Fyns Hoved, Denmark close to shore, overlooked by visual observers
- Snapshot-based method: object counted is the number of 15s intervals where porpoises are detected (assumes max 1 porpoise)
- Detection probability obtained by using visual observers to set up trials

Estimator is just like the Fin whale snapshot estimator, except here the *p* will come from the visual observer trials

$$\hat{D} = \frac{n(1-\hat{c})}{at\hat{p}}$$

Example: Baltic harbour porpoises

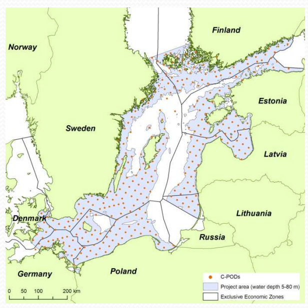
- Getting the *p*:
- Observers tracked porpoises visually. Assuming linear movement between surfacings, this gives us a patch. Can therefore estimate true position every 15 seconds.
- Model the relationship between probability of detection against distance
- Assuming triangular distribution of animals around hydrophone, can get average *p*
- This approach is called a “trapping point transect” in the terrestrial literature (Buckland et al. 2006)



Example detection function (unpublished)

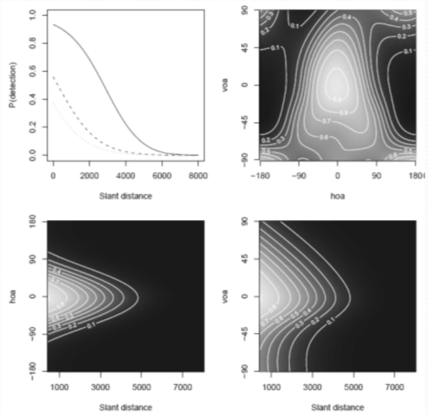
Example: Baltic harbour porpoises

- Issues:
  - Assumes max 1 animal per snapshot
  - Assumes triangular distribution of animals around the T-POD
  - In practice, we wish to apply estimates of *p* to PODs placed throughout the Baltic (SAMBAH project). But visual observations can only take place in limited places.
  - For more SAMBAH, see presentation in conference by Julia Carlström



Example: beaked whales at AUTEC with auxiliary tag data

- Marques et al. (2009) Cue-based method – object counted is beaked whale clicks over 82 hydrophones for 6 days
- Detectability estimated from separate tagging experiment to set up trials
- Detection function estimated by logistic regression – more complex than porpoise as covariates were used



Fitted detection function

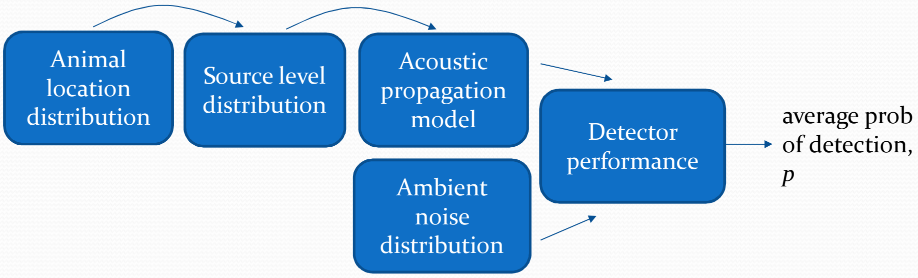
Example: beaked whales at AUTEC

$$\hat{D} = \frac{n(1-\hat{c})}{a\hat{p}Tr}$$

- Issues:
  - Tag data was not collected at the same time as the main dataset. For one thing, the weather was calmer, on average when tags deployed. See Ward et al. (2011) for more on this.
- Note:
  - False positive rate in this case study was around 50%! Doesn't matter what it is, so long as you can characterize it precisely.

Example: Beaked whales via acoustic modelling

- Kusel et al. (2011); see also Harris (In prep PhD thesis) for a blue whale example
- Here, we use assumptions about source level combined with acoustic modelling of transmission loss and detector characterization to predict the detection function, and then estimate *p*.



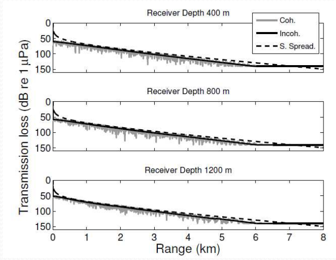
Example: Beaked whales via acoustic modelling

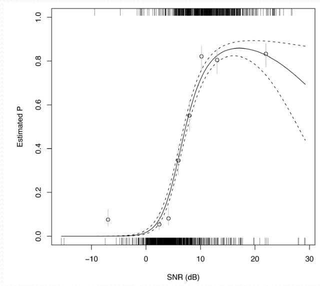
- Used 6 days of click detection data from 1 hydrophone
- Cue counting estimator, just like Marques et al. (2009) except *p* obtained from modelling rather than tag data

$$\hat{D} = \frac{n(1-\hat{c})}{a\hat{p}Tr}$$

Example: Beaked whales via acoustic modelling

- Estimating *p*:
  - Animal distribution and orientation – assumed uniform in x,y, depth from literature
  - Source level and beam pattern – from literature
  - Propagation model – Bellhop
  - Ambient noise – measured at different hydrophones from the one used to estimate density (not ideal)
  - Detector characterization – measured from small sample of marked-up data (not ideal)
  - All of these integrated in a Monte-Carlo simulation to estimate average *p*





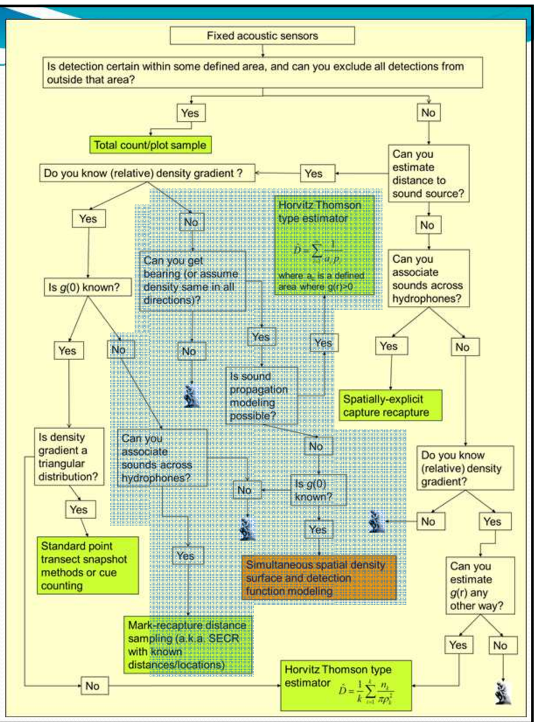
Comments on acoustic modelling approach

- Advantage (relative to other auxiliary information methods): no expensive tagging/visual observations needed
- Disadvantage: answers only as good as the modelling!
- In general, our view is this should be a last resort!

Summary – methods considered

- Towed acoustic line transects on individuals/groups
- Fixed sensors:
  - Plot sampling on cues (Beaked whale dive starts) and individuals (sperm whales)
  - Point transects on cues (right whales) and individuals via snapshot (fin whales)
  - SECR on cues (minke whales)
  - Trapping point transect on individuals via snapshot (harbour porpoise) and cues (beaked whales)
  - Cue counting with *p* estimated from acoustic modelling (beaked whales and blue whales)

Methods for fixed sensors not considered



Conclusions

- Estimation of whale density from passive acoustics is a rapidly developing and expanding field
- Which method when? – hopefully roadmap will help
- Density estimation often hampered by lack of auxiliary data, e.g., vocalization rates
  - Need more studies on basic acoustic ecology

Conclusions

- Survey design is a critical issue
  - Good spatial and temporal coverage of samplers
  - Minimize use of multipliers (e.g., use individuals rather than cues; certain detection rather than *p*)
  - Measure multipliers as part of the main survey (e.g., get distances to estimate *p*). If not possible, use a good sampling design in same time and place as survey. If not possible, do this with any component you can (e.g., detector characterization)
- Need for development of inexpensive, capable and accessible hardware
  - (e.g., buoyed sensor capable of ranging)

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For many, see http://www.creem.st-and.ac.uk/decaf/

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Dealing with $g(0)<1$: perception bias

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Dealing with $g(0)<1$: perception bias

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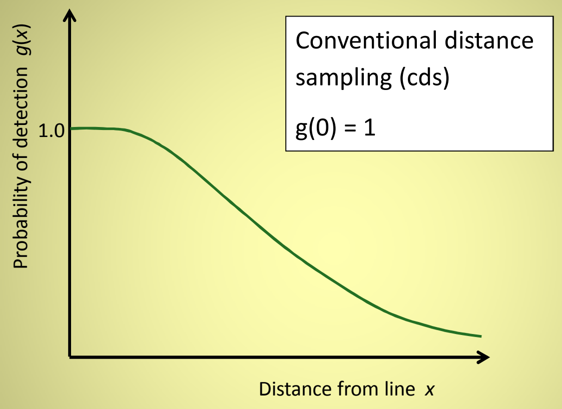
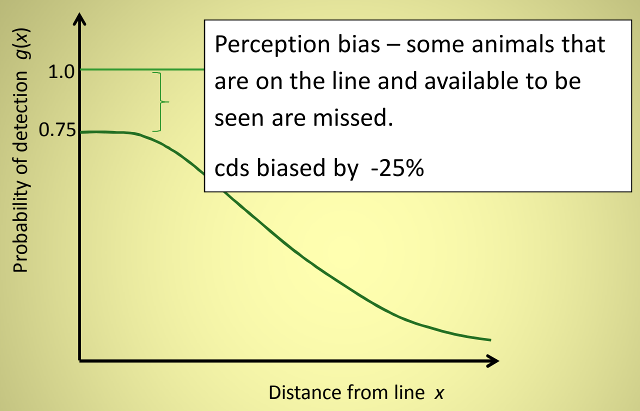
and David Borchers
Centre for Research into Ecological and Environmental Modelling,
University of St Andrews

The detection function $g(x)$



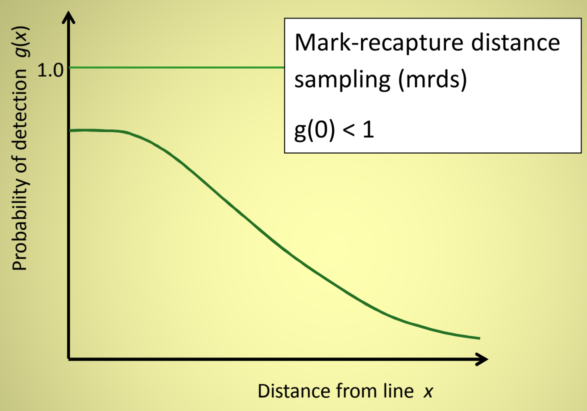
Probability of detection as a function of distance from the line

The detection function $g(x)$



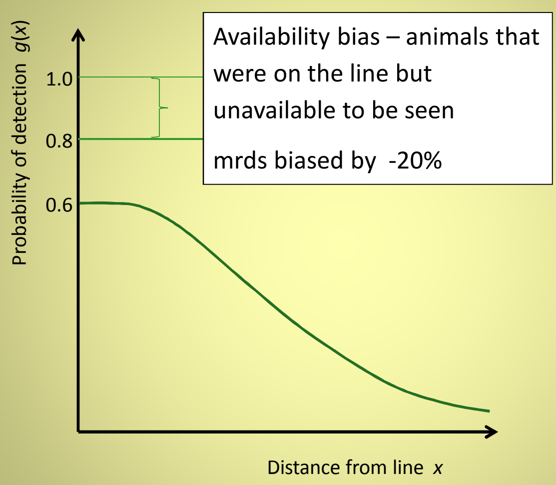
Probability of detection as a function of distance from the line

The detection function $g(x)$



Probability of detection as a function of distance from the line

The detection function $g(x)$



Probability of detection as a function of distance from the line

Are ‘independent observers’ really independent?

Suppose we have 2 observers, A and B, and 200 whales.

Suppose for each observer, 100 whales have probability of detection $p = 0.75$ and 100 have $p = 0.25$.

(We ignore for now the effect of distance from the line on probability of detection.)

If the observers are independent, then the probability that B detects a whale is unaffected by whether A detects that whale.

Are ‘independent observers’ really independent?

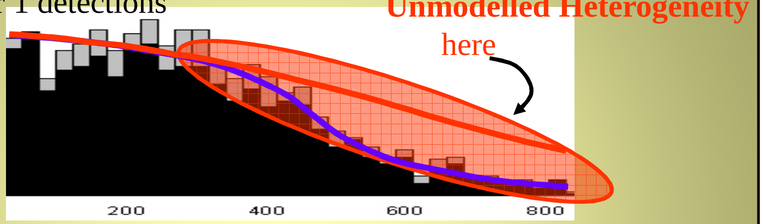
100 whales have $p = 0.75$ and 100 have $p = 0.25$.

B expects to detect 75 + 25 whales, so if we cannot identify whether a whale belongs to the first or second group, its (unconditional) prob of detection by B is 100/200 = 0.5.

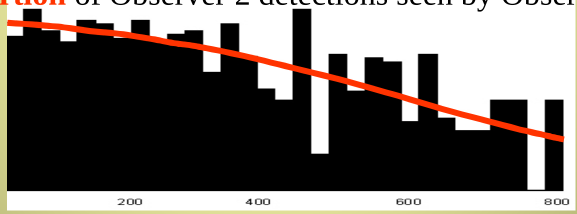
Suppose now we are told that the whale was detected by A. A expects to see 100 whales, of which 75 are of the first type. B expects to see $75\times0.75 + 25\times0.25 = 62.5$ of these, so prob of detection by B *given detection by A* = 62.5/100 = 0.625.

Example: pack-ice seals

Observer 1 detections



Proportion of Observer 2 detections seen by Observer 1



Are 'independent observers' really independent?

Conclusion:

Even if two observers operate entirely independently, *we cannot assume* that whether one observer detects a whale is independent of whether the other observer detects it.

However, if for each whale detected, we were able to identify the group to which it belonged, we could analyse the whales as two groups, and then we *could* assume independence of the two observers.

Are ‘independent observers’ really independent?

Generalizing, if we can record covariates that fully explain the variability in detectability among whales, and incorporate those covariates in our detection function, we can assume that the observers are independent and we can use a **full independence** model.

In reality, we will be unable to record all relevant covariates, and our detection function model will be imperfect. In this circumstance, including covariates in our model will reduce the dependence between observers, but not eliminate it.

How does distance from the line affect the independence assumption?

Far from the line, many animals have very low probability of detection, while a few (e.g. those in large groups, active at the surface, in sea state 0) may be easily detected.

Close to the line, the heterogeneity in the detection probabilities will tend to be much smaller (e.g. seals in pack-ice), and hence the conditional probability that one observer detects a whale given that the other does will be much closer to the unconditional probability.

Point independence exploits this by assuming that independence between observers operates only on the line.

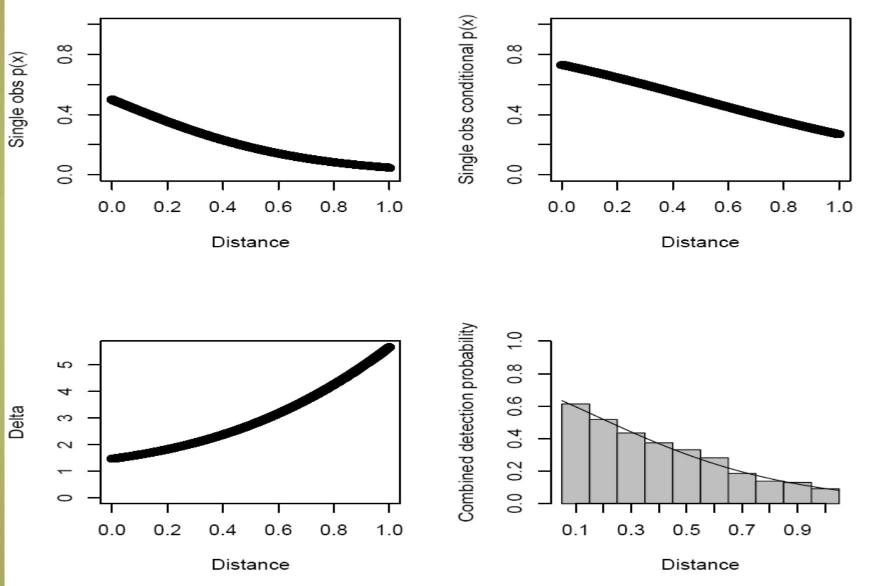
How does distance from the line affect the independence assumption?

