

### Ecological modelling – the issues

*Examining patterns of marine mammal distributions to insights into ecological processes*

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Ecological modelling workshop  
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### Why model?

- Models are how we understand the world
  - We see our world through implicit cognitive models
  - We learn about our world using formal descriptions
- For marine mammals
  - What?
    - Distribution, abundance, ecosystem role, stock structure
  - Why?
    - Ecology, conservation, competition studies, critical habitat, EBM, MPAs, climate change

### Challenges to effective modelling

- Complexity
  - Accuracy, precision & uncertainty
- Data sources and limitations
- Space and scale
- Model evaluation & testing

### Accuracy, precision, & uncertainty

Uncertainty:

- Parameter estimation
- Observational
- Design
- Stochasticity

**Complexity**  
Data  
Scaling  
Evaluation

### Complexity

Few variables Less data	More variables More data
Biological linkages assumed	Biological linkages modelled
Increased accuracy	Increased precision
Low uncertainty	High uncertainty

*Complexity can increase in a number of ways, including biologically, spatially, and temporally*

**Complexity**  
Data  
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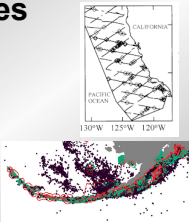
### Does model complexity guarantee a better model?

Not necessarily ...

**Complexity**  
Data  
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## Data sources



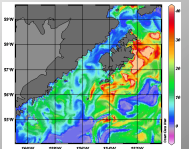
**Biological**

- Systematic surveys, tagging
- Platforms of opportunity, historic observations, catch data

**Physical**

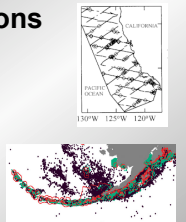
- Field sampling, remote sensing, circulation models, floats

*For most applications, need continuous predictions over large spatial extents*

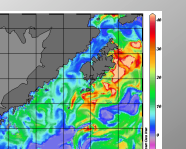


Complexity  
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## Data considerations



- Field data
  - Limited in time and space
  - Effort bias?
- Opportunistic data
  - Always effort biased
  - Absences rarely recorded
- Defining a sampling unit
  - Mixed resolution data sets
  - Gridded data
  - Autocorrelation
  - Colinearity

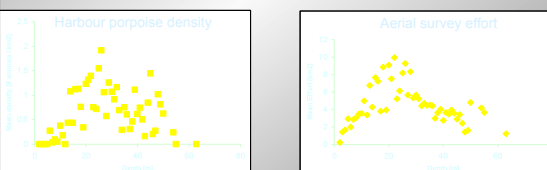


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## Effort bias

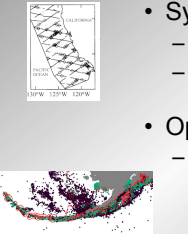
- Work concentrated on-shelf
- Species are often cosmopolitan in distribution

➤ Does sampling cover a species' range?



Complexity  
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## Getting physical with biology



- Systematic data
  - Presence-absence
  - Standard correlative methods (e.g., regression)
- Opportunistic data
  - Presence-only
  - Envelope models (e.g. BioClim)
  - Machine learning (e.g., MaxEnt)
  - Niche breadth (e.g., ENFA)

Complexity  
Data  
Scaling  
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## Defining a sampling unit

- Spatio-temporal resolution
- Depends on data
- Depends on the question
  - Pattern or process?

Complexity  
Data  
Scaling  
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## Gridding your data (raster aspects of scale)

- Extents
  - Influence of study area size on analysis
    - Prediction → extrapolation?
    - Prevalence → presence-only analyses
- Resolution
  - Autocorrelation
  - Influences summary results

### Effects of grid cell size ...

Complexity Data Scaling Evaluation

$Pr(x) = 5/16 = 0.3125$   
 $Pr(x) = 4/4 = 1.0$

Sinclair (2007): Area impacted by trawl:  
 30,000 km<sup>2</sup> at 5x5 km<sup>2</sup>  
 9,000 km<sup>2</sup> at 1x1 km<sup>2</sup>

### Evaluation and testing

Complexity Data Scaling Evaluation

- Most important
- Frequently ignored
- Recognise that not all models need same level of validation (Rykiel 1996)
- Sensitivity analysis can increase confidence in model accuracy

### Model evaluation

Complexity Data Scaling Evaluation

- Correlation studies
  - Statistical assumptions regularly violated
- Performance based on contingency table

		Observed	
		+	-
Expected	+	a	b
	-	c	d

→

- Chi square
- ROC plot
- Kappa statistic

Presence-only data contain no true (i.e., observed) absences.

### Possible solutions

Complexity Data Scaling Evaluation

- Pseudo-absence data
  - Assumes no bias in presence sampling
  - Influenced by extent of study
- Null model comparisons
- Skewness test
  - Let the presence data tell you what is best

### Skewness

Complexity Data Scaling Evaluation

Assumption:

- A better model gives higher probabilities at "presence" locations
- i.e., the distribution of probabilities at observations will be more negatively skewed

### Model comparison

Complexity Data Scaling Evaluation

WA – Winter accessibility  
 PS – Population-based suitability  
 HS1 – Partial habitat suitability model  
 HS2 – Full habitat suitability model

Gregor and Trites 2008. *Marine Ecology Progress Series*

### Two warnings ...

- Spatial models are pattern descriptions. Describing patterns is potentially risky (just ask stock assessment).
- Sample unit definition requires data pooling. Pooling creates biases in data that can lead to unexpected results.

### Modelling tips

- Ask a clear question
- Add complexity only where necessary
- Judiciously ignore available data
- Ensure transparency
  - in purpose
  - in relationships between inputs and outputs
- Document assumptions and limitations
- Pay attention to sensitivity and validation
- Remember that all models are wrong
- Terrestrial literature is informative, but not always useful

*"If we study a system at an inappropriate scale, we may not detect its actual dynamics and patterns but may instead identify patterns that are artifacts of scale. Because we are clever at devising explanations of what we see, we may think we understand the system when we have not even observed it correctly." – Wiens (1989).*