In reality, some degree of dependence is still likely to occur even on the line, especially when mean probability of detection on the line is appreciably less than one.

If we consider the limit as probability of detection tends to one, then independence must apply, as there will no longer be any heterogeneity in the detection probabilities.

This is the idea underlying **limiting independence**.

Simulated example



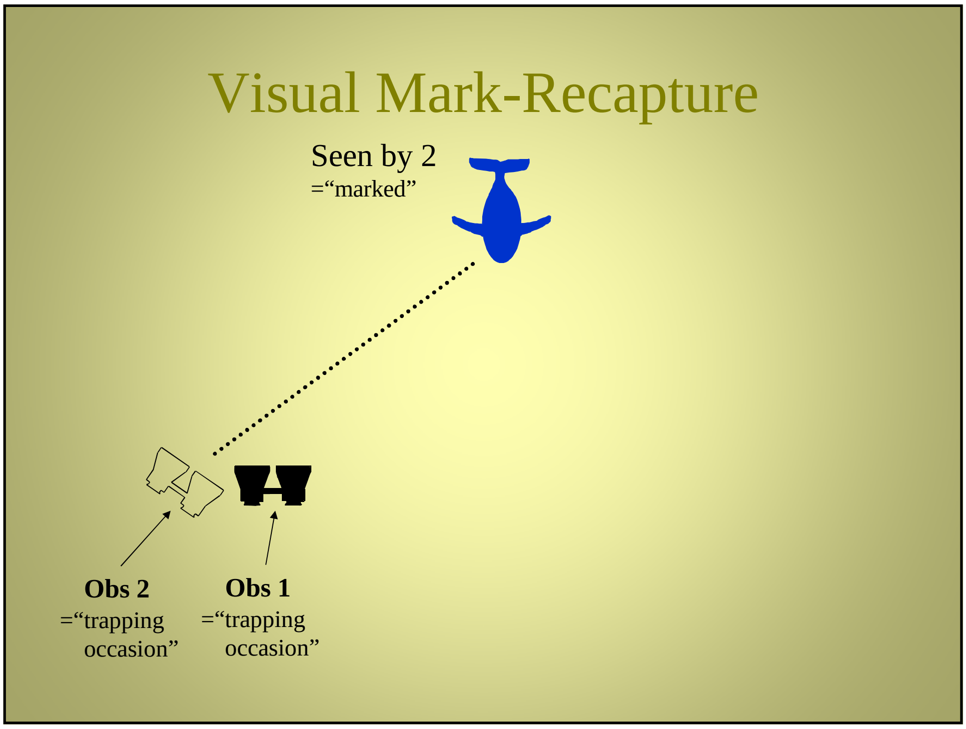
Model selection

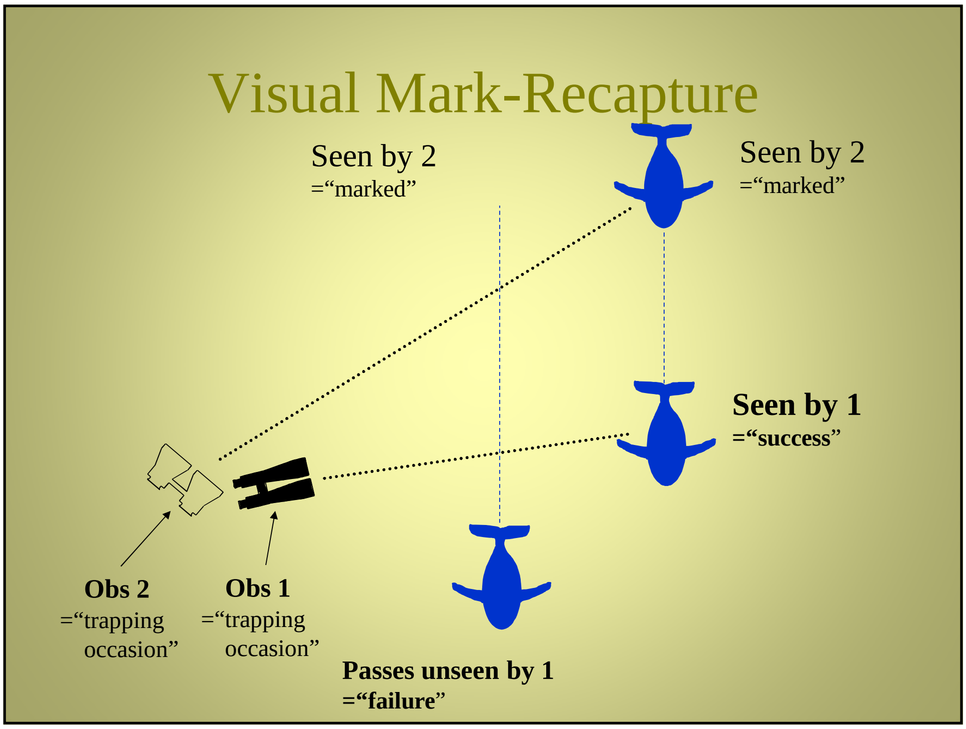
- Point independence and full independence models are special cases of a general limiting independence model
- So we can use e.g. AIC to decide whether a point independence or a full independence model is adequate given our data

Estimation

For single-observer line transect surveys, there is no information in the data to allow estimation of $g(0)$, the probability of detection of an animal that is on the line.

For double-observer surveys, we can add a mark-recapture component to the likelihood, allowing the development of models under any of the three assumptions of full independence, point independence or limiting independence.


Visual Mark-Recapture
Seen by 2
="marked"
Obs 2
="trapping occasion"
Obs 1
="trapping occasion"


Visual Mark-Recapture
Seen by 2
="marked"
Seen by 2
="marked"
Seen by 1
="success"
Obs 2
="trapping occasion"
Obs 1
="trapping occasion"
Passes unseen by 1
="failure"

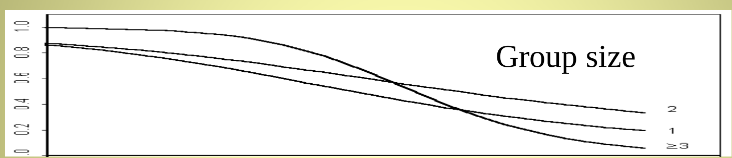
Estimation

By adding a mark-recapture component to the likelihood, we lose the ‘pooling robust’ property of line transect estimators, and so it becomes important to model heterogeneity through covariates.

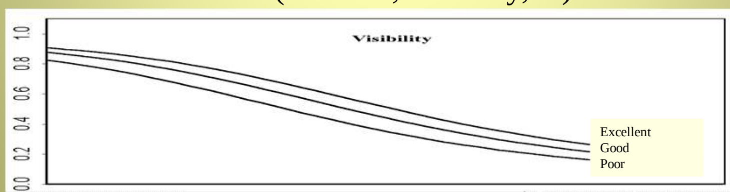
What sources of heterogeneity should be measured?

Sources of Heterogeneity

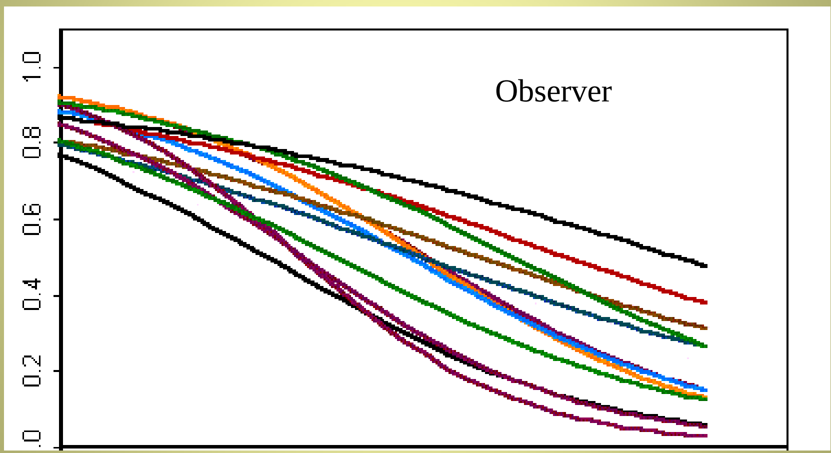
- The **animals** themselves (distance, size, behavior, ...)



- The **environment** (sea state, visibility, ...)



- The kind of **survey effort** (the observers, their platforms, ...)



Configuration: Trial-Observer

Observer 2

sets up trials for

Observer 1

to estimate p_1

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

Configuration: Independent Observer

to estimate p_2

Observer 2

sets up trials for

Observer 1

to estimate p_1

$$\boxed{p_{\cdot} = p_1 + p_2 - (p_1 p_2)}$$

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

Abundance Estimation

- Trial-Observer

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

(note)

- Independent Observer

$$\hat{N} = \sum_{\text{all } i \text{ seen}} \frac{1}{\hat{p}_{\bullet}(x_i, \cdots)}$$

(note)

Duplicate Identification

Field methods

- Use a dedicated “duplicate identifier”
- Record measure of confidence in duplicate identification.
- Record positions and times as precisely as possible
- Record ancillary data
- Have at least one observer “track” animals

Duplicate Identification

Analysis methods

- Bracket "best" estimate by two extremes
- Rule-based duplicate identification after the survey. (e.g. Schweder et al., 1996)
- Probabilitistic duplicate identification after the survey. (e.g. Hiby & Lovell, 1998)

Schweder, T., Hagen, G., Helgeland, J. and Koppervik, I. 1996. Abundance estimation of northeastern Atlantic minke whales. *Rep. Int. Whal. Commn.* **46**: 391-405.

Hiby, A. and Lovell, P.1998. Using aircraft in tandem formation to estimate abundance of harbour porpoise. *Biometrics* **54**: 1280-1289.

Estimation with incomplete detection at distance zero

"g(0)<1"

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Dealing with g(0)<1
Availability bias

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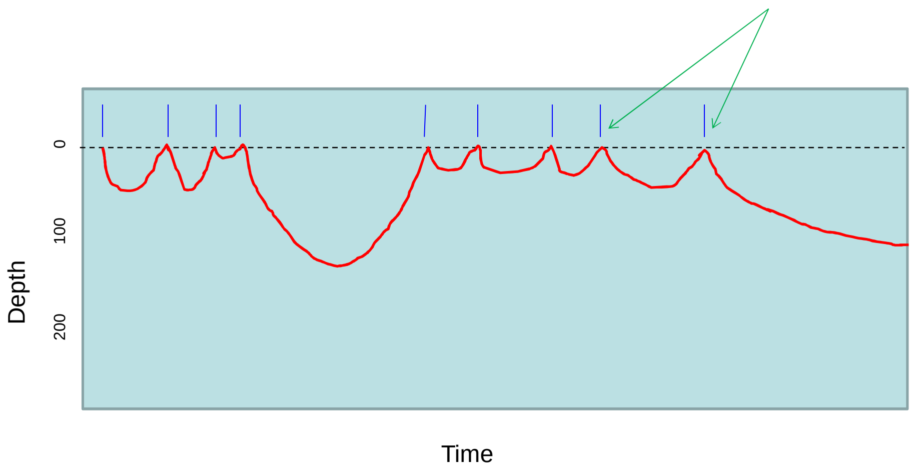
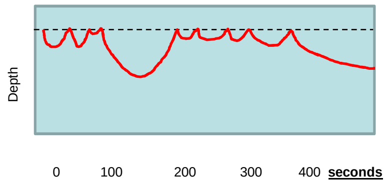
Availabilty bias: diving whales

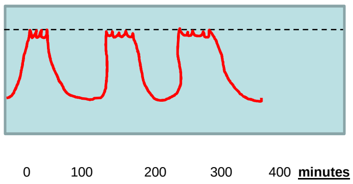
- Whales can only be detected at surface



Long versus short diving whales



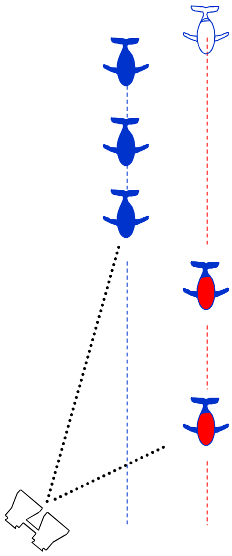
Minke whale dive pattern
- Multiple cues made within detectable range of observer (< 1000m)
- Topic of this lecture



Sperm whale dive pattern.
- Long (deep) dives during which the observer can pass the whale
- See Okamura et al. (2011)

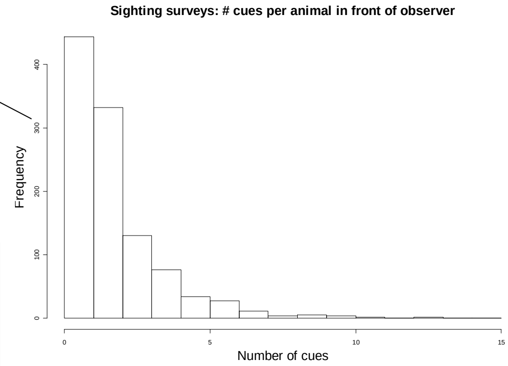
Availability bias caused by diving

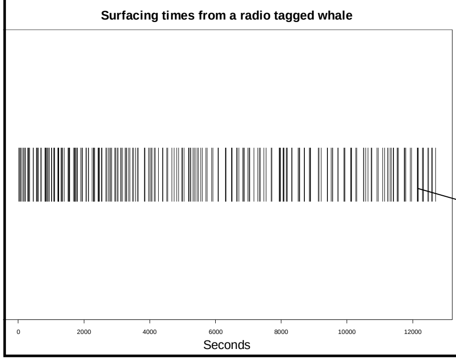
- Whales on the trackline may be diving when passed by the observer
  - ➢ g(0) < 1
- Diving pattern in front of observer determines the probablity of detection
  - – Diving pattern = heterogenity factor
  - – At ”animal” level
- Diving pattern only **partly** observed
  - – ”Diving pattern” is not simple covariate
  - – Difficult to account for in standard statistical analysis
  - – Mathematical model: Poisson process



Minke whale diving behaviour

Internal data
Number of times the observer saw the whale at surface
- Selection bias

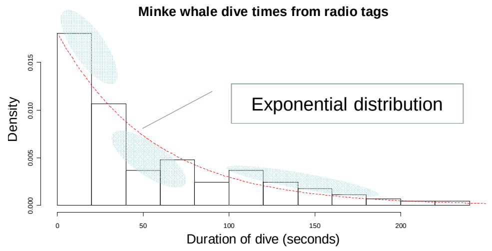




External data
Time points when the whale was at surface from radio-tagging a minke whale
- Small number of animals

Poisson process model

- **Assumption**: dive times follow Poisson process with intensity α surfacings/second
  1. Individual dives exponentially distributed
  2. Dive times are serially independent (no correlation)
- Not a perfect dive time model for minke whales

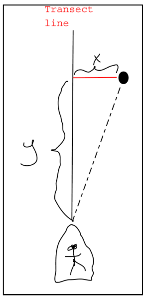


Serial correlation in minke whale dive times (radio tags):

r = -0.32

Hazard models for the detection function

- If you accept that dive times follow a Poisson process you have to (mathematically) accept the hazard model for the detection function



$x = \text{Perpendicular distance}$

$g(x) = \Pr(\text{detect animal at distance x})$

Surfacing rate

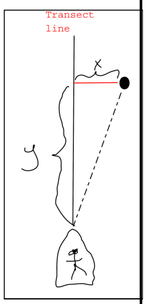
Forward distance

$$\mathrm{g(x)} = 1 - \exp\left(-\frac{\alpha}{v}\int_0^{\infty} h(x,y)dy\right)$$

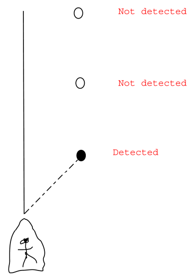
Observer speed

Hazard probability function

Hazard probability: h(x,y)



- Probability of detecting individual cue/surfacing = h(x,y)



- Multiple opportunities for detecting the whale
  - g(x) is the ”total probability” of detecting the whale

Independent observers and discrete availablity

Not full independence:

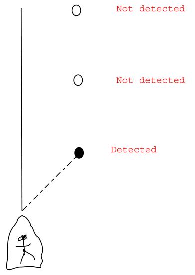
$g_{AB}(x) \neq g_A(x)\, g_B(x)$

- Two independent observers: A and B
- Positive "dependene" between A and B

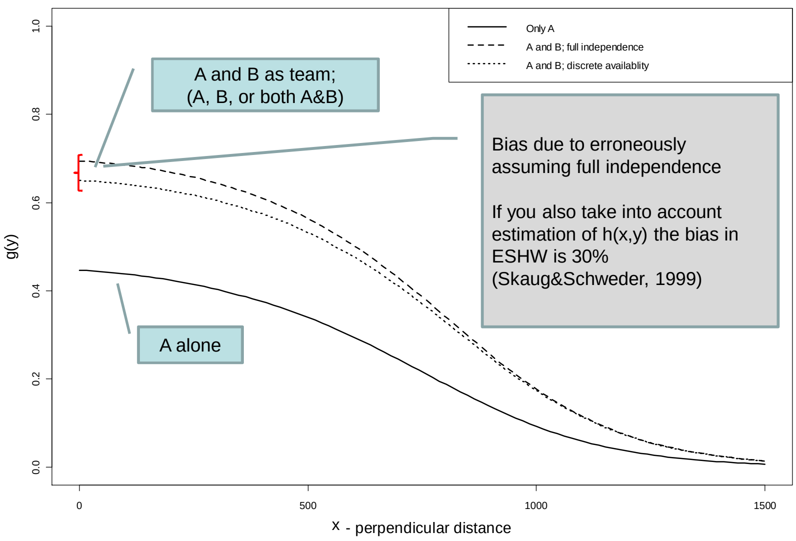
$$g_{AB}(x) > g_A(x)\, g_B(x)$$

  - B-detects → increased probability of A-detects.
- What does «independent observer» mean?
  - No physical communication
  - Independence at cue/surfacing level

$$h_{AB}(x,y) = h_A(x,y)\, h_B(x,y)$$



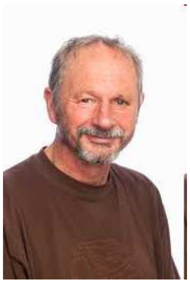
Full independence versus discrete availablity



Ending remarks, future development

- Not integrated into standard software packages (Distance)
  - Limits the use of the approach
- To which extent can point independence account for discrete availablity?
- Robustness of the hazard probability model wrt. choice of parametric form of h(x,y) has been studied (Kleppe et al, 2010)

References



Tore Schweder

- Father of the hazard probability model:

- Buckland, S. T., Anderson, D. R., Burnham, K. P., Laake, J. L., Borchers, D. L., and Thomas, L. (**2004**). *Advanced Distance Sampling* ({Oxford: Oxford University Press}).
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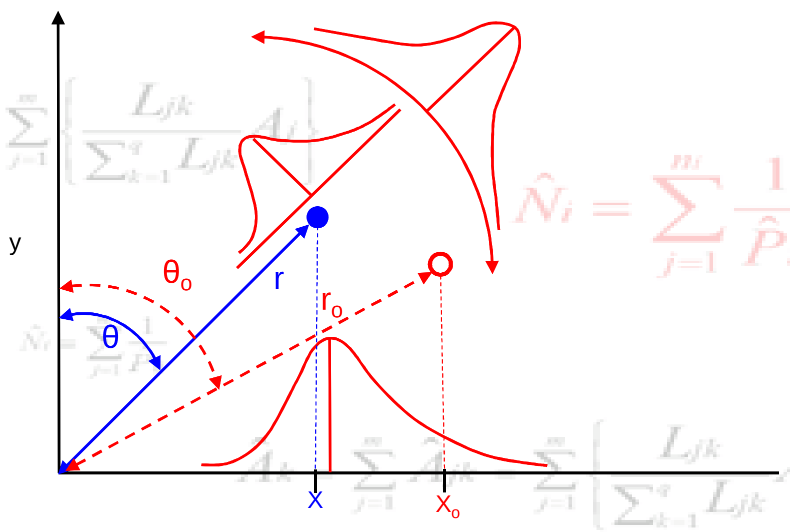
New Developments in Cetacean Survey Methods

Dealing with Measurement Error

David Borchers & Tiago Marques

University of St Andrews

Measurement Errors



The Problem

1. Rounding to favored values ➡ Biased Estimates
   – (Also called “heaping”)
   – Rounding to zero most serious
   – Can be dealt with by grouping
   – (Smearing: ad-hoc; introduces dependence)
2. Biased measurement ➡ Biased Estimates
   – Regression correction method: correct distances before fitting; neglects variance
3. Random measurement errors ➡ Biased Estimates
   – Worse for point transects than line transects
   – ➡ Negatively Biased variance and CI estimates

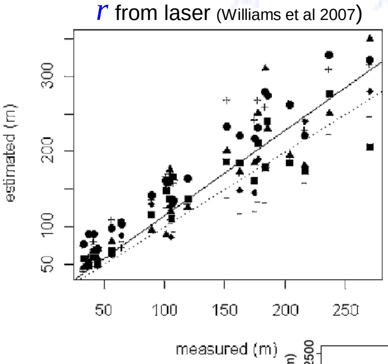
Some History

1. Regression bias correction methods (various authors)
2. Smearing (developed for rounding errors)
   – Butterworth (1982): ad-hoc method; Buckland & Anganuzzi (1988) improved
3. Hiby et al. (1989): MLE for cue-counting with grouped distance data, allowing g(0)<1
4. Alpizar-Jara (1997), Chen (1998), Chen & Cowling (2001)[1]: Line Transect with additive distance errors
5. Marques (2004): Line Transect with multiplicative distance errors
6. Borchers et al. (2009, 2010a) Line & Point Transect with any kind of errors
7. Schweder et al (1999) Method of simulated likelihood for errors with instantaneous hazard & Poisson availability

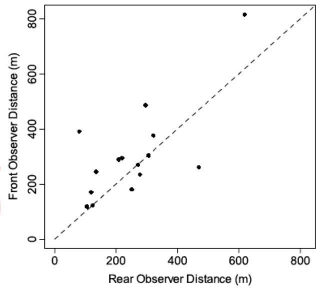
1: Incorporated errors in group size estimation too

Data on Measurement Error

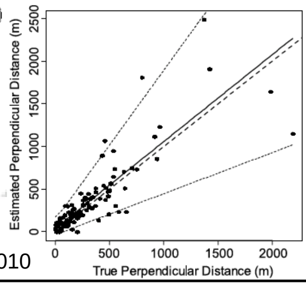
r from laser (Williams et al 2007)



r from duplicates
(Borchers et al 2010)

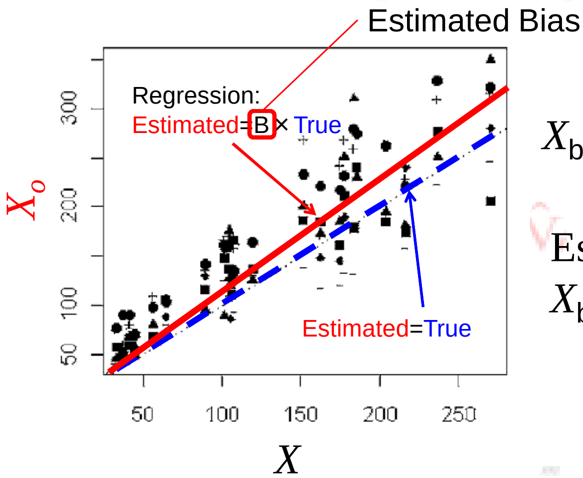


X from photos[1]
(Borchers et al 2010)



1: Method of Leaper et al. 2010

Regression Bias Correction Method(s)



$X_{\text{bias corrected}} = X_o \div B$

Estimate using $X_{\text{bias corrected}}$.

(Neglects uncertainty in $X_{\text{bias corrected}}$)

Correction Factor Methods

- Line Transects (Marques, 2004)
  - Density estimator: $\hat{D} = \dfrac{n \times \hat{f}(x=0)}{2WL}$
  - Multiplicative error: $x_o = x\varepsilon$

Fitted to observed distances (with measurement error)

$$\hat{D} = \frac{n \times \boxed{\hat{f}(x_0 = 0)}}{2WL} \boxed{\div \hat{E}\left[\frac{1}{\varepsilon}\right]}$$

Estimated from pairs of true and measured distances

- Variance & CI
  - Bootstrap for correction factor
  - Delta method

Correction Factor Methods

- Point Transects (Borchers et al., 2010)
  - Density estimator: $\hat{D} = \dfrac{n \times \hat{h}(r=0)}{\pi K}$
  - Multiplicative error: $r_o = r\varepsilon$

Fitted to observed distances (with measurement error)

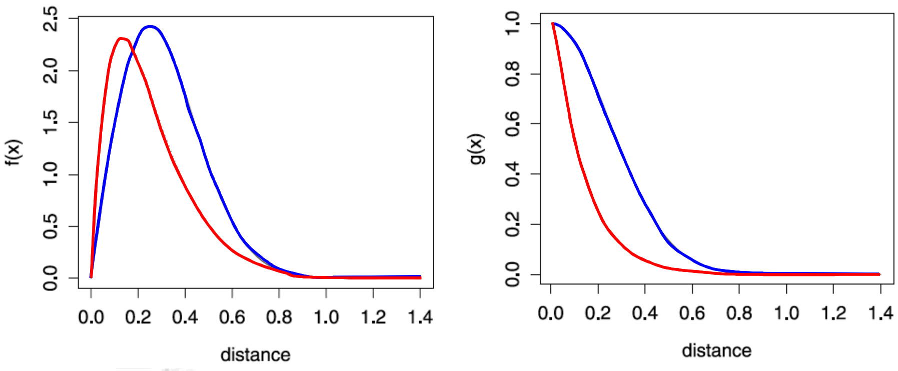
$$\hat{D} = \frac{n \times \boxed{\hat{h}(r_0 = 0)}}{\pi K} \boxed{\div \hat{E}\left[\frac{1}{\varepsilon^2}\right]}$$

Estimated from pairs of true and measured distances

- Variance & CI:
  - Bootstrap

4

Potential problem with Correction Factor Methods



May choose wrong model by fitting to observed distances (those with measurement error)

More General (but less convenient) Method

- Conventional Distance Sampling (CDS) likelihood:

$$L(\phi) = \prod_{i=1}^{n} f(x_i;\phi)$$ … for Line Transects (same for point but r instead of x)

- Likelihood with Measurement Error:

$$L(\phi \mid \beta) = \prod_{i=1}^{n} \int_{0}^{\infty} f(x;\phi) \times \boxed{\delta(x_{O,i} \mid x;\beta)}\, dx$$

Unobserved True distance

Measurement Error Model

Measured distance

- Likelihood with Measurement Error and Experiment Data:

$$L(\phi,\beta) = L(\phi \mid \beta) \times \boxed{\prod_{i=1}^{m} f(x_{O,i} \mid x_i;\beta)}$$

Experiment data Regression Model

- Variance & CI: bootstrap

Estimator %Bias (small sample: LT n=60; PT n=80)

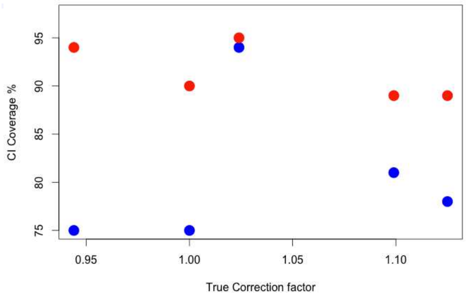
det. fun.	Error Model	Line transect CDS	Line transect E_{CDS}	Line transect Corr	Line transect Err	Point transect CDS	Point transect E_{CDS}	Point transect Corr	Point transect Err
1 ½norm narrow	$E_{1.0}CV_{10}$	2	1	1	2	0	3	−3	3
	$E_{1.0}CV_{30}$	8	10	−2	0	19	34	−11	2
	$E_{1.0}CV_{50}$	23	33	−8	1	72	167	−35	0
2 ½norm wide									
3 hazard rate									

Estimator %Bias (large sample: n=300)

det. fun.	Error Model	Line transect CDS	Line transect E_{CDS}	Line transect Corr	Line transect Err	Point transect CDS	Point transect E_{CDS}	Point transect Corr	Point transect Err
1	$E_{1.0}CV_{10}$	−1	1	−2	0	0	3	−3	1
	$E_{1.0}CV_{30}$	5	10	−5	1	17	34	−13	1
	$E_{1.0}CV_{50}$	16	33	−13	0	73	167	−35	0
	$E_{0.8}CV_{30}$	32	37	−4	0	82	109	−13	1
	$E_{1.2}CV_{30}$	−12	−8	−4	1	−19	−7	−13	0
2	$E_{1.0}CV_{10}$	−1	1	−2	0	0	3	−3	1
	$E_{1.0}CV_{30}$	6	10	−4	0	20	34	−11	1
	$E_{1.0}CV_{50}$	18	33	−12	0	76	167	−34	0
	$E_{0.8}CV_{30}$	32	37	−4	0	84	109	−12	0
	$E_{1.2}CV_{30}$	−13	−8	−5	0	−19	−7	−13	1
3	$E_{1.0}CV_{10}$	6	1	5	0	3	3	0	−1
	$E_{1.0}CV_{30}$	10	10	0	0	18	34	−12	0
	$E_{1.0}CV_{50}$	22	33	−9	−1	68	167	−37	−2
	$E_{0.8}CV_{30}$	37	37	0	−1	86	109	−11	−1
	$E_{1.2}CV_{30}$	−9	−8	0	0	−17	−7	−10	0

Variance and CI Coverage

- Correction factor CI:
  - (Marques, 2004, Table 1)
  - Blue=CDS; Red=Corrected



- MLE CVs (Borchers et al. 2008)
  - Cue-counting survey:
    - Point estimate: MLE 9% lower than CDS
    - **MLE CI width: 58% wider than CDS**
  - Line Transect survey:
    - Point estimate: MLE 9% lower than CDS
    - **MLE CI width: MLE 19% wider than CDS**

What about when g(0)<1?

- Have duplicates, so don't have to have experimental (true, estimated) data (although it helps): duplicates allow estimation of error process (with assumption of common process)
- Hiby et al. (1989): cue-counting with grouped distances
- Schweder et al. (1999): Method of Simulated Likelihood. Uses 2-D detection hazard and Poisson availability
- Royle & Dorazio (2008) and Borchers (2010) outline Bayesian & Max Likelihood approaches based on Spatially Explicit Capture-Recapture (SECR) methods (but don't do any actual implementation)

Preliminary Results using SECR MLE Method

(If available in time, some Line Transect Simulation Results to go here)

Preliminary Results using SECR MLE Method

(If available in time, some Point Transect Simulation Results to go here)

Summary

- Systematic errors (measurement bias) always a problem.
- Random errors add variance but little bias with CDS[1] if
  - Error CV < about 30% for Line Transects
  - Error CV < about 10% for Point Transects (& Cue-counting)
- Correction factor method easy (can use Distance) but occasionally does not work well (esp. Point Transects)
  - Only applies with multiplicative error models
- Full likelihood method works well (but no general user-friendly software available)
  - Applies with any error model
- SECR Method under development
- Should incorporate uncertainty associated with measurement error.

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Habitat-based Models of Cetacean Density in the eastern Pacific

Jay Barlow, Elizabeth A. Becker,
Jessica V. Redfern, and Karin A. Forney
NOAA Southwest Fisheries Science Center

WHY IS CETACEAN DENSITY IMPORTANT?

Density = # animals per km^2

Abundance = Density * Area

- Plan potentially harmful human activities to avoid areas of high cetacean density

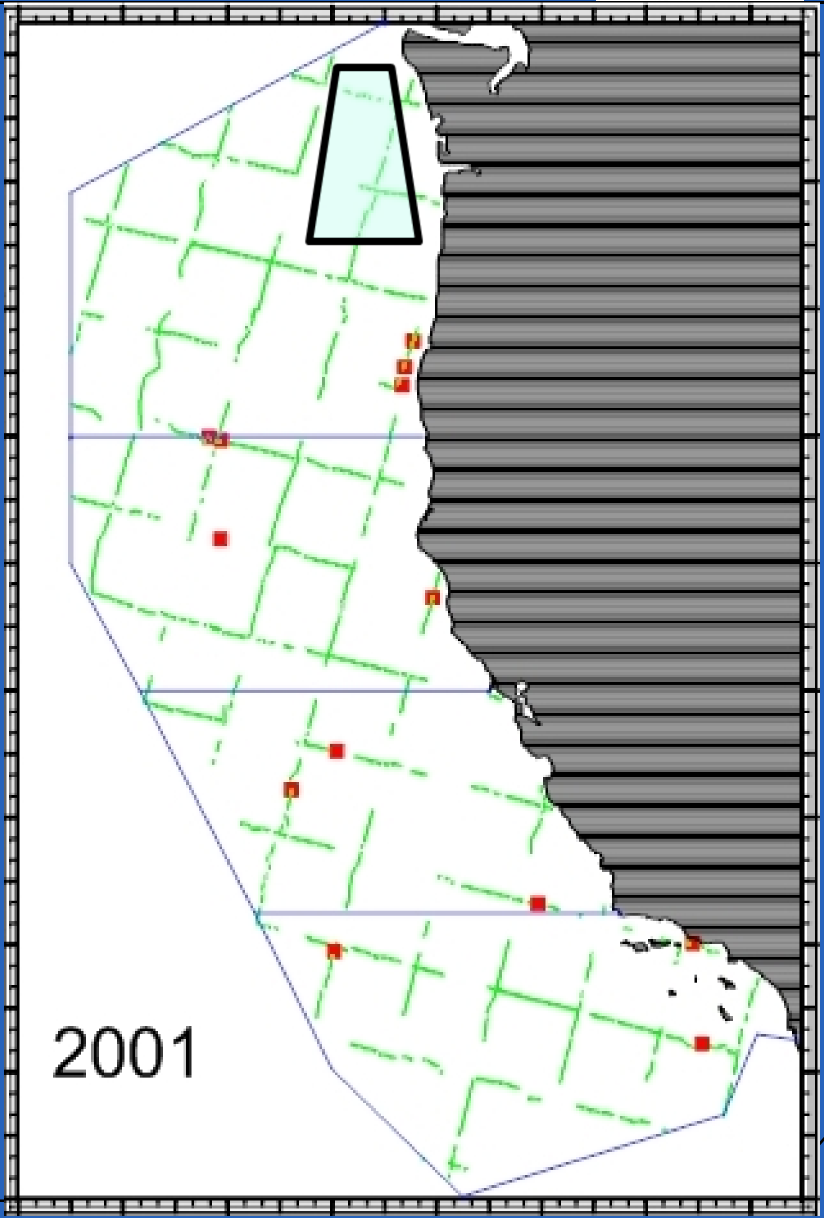
- Estimate the number of animals potentially affected by human activities

SURVEY EFFORT AND BLUE WHALE SIGHTINGS: 2001

Why model density?

Data are sufficient only to estimate density w/in the entire study area

But what is the density in the area of interest?



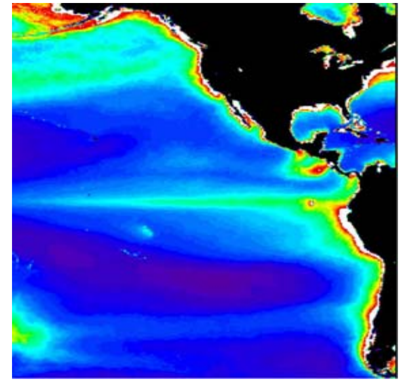
OBJECTIVES

Develop methods to model and predict cetacean density based on environmental variables.

Make resulting models readily available to the public.

SERDP Strategic Environmental Research and Development Program

TECHNICAL APPROACH



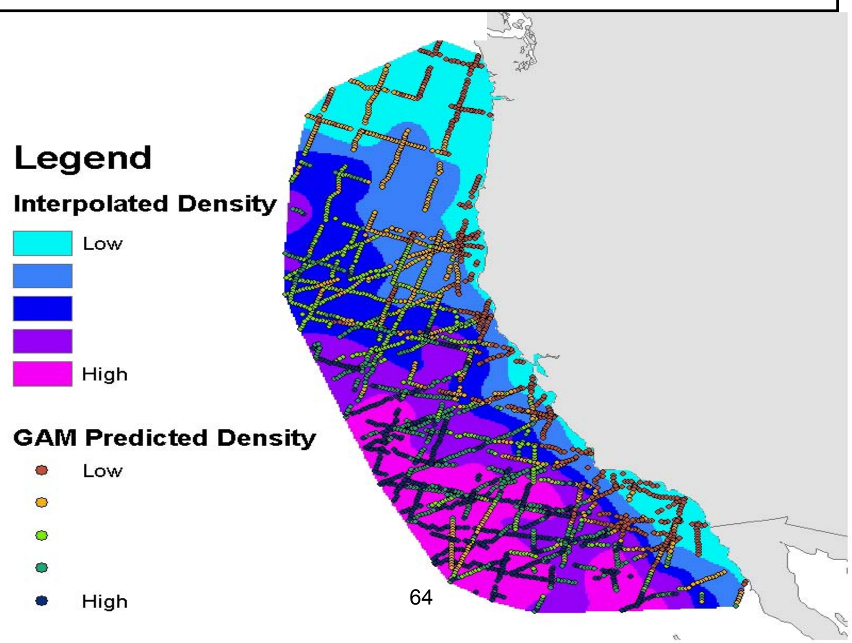
Cetacean Survey Data

Habitat Data

Mathematical Models of Cetacean Density

Cetacean Survey Data 1986-2006:

- Ship and aerial surveys *Southwest Fisheries Science Center*



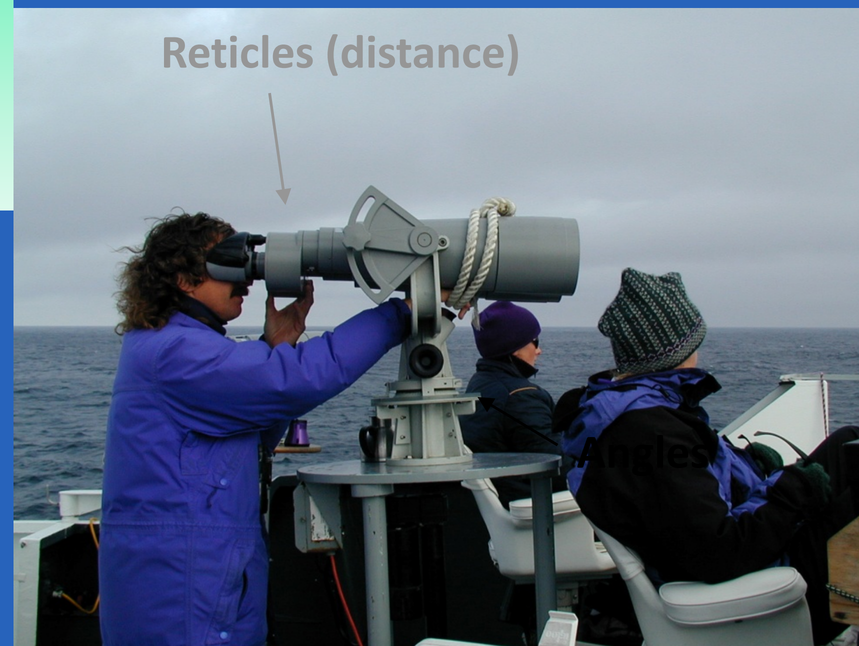
Habitat Data 1986-2006:

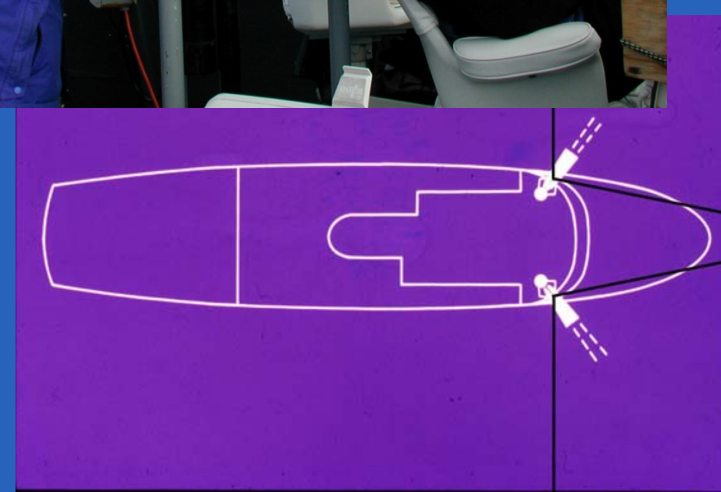
- Oceanographic data from *Southwest Fisheries Science Center* surveys
- Remotely sensed data

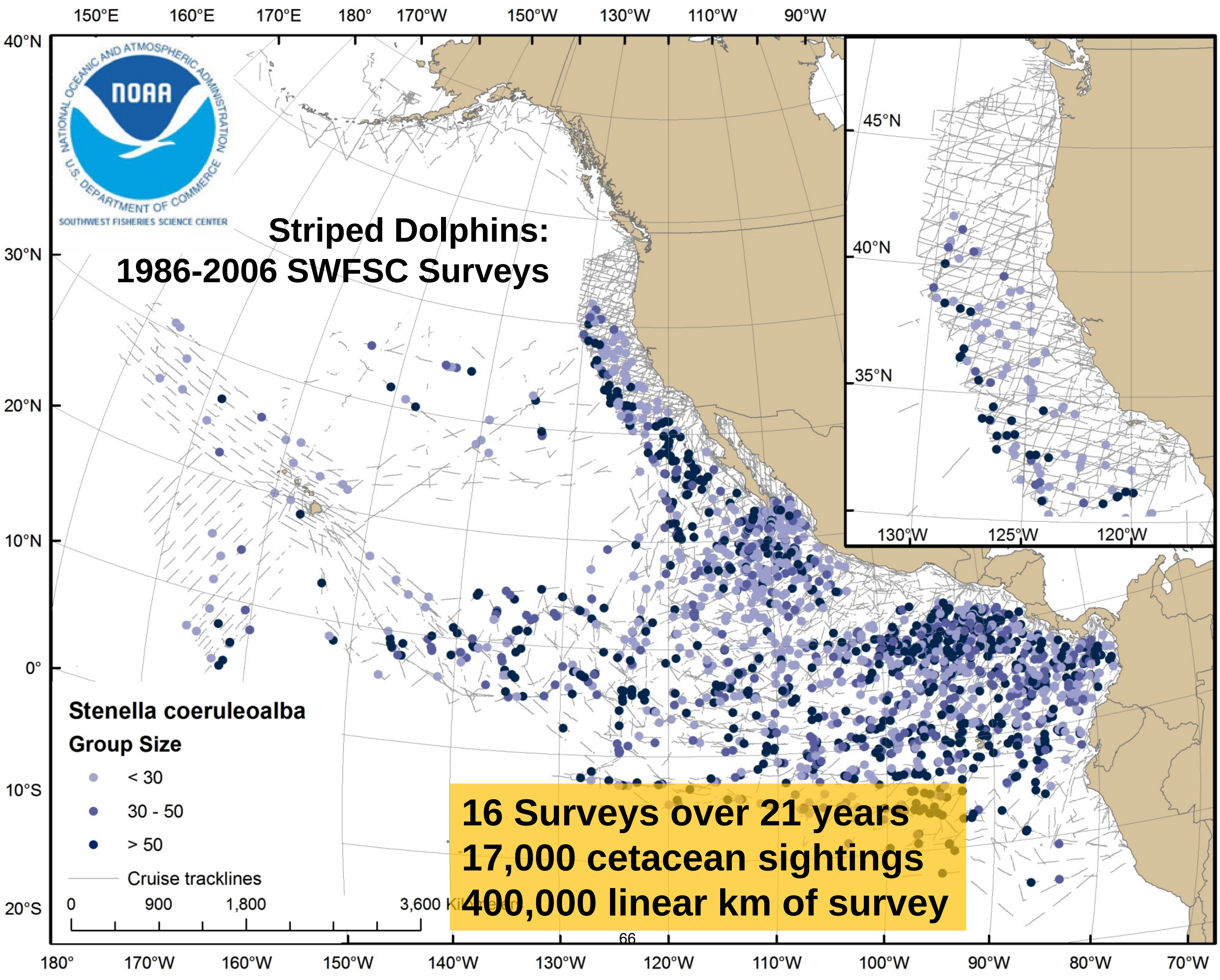
Cetacean Line-transect Surveys by the Southwest Fisheries Science Center

3 Observers

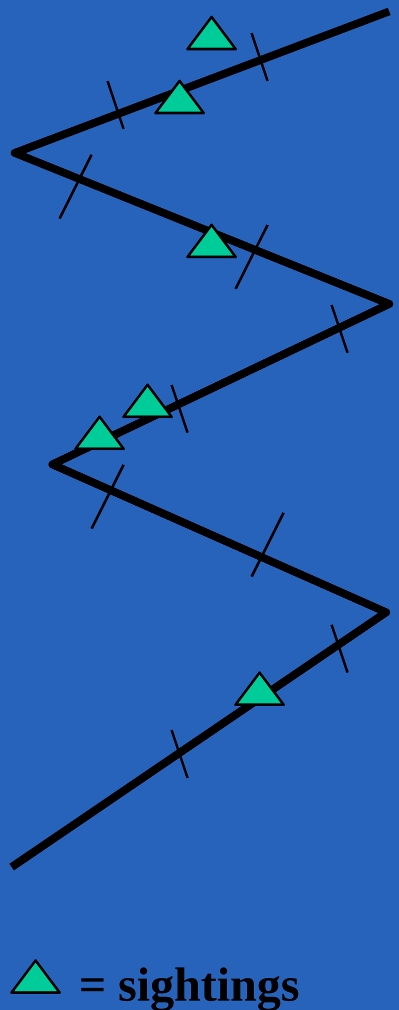
two 25x "big eyes" binoculars
one 7x binocular & naked eye






NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
NOAA
U.S. DEPARTMENT OF COMMERCE
SOUTHWEST FISHERIES SCIENCE CENTER
Striped Dolphins:
1986-2006 SWFSC Surveys
150°E
160°E
170°E
180°
170°W
150°W
130°W
110°W
90°W
40°N
30°N
20°N
10°N
0°
10°S
20°S
45°N
40°N
35°N
130°W
125°W
120°W
Stenella coeruleoalba
Group Size
< 30
30 - 50
> 50
Cruise tracklines
0
900
1,800
3,600 Kilometers
16 Surveys over 21 years
17,000 cetacean sightings
400,000 linear km of survey
180°
170°W
160°W
150°W
140°W
130°W
120°W
110°W
100°W
90°W
80°W
70°W

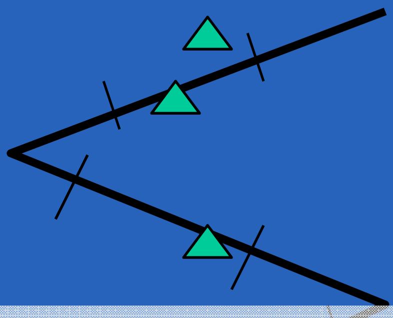
Density Modeling Methods



Segment	Length	# sightings	group size
1	10	0	
2	10	2	10.2
3	11	0	
4	11	1	8
5	10	0	
6	10	0	

3. **Estimate mean group size for each segment that contains a sighting.**
4. **Create a data frame (spreadsheet) with survey information for each segment.**

Density Modeling Methods



1. Add location info for each segment.
2. Add habitat variables for each segment.

Length	# sightings	group size	Latitude	Longitude	Depth	SeaSurf Temp	Thermo-cline D
10	0		59.3	-125.2	120	12.2	50
10	2	10.2	59.0	-125.5	550	13.4	40
11	0		58.7	-125.7	600	15.3	30
11	1	8	58.4	-125.5	604	13.2	40
10	0		58.1	-125.1	400	10.2	30
10	0		57.8	-125.3	100	10.5	50

△ = sightings

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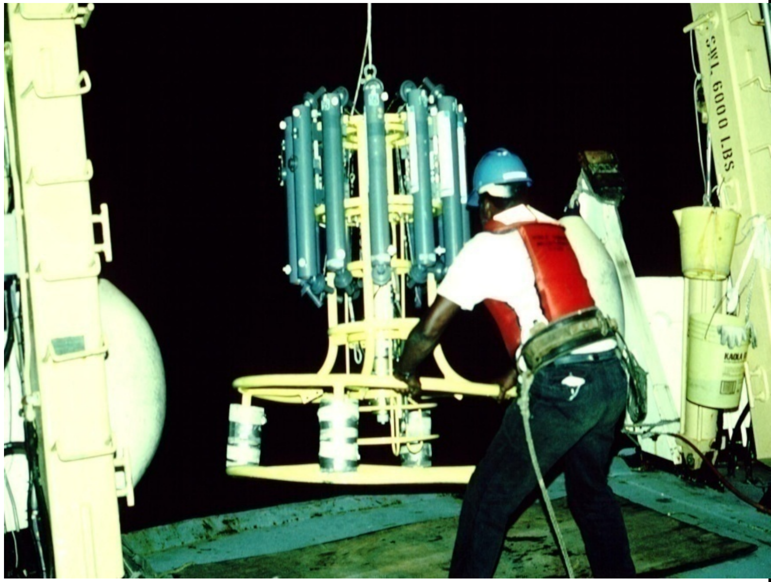
HABITAT VARIABLES

NOAA

- **NMFS/SWFSC Ecosystem Data from Cetacean Surveys:**
  - **1.) sea surface temperature**
  - **2.) sea surface salinity**
  - **3.) thermocline depth**
  - **4.) thermocline strength**
  - **5.) surface chlorophyll concentration**
  - **6.) Beaufort sea state**
  - **7.) latitude**
  - **8.) longitude**



- **NOAA NGDC's TerrainBase Global Terrain:**
  - **1.) water depth**
    - **→slope**

- **NASA Satellite-based Oceanographic Measurements:**
  - **1.) sea surface temperature**
    - **→spatial fronts**

Line-transect Modeling Approach using Generalized Additive Models

$$D = (1/2) \cdot f(0) \cdot g(0)^{-1} \cdot ER \cdot s$$

Encounter Rate (*ER=n/L = # sightings / distance surveyed*)

- ***log(n) = mean + f(oceo) + f(geo) + log(L) + error***
- ***error* ~ quasi-likelihood distribution**

  variance proportional to mean

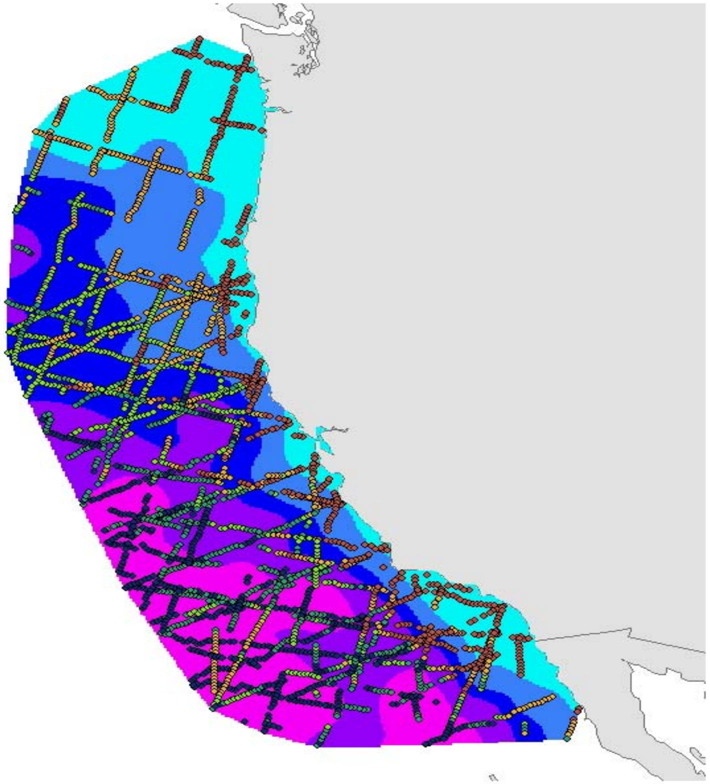
  log link w/ *distance surveyed (L)* as an offset

Group Size (*s*)

- ***log(s) = mean + f(oceo) + f(geo) + error***
- ***error* ~ Gaussian distribution on *log(s)***

  identity link

Spatial Model Nomenclature



Habitat suitability model:
presence/absence info
habitat data

Spatial density model:
line-transect survey info
spatial coordinate data

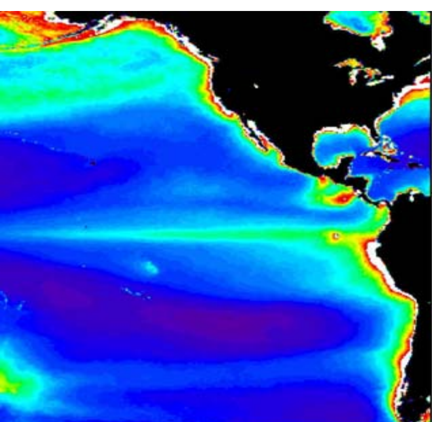
Habitat-based density model:
line-transect survey info.
habitat data
(spatial coordinate data)

Marine Mammal Density Modeling

Sighting Data

Effort Data

Habitat Data



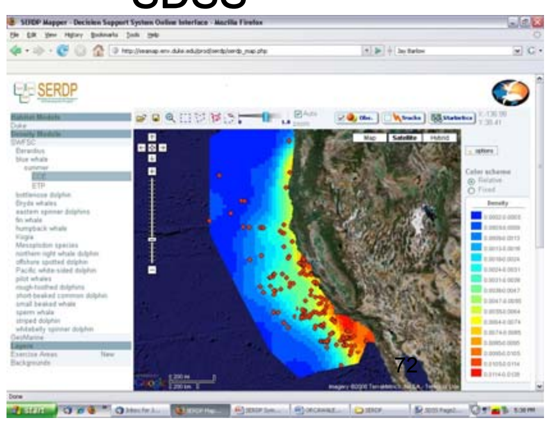
Preliminary Density Models

"Acceptable" Density Models

Review Team

Best & Final Density Model

SDSS



ADVANCING THE SCIENCE OF PREDICTIVE DENSITY MODELING

MODELING FRAMEWORK

Generalized Linear Models
Generalized Additive Models
Tree-based models
Area effectively search as offset

DATA SOURCES

In situ
Remotely Sensed
Mid-trophic indices

ERROR STRUCTURE

Poisson
Quasi-likelihood
Negative Binomial

MODEL SELECTION

AIC Information Theory
Cross-validation

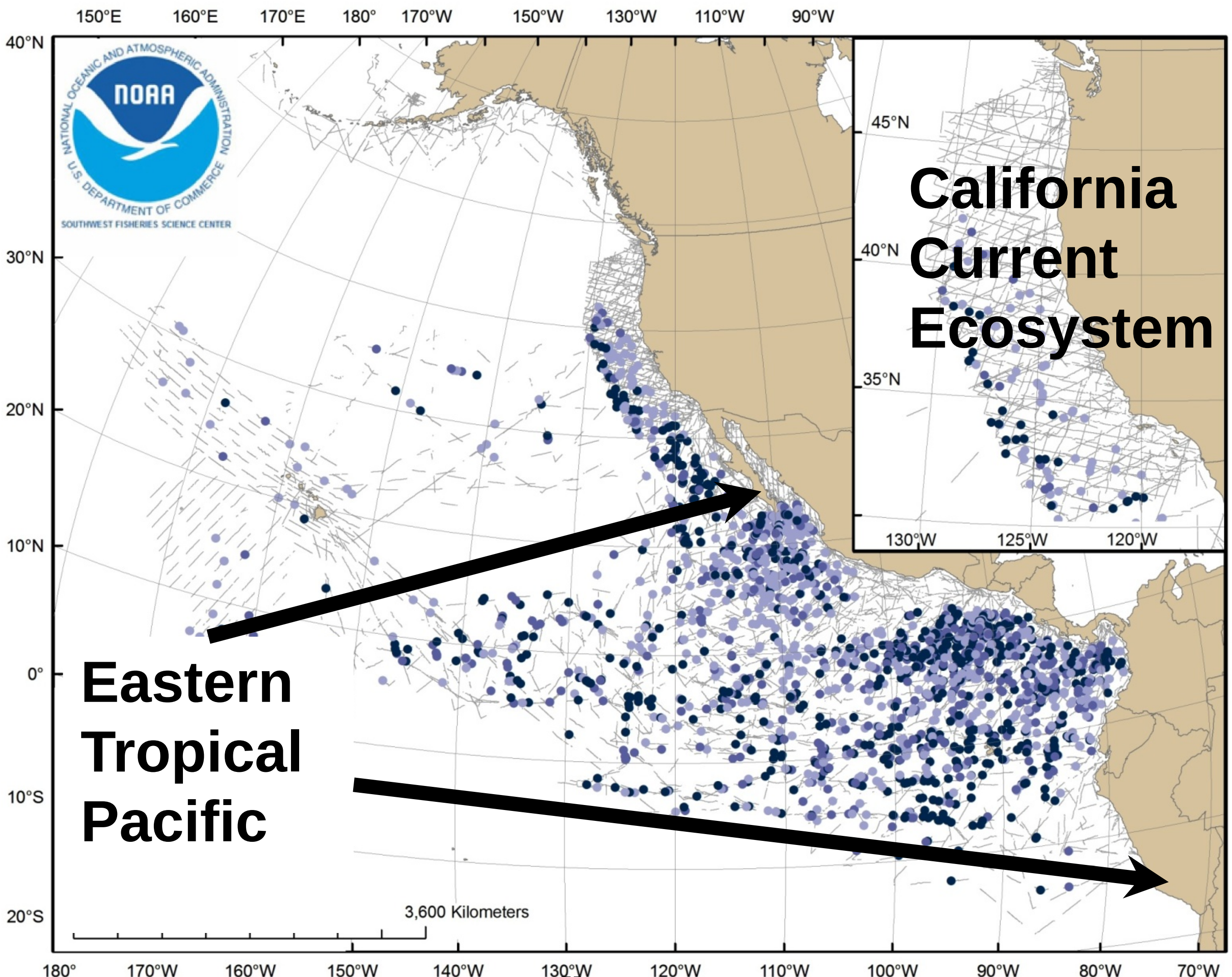
EFFECT OF SPATIAL RESOLUTION

Blue whale prediction ratios (observed/predicted)

	10 km	20 km	40 km	80 km	160km
1986	0.714	0.700	0.788	0.654	0.627
1988	1.383	1.419	1.246	1.144	1.179
1989	1.618	1.598	1.339	1.367	1.356
1990	1.937	1.989	1.926	2.143	1.877
1998	0.628	0.707	0.651	0.720	0.586
1999	0.583	0.627	0.627	0.709	0.626
2000	1.075	1.174	1.030	0.945	1.163
All years	0.999	1.063	1.002	1.023	0.983

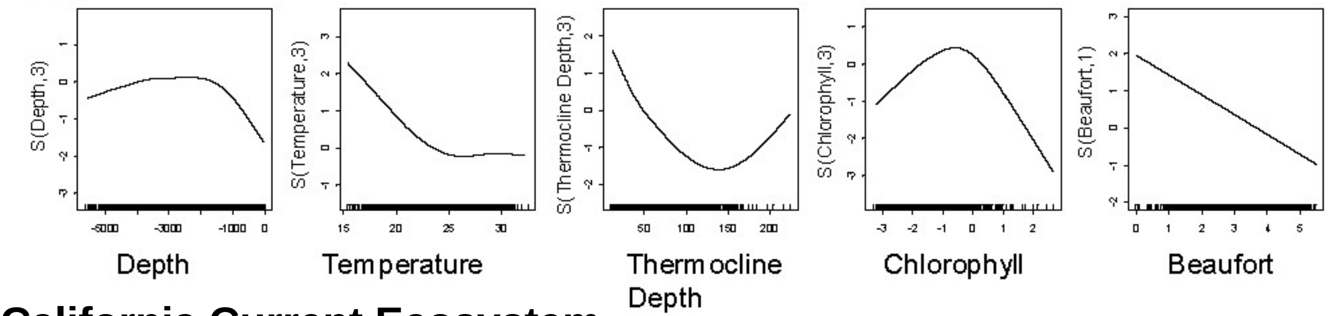
Variability in prediction ratios among years is much greater than the variability in ratios among scales.

EFFECT OF SPATIAL EXTENT

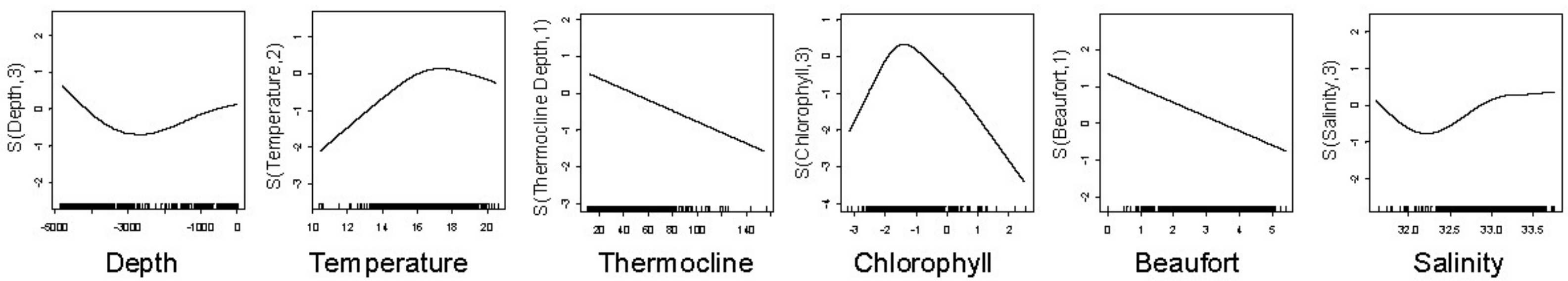


EFFECT OF SPATIAL EXTENT

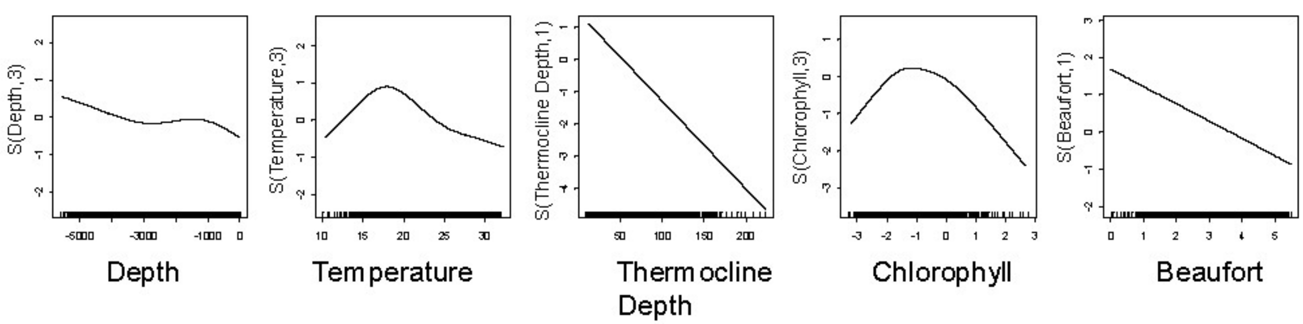
Eastern Tropical Pacific



California Current Ecosystem



Eastern Tropical Pacific & California Current, combined



Ecosystems are best modeled separately.

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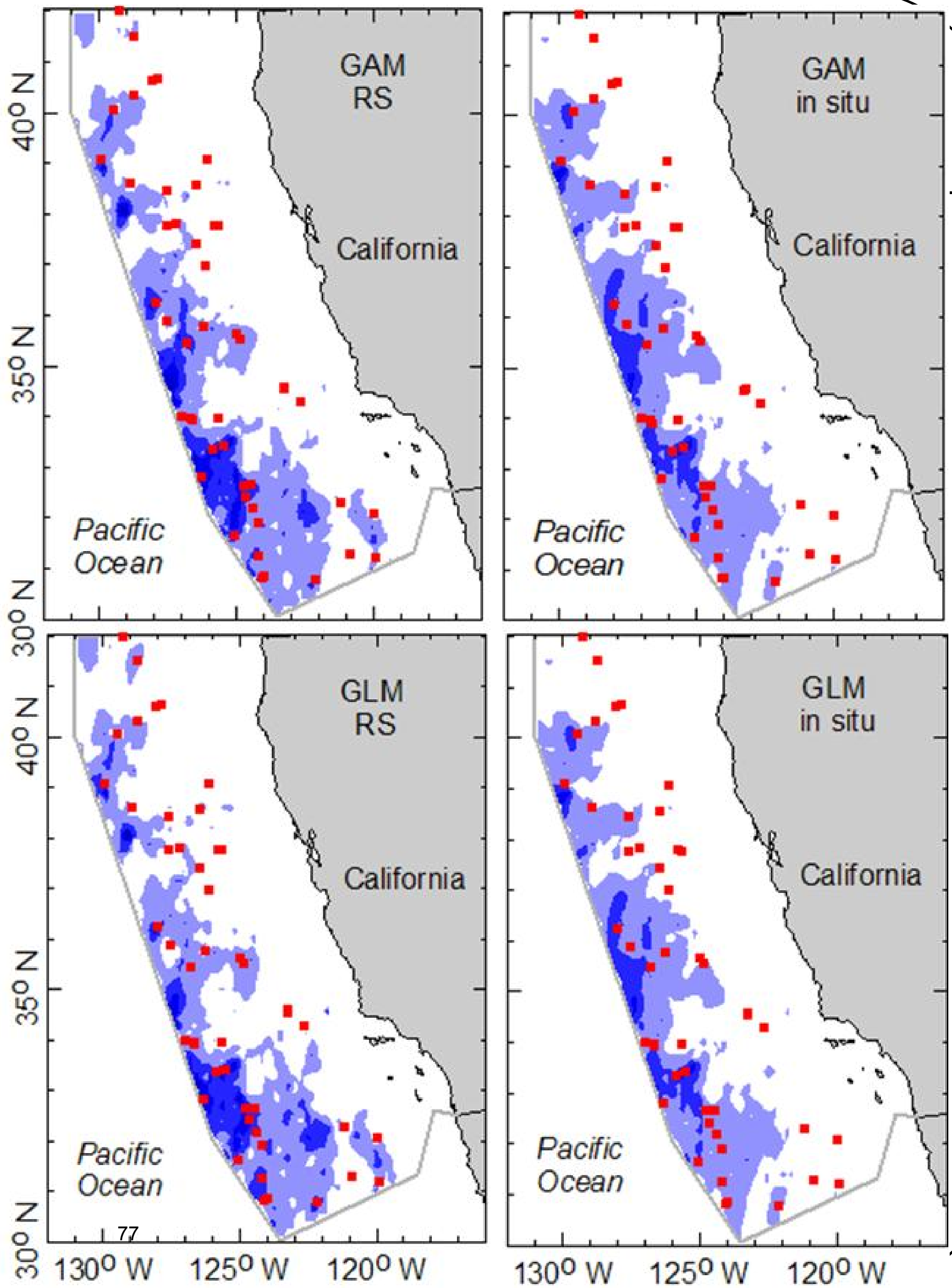
Model Comparisons for striped dolphins:

Remotely Sensed vs.
***In Situ* Data**
(left vs. right)

Generalized additive vs.
Generalized linear models
(top vs. bottom)

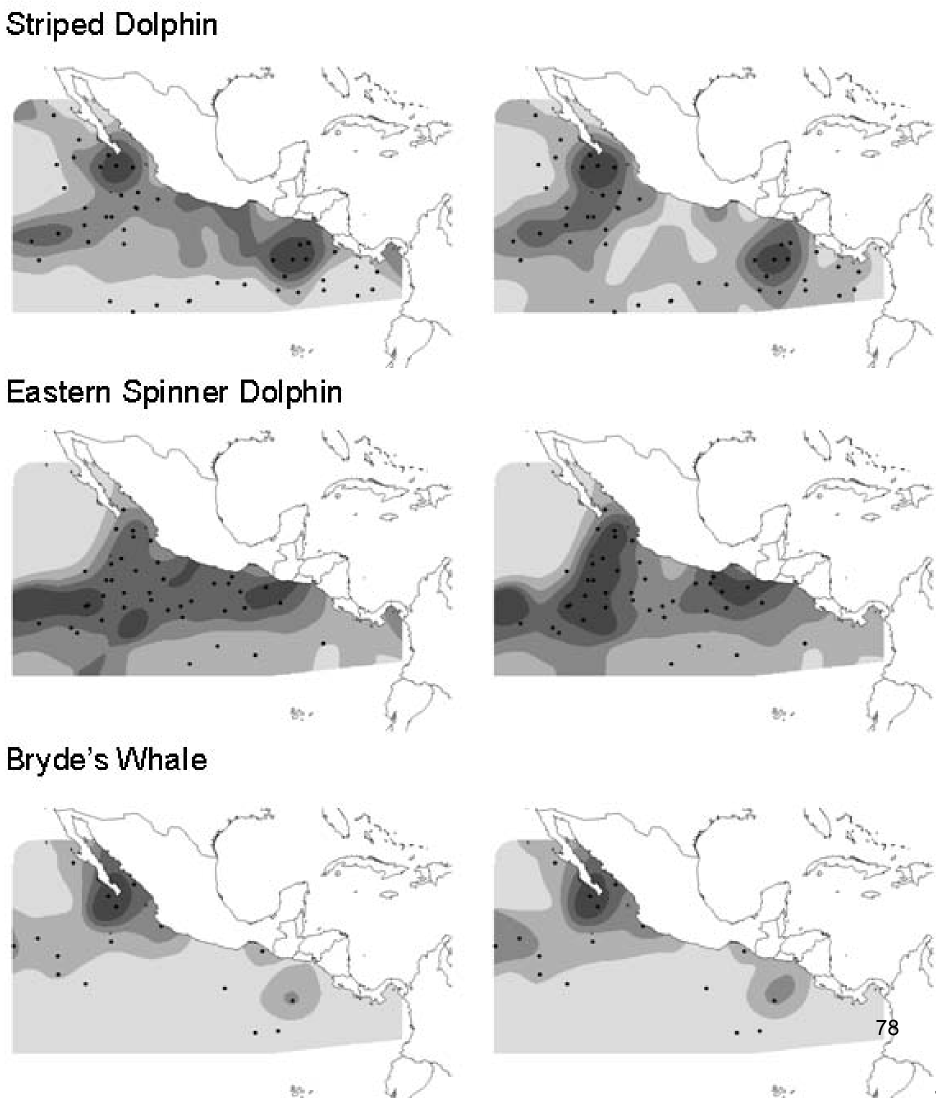
Different data sources and different modeling methods typically produce very similar models.



Mid-Trophic Data Sources

Oceanographic Data

Oceanographic Data + Acoustic Backscatter & Net Tow Data



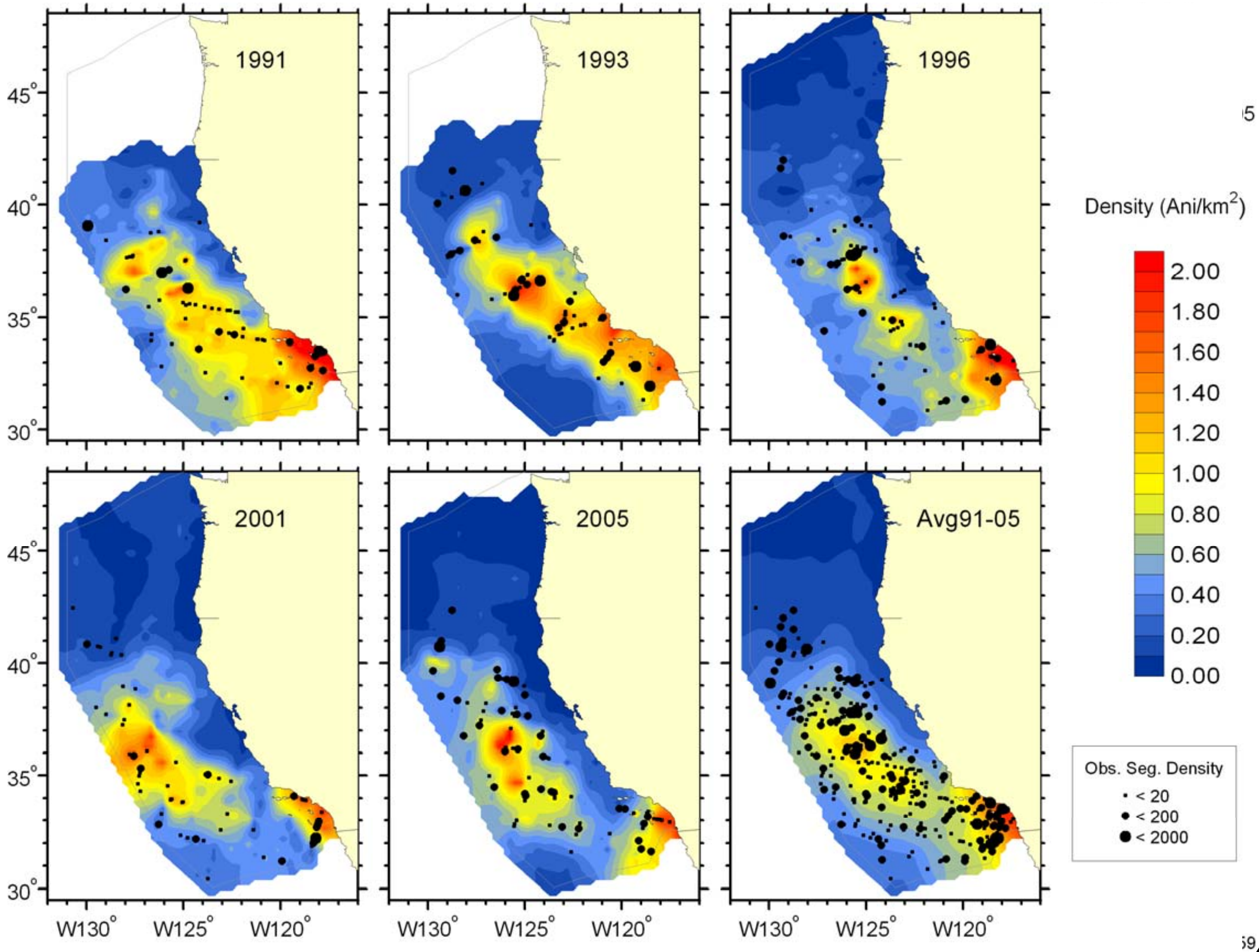
Does the inclusion of data from mid-trophic components of the food web improve our models of cetacean density?

Mid-trophic data improved some models, but only marginally.

How Do Model Predictions Vary Among Years?

Short-beaked Common Dolphin

Density per Square Kilometer



Preview of preliminary cetacean density models for the Central Pacific

Co-PIs

Elizabeth Becker
Karin Forney
Jay Barlow
(SWFSC)

Dave Foley
(JIMAR/SWFSC)

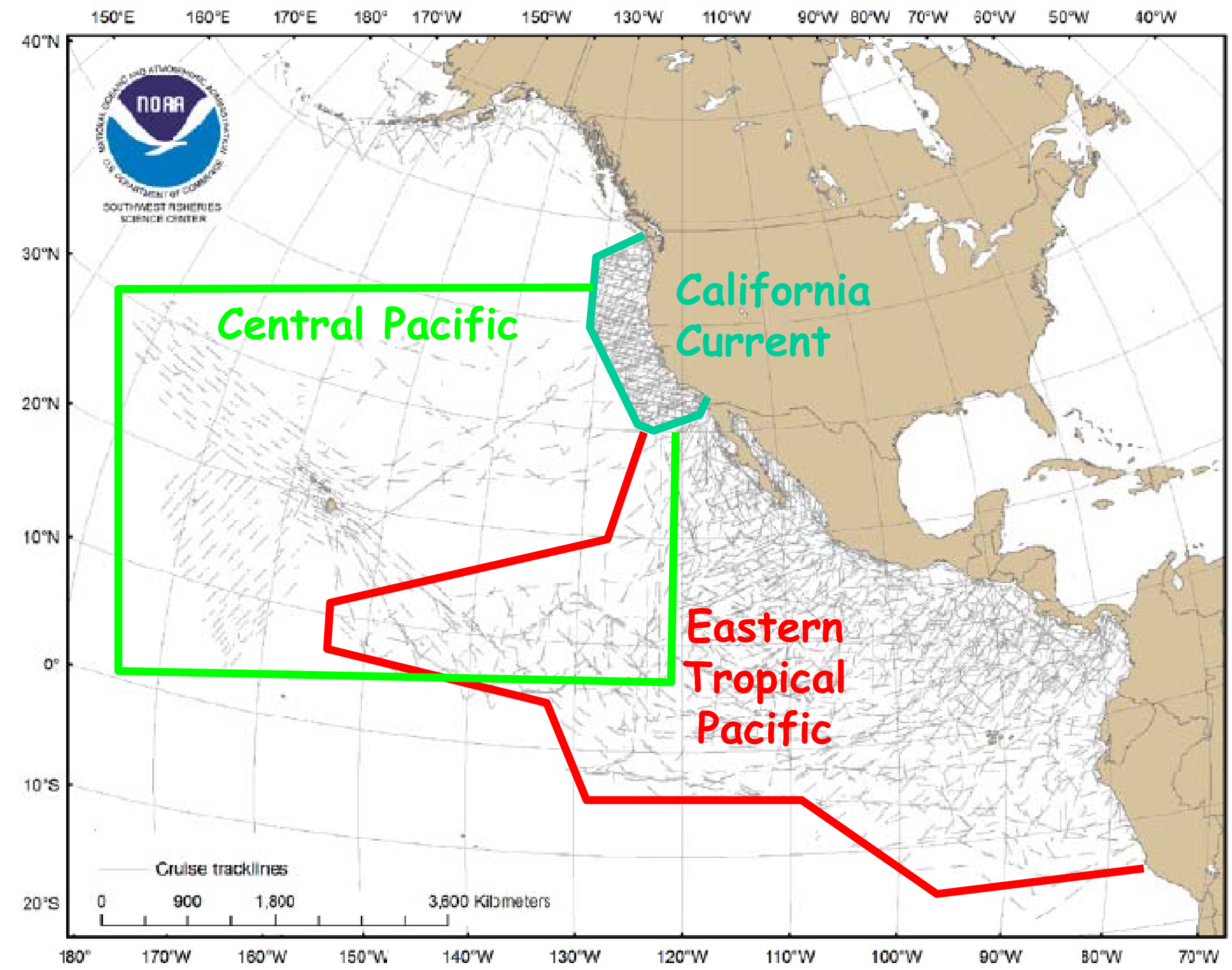


Figure 1. Cruise tracklines surveyed by the Southwest Fisheries Science Center, 1986-2005.

CenPac: Include area effectively searched as an offset

$$\boxed{D = (n/A) * s * g(0)^{-1}}$$

$A = 2*L*ESW$
(effective area searched)

<u>"Encounter rate" (n/A):</u>

$ln(n) = offset(A) + f(SST) + ...$

<u>Group Size (s):</u>

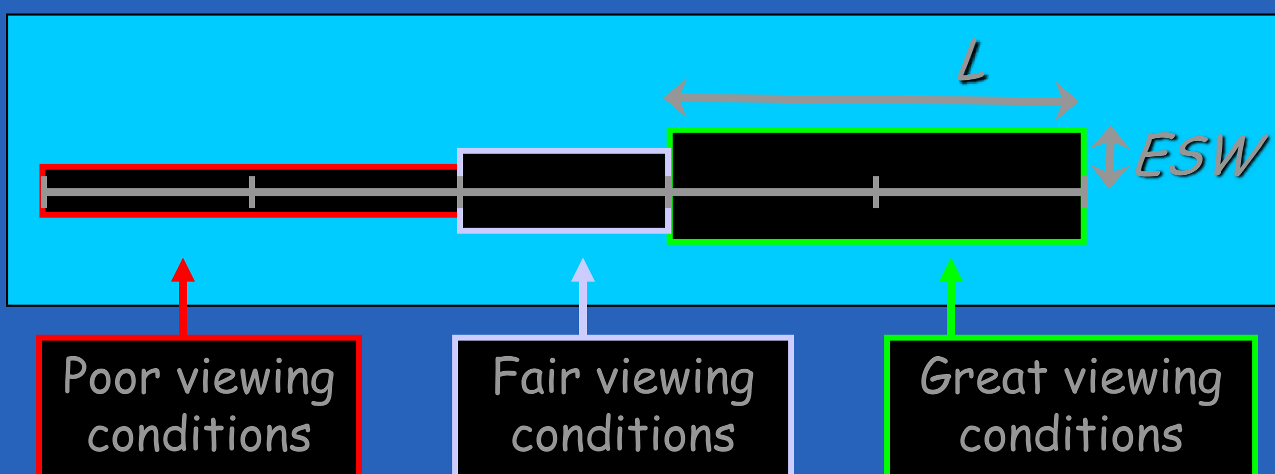
$ln(s) = f(SST) + f(depth) + ...$

**ESW calculated per segment using multi-covariate approach (Barlow et al. NOAA Tech Memo)

Estimation of segment-specific effective area searched, $A_E = 2*L*ESW$

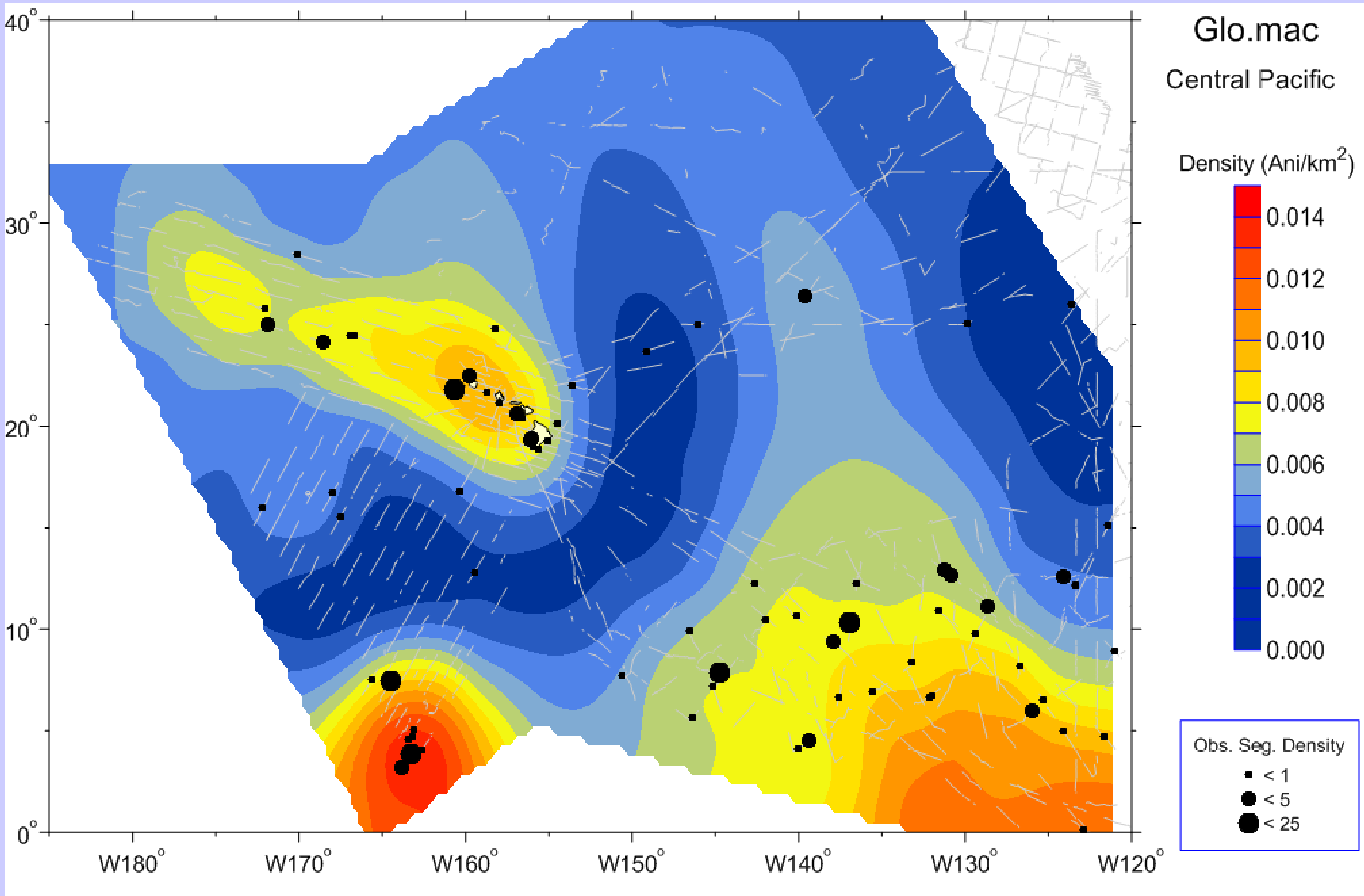
Key effects on viewing conditions:

- Beaufort sea state (0-6)
- Swell height (deviation from Beaufort expectation)
- Visibility (in nmi)



ESW calculated per segment using multi-covariate approach
(Barlow et al. NOAA Tech Memo)

CenPac Results: short-finned pilot whale



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Integrating new satellite-derived products into habitat-based density models

Co-PIs

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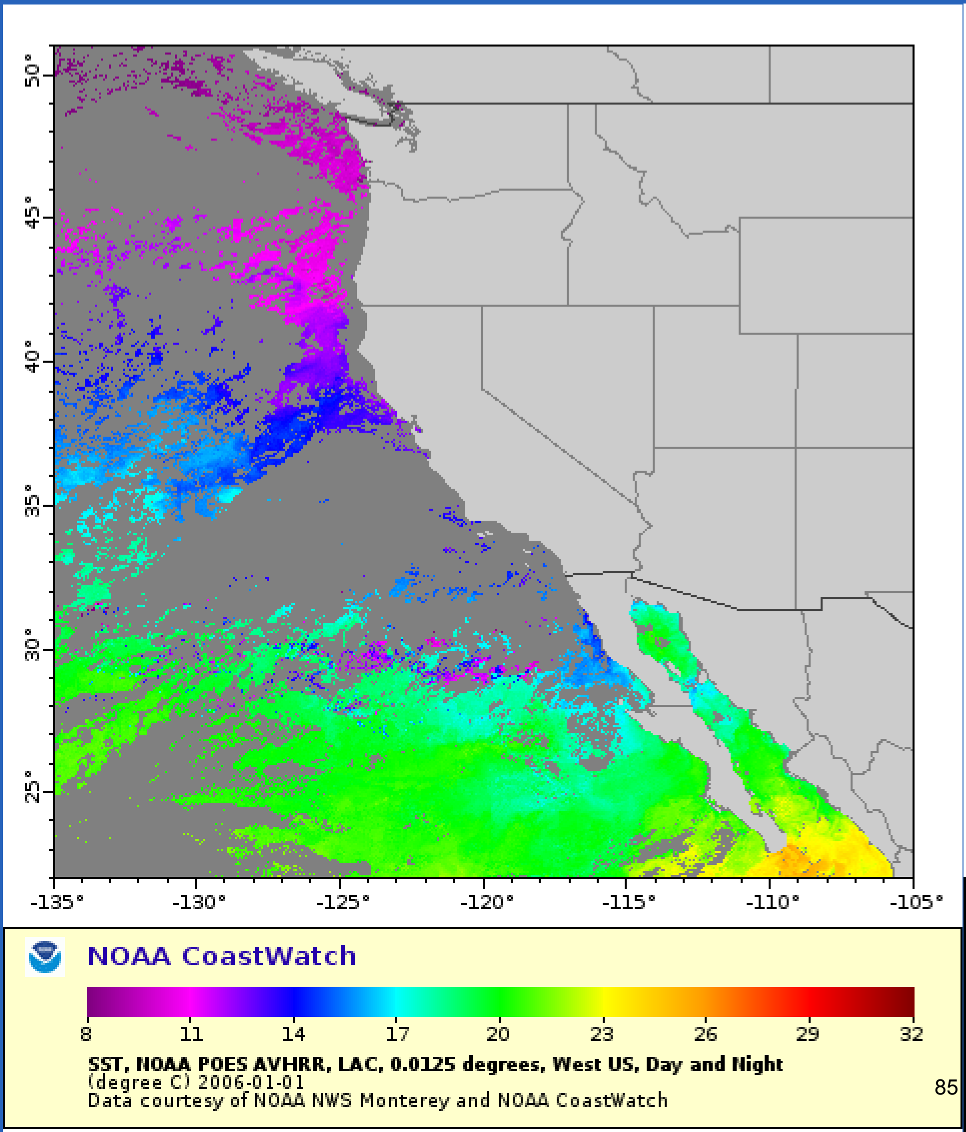
Global High Resolution SST (GHRSST)

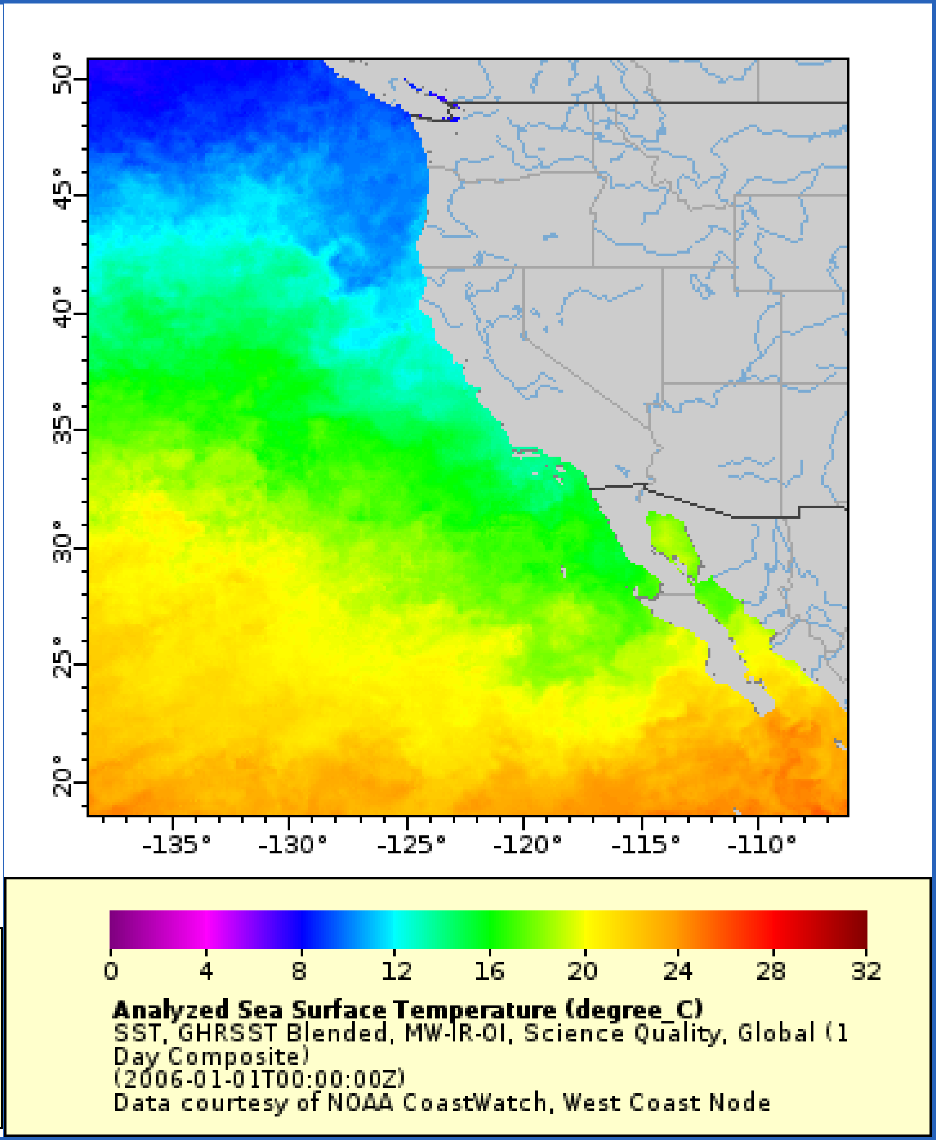
Multi-sensor approach ("blended SST")

- High-resolution infrared data
- Microwave (data for cloudy areas)
- Optimal interpolation
- Pixel-by-pixel error characterization

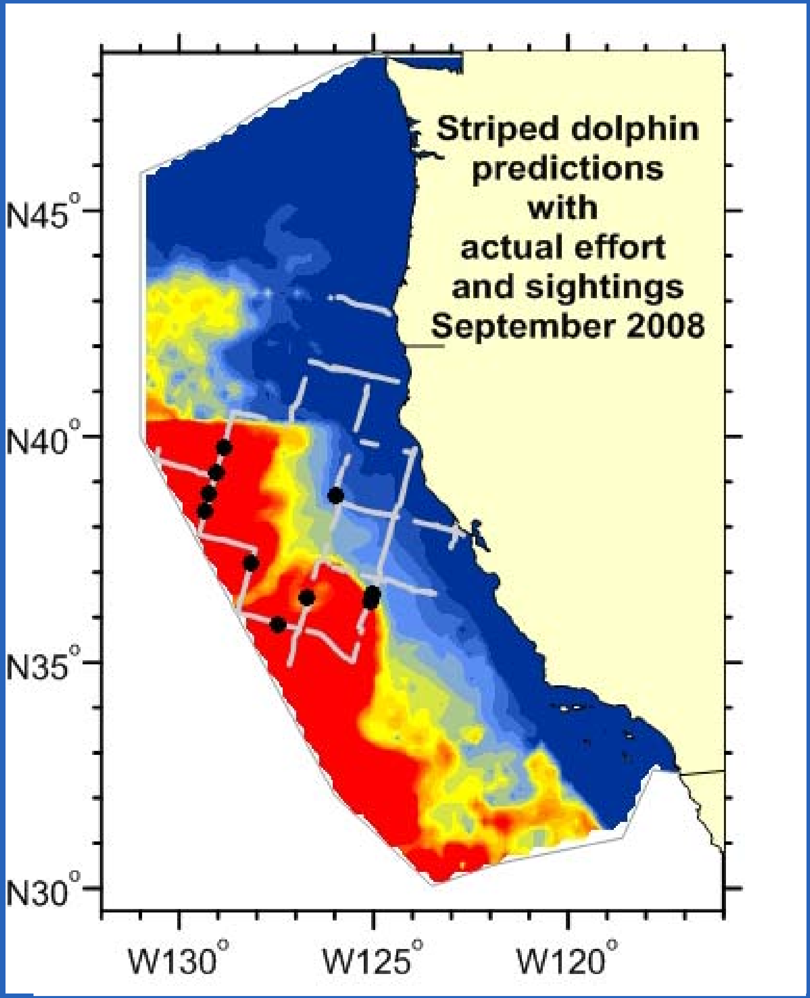
Developed by Remote Sensing Systems, Santa Rosa, CA (Gentemann et al. 2009).

AVHRR vs. GHRSST



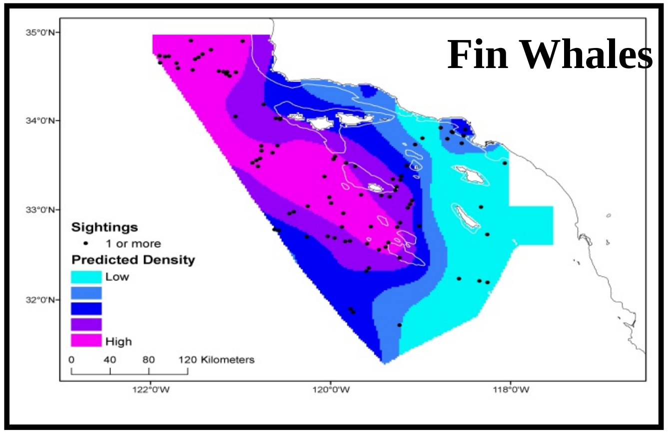


NOWCASTS (using GHRSST 'blended SST')

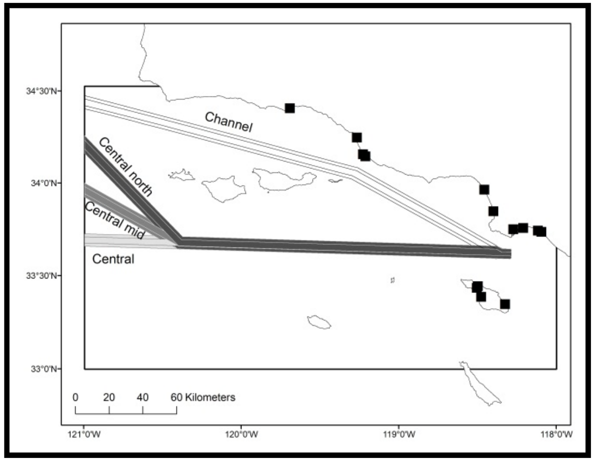


Spatially Explicit Risk Assessment: Large Whale Ship Strikes (Jessica Redfern)

Estimate whale density using habitat models

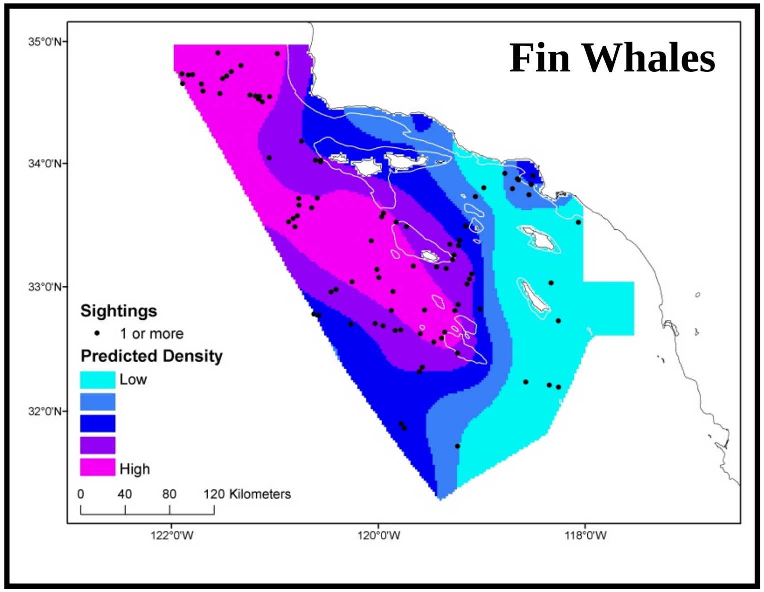


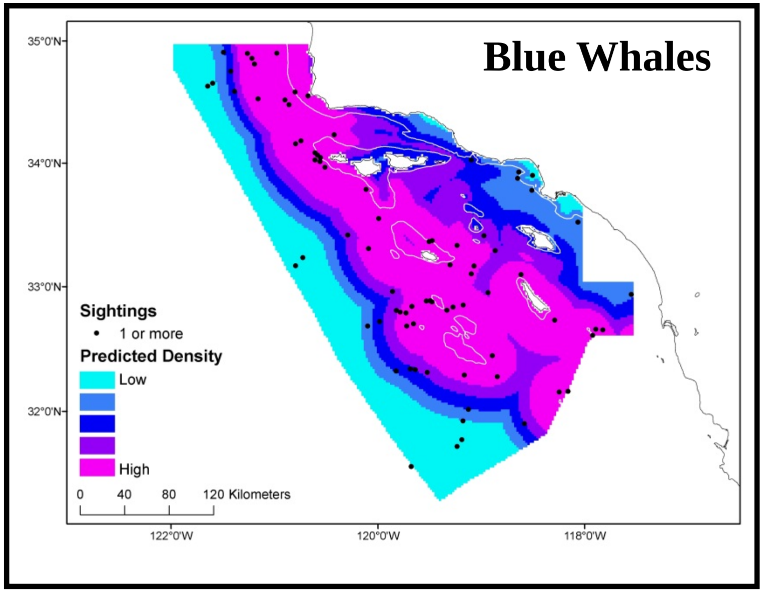
Alternative shipping routes derived from shipping data

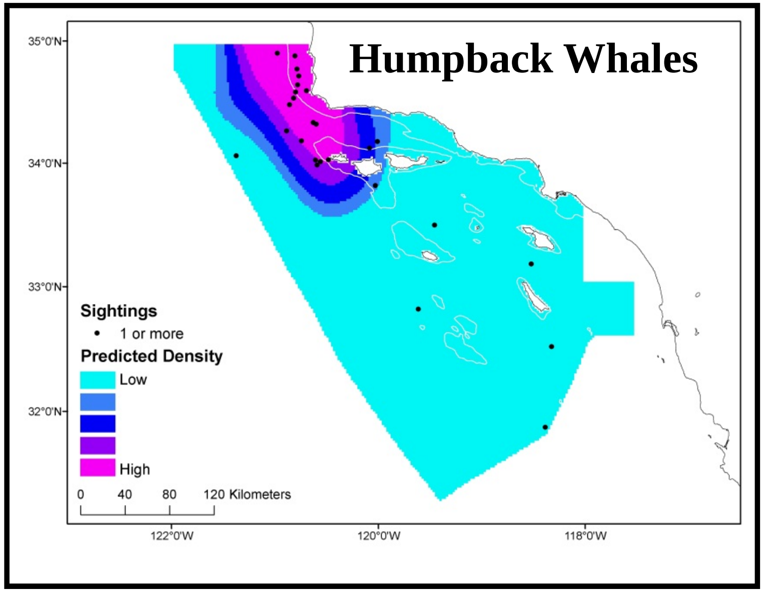


Assume risk is proportional to the predicted number of whales in each route

Habitat Models





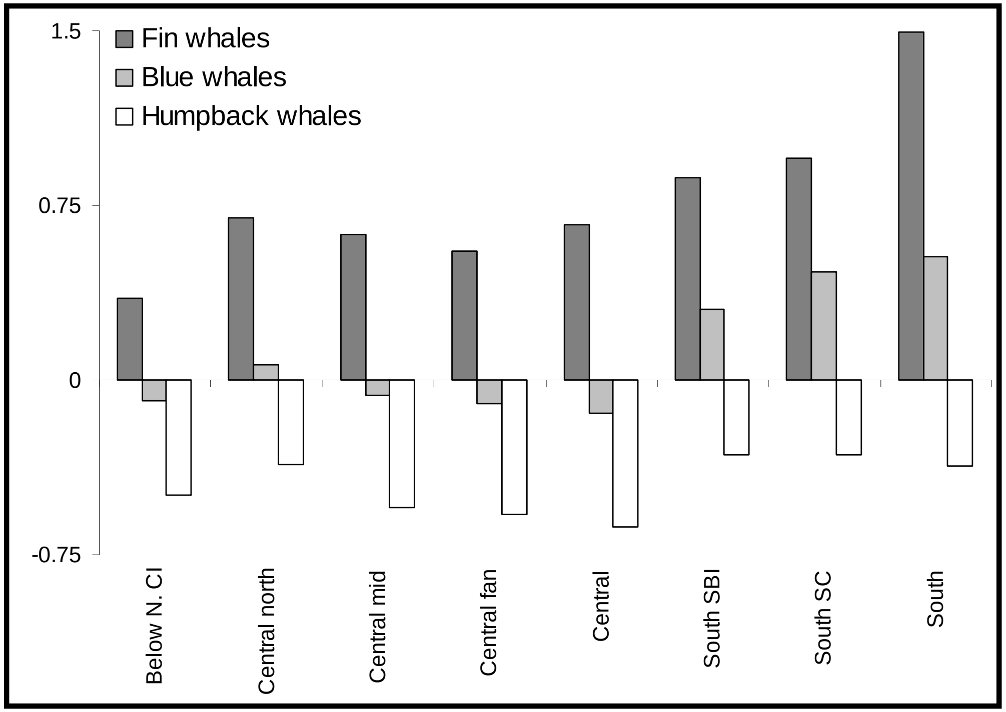


- Fin and humpback whales have opposing hot spots
- Blue whales are more evenly distributed throughout the area

Ship-Strike Risk

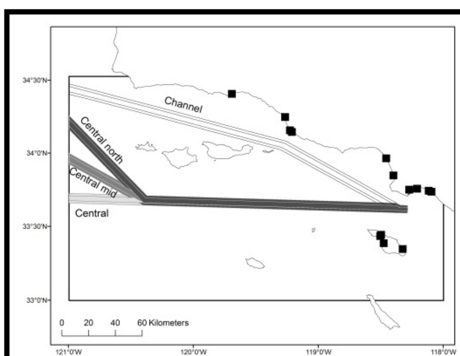
Percent change in risk between the Channel and the alternate routes

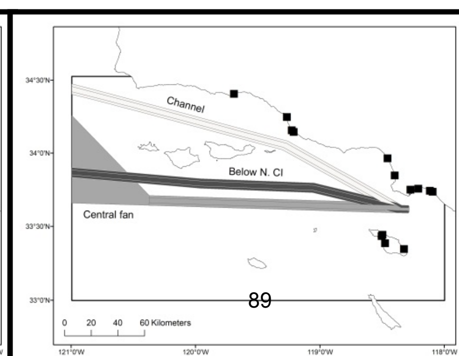
Increase risk in alternate routes

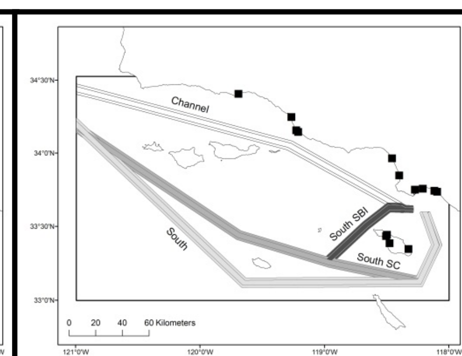


Decrease risk in alternate routes

Risk







SERDP
Strategic Environmental Research and Development Program

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- Duke SERDP Team (esp. Pat Halpin, Andy Read, Ben Best, & Ei Fujioka).

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Notes on discussions from the "New developments in cetacean survey methods" Workshop at the Society for Marine Mammalogy biennial conference, Tampa, Florida, Sunday 27th November, 2011

Thanks to Danielle Harris for recording these notes.

Discussion 1 – following talks by LT, SB and HS

1. There was a question about estimation of g(0) for an acoustics survey, using an independent sightings platform. Would this be useful, given that animals that are vocalizing under the water cannot be seen.

   Reply (SB and LT): Limiting independence models can have delta going in the other direction – in other words allow for negative dependence between platforms.
   Duplicate identification is very difficult for a visual/towed acoustics joint effort as the array is typically on the back of the ship, and the observers look out to the front. In addition, current methods for towed acoustics also do not account for animal movement, which is likely to be an issue (as the array is on the back of the ship, and animals may have already responded to the ship). Two options to help with responsive movement and duplicate identification – bow mounted hydrophones or the observers look to the back of the ship (though animals might also have moved by the time of detection).

2. There was a question regarding the issue of measurement error in acoustics surveys – where depth is ignored, and so horizontal perpendicular distances to acoustically detected animals are positively biased (e.g., if a sperm whale is detected at a depth of 2000m directly beneath the transect line, the "perpendicular" distance would be recorded as 2000m, but it is really 0m). Distance sampling can be considered in a 3D context, so why not consider acoustic surveys as a 3D problem?

   Reply (LT and DB): (1) If distance sampling is considered in a 3D context, then you need to make the assumption that the distribution of depths of animals is also uniform, or known (analogous to the assumption that the distribution of the animals in relation to distance from the line or point is uniform/triangular or known in a 2D context, usually achieved by placing lines/points at random to the distribution of the animals). It is not possible to place hydrophones at randomly located depths, and marine mammals are unlikely to have a uniform distribution of depths, but their depth distribution could be deduced from TDR (Time Depth Recorder) data. LT is working (with JB) on methods that allow an estimated depth distribution to be used to undo the bias caused by overestimation of the distance.
   (2) If there are double platform data, then a full independence double-observer approach could be used, which does not require an assumption about the distribution of animals. However, full independence models have other problems (due to modelled heterogeneity causing non-independence). (3) Relatedly, underwater gliders are potentially a very useful tool for towed passive acoustic line transects (although they move slowly relative to a surface vessel, so animal movement may be a problem).

3. There was a question regarding the issue of having few sensors, but deploying them in the same place for a long time, so does that get around the issue of not having enough sensors to satisfy the assumption that the distribution of the animals in relation to distance from the line or point is uniform/triangular or known.

   Reply (LT/SB): You get good temporal information, so may be more confident that around the few sensors the distribution of animals is triangular with respect to distance, but you're missing the spatial coverage required to make inference about density/abundance over a larger study area – i.e., to extrapolate from the surveyed sites to a larger area of interest.

4. There was a discussion about detectability issues related to groups. It was pointed out that probability of detection of a large group at a given distance will be greater than the probability of detection of a smaller group at the same distance. It is advised to add group size as a covariate for the detection function, either as a continuous variable or a factor.

5. Availability bias was also discussed, and how the use of dive profiles for the study species can help. JB is preparing a paper on this, estimating availability for several species of deep-diving cetacean based on TDR tag data. A question was raised about whether the abundance estimate is over- or underestimated (i.e. the direction of the bias), and it was concluded that it was hard to say. It was also concluded that, as mentioned in HS's presentation, to assess availability you need to be able to sight an individual more than once, but it is difficult for long-duration diving marine mammals.

6. Also linked to assessing availability bias was whether 'time under the water' was actually the best metric, as especially from an aerial survey, animals can be spotted underwater by a few feet (depending on turbidity), so the definition needs to be decided and kept consistent.

7. 7. There was a discussion about the SCANS dataset (Small Cetacean Abundance in the North Sea).

   STB noted that application of limiting independence models to these data indicated that the full independence assumption was supported by the data. This suggests that the SCANS protocol is effective at removing unmodelled heterogeneity due to surfacing pattern (or anything else).

8. An issue regarding the use of acoustics for density estimation was raised – what if the relationship between the number of cues produced and the number of animals producing the cues plateaus at some point, i.e., cue rate is density dependent?

   Reply (LT): There is an issue that cue rate may be density dependent. This means that for any density estimation analysis, the cue rate must be carefully collected and applied. For any given survey, the cue rate should come from the surveyed animals, at the same time and place as the survey. This helps to ensure that the cue rate estimate is accurate. This issue highlights the need to have as much knowledge of the vocal behaviour of the study species as possible.

9. Further discussion points about cue rate were also raised:
    - Dealing with individual variability of cue rate production? Reply (LT): for a good sample size of individuals, a cue rate that encapsulates periods when the animal is both vocalising and quiet is required.
    - Other methods to estimate cue rate, other than tagging animals? Reply (LT): animals could be tracked during a focal follow, and cue rate could be estimated. However, groups are often initially found using acoustics, so there will be a bias in cue rate, if the fact that animals are the most vocal are more likely to be detected and followed.
    - Do you need cue rates for specific areas? Reply (LT): You need a cue rate that is relevant for the time frame and area that you want to make inference about density over.

10. There was a further question about combining visual and acoustic methods i.e. for a double platform approach. It was noted that it is difficult to combine the methods (see Point 1) and that the two methods would have different effective strip widths. It was mentioned that Lex Hiby developed an approach that utilised information from both acoustic and visual data, and that the issue of varying effective strip widths is overcome by just using the parts of the effective strip width that overlap.

<u>Discussion 2 – following talks by DB and JB</u>

11. There was a discussion about whether remote or *in situ* environmental data are preferred for spatial modelling.

    Reply (JB): Remotely sensed data are advantageous as these datasets covers a wider geographic area. However, sometimes *in situ* data are better for some variables such as thermocline information though models exist that can predict thermocline depth and other sub-surface features. So a synthesis of both data sources might sometimes be appropriate.

12. The possibility of including opportunistic data in density surface modelling and whether it would improve results or introduce bias was also discussed.

    Reply (JB): There is work being done on this. For example, there is work being done that is considering sightings where the effort and position has been recorded, but the research vessel was directed by whale watching boats to the animals, so bias is a potential problem. Could use a cross validation approach, to test whether predictions are accurate.

13. The issue of extrapolating density surface models outside of the surveyed area was raised. This is not recommended due to the issue of edge effects – one would need to be confident that the ecosystem in the unsurveyed area was comparable. Another point is that it is important to remember that the variables used to produce the density surface models are

likely to be proxies for the variables that really do dictate where the animals are distributed. This is another reason to be very careful about extrapolation.

14. The scale of density surface modelling was raised. The study discussed by JB covered a large geographic area, but density surface modelling has been conducted on smaller scales (see work by Cañadas). One benefit of density surface modelling is that you can account for non-random placement of transect lines, which is why it might be useful on smaller scales.

15. The topic of the best way to measure distances was also covered. DB and JB briefly summarised the preferred methods for various types of survey. Laser range finders should be used for terrestrial surveys. At sea, a video and/or photo can be used to get the exact declination from the horizon. Reticle binoculars are also useful for removing observers' subjectivity, but small errors in reticle measurements can still translate into large errors in distance, if close to the horizon. In aerial surveys, the angle of declination is used (when used in an aircraft, this method is less error-prone than when used on a boat, due to the height of the aircraft).

    The question was also raised whether digital photography could be used to estimate range by knowing the size of a pixel, the size of the study animal and the focal length, and using this information to back-calculate range. However, it was decided that this would be difficult at sea as animals can appear fleetingly and show little of their bodies, though it might work for a leaping dolphin (for example).

16. There was a discussion regarding studies with limited resources. Given all the issues relating to availability bias/perception bias/measurement error, which is the best to try to resolve, if you can't do everything?

    Reply: It really is study specific. In terrestrial surveys, measurement error should be solved by using laser range finders, or other technology. This may be the case for marine surveys in the future too. Perception/availability bias still remains an issue though. Movement issues and perception bias have been addressed in some European visual cetacean surveys by switching to digital aerial surveys. In general, methods are becoming more automated. Availability bias is still a difficult subject. Group size estimation is another potential source of large bias, if inaccurate. It is difficult to estimate sizes of groups from transect lines, but prioritising group size estimation (by breaking from the transect line?) can compromise methods to account for availability and perception bias.

17. New technologies were briefly mentioned. Drones have potential as future survey vehicles, and satellite images could also be useful, though the images publicly available at present do not have a high enough resolution.

18. Finally, the question was asked – which is the best method to use for abundance estimation - spatial modelling or standard distance sampling/mark recapture?

Reply (JB): If you are not interested in habitat preferences, then use standard distance sampling. In particular, a stratified distance sampling analysis can (in some cases) provide better precision, and will be more robust than spatial modelling.