

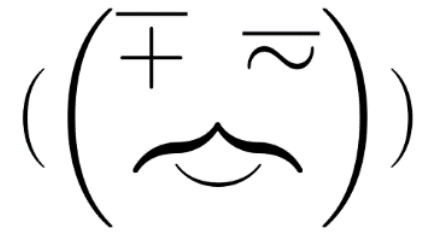
# Analyses of telemetry data from migrating fish

Examples from the river Frome, Dorset

Stephen Gregory, Bill Beaumont, Rasmus Lauridsen, Andy Moore, Bill Riley



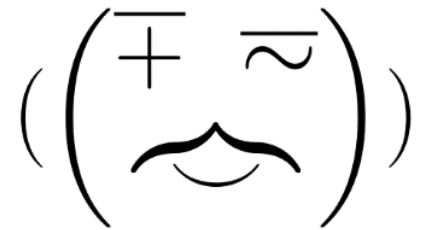
# Outline



- Telemetry data: challenges
- State-Space modelling
- Examples (from the Dorset Frome):
  - Poole harbour sea trout
  - Frome PIT tag movements
- Take away points



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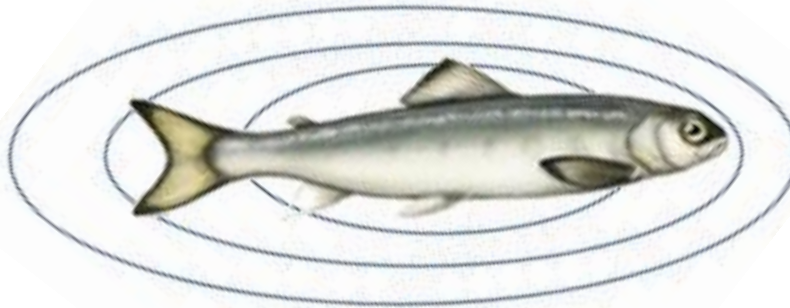
# Telemetry data: challenges

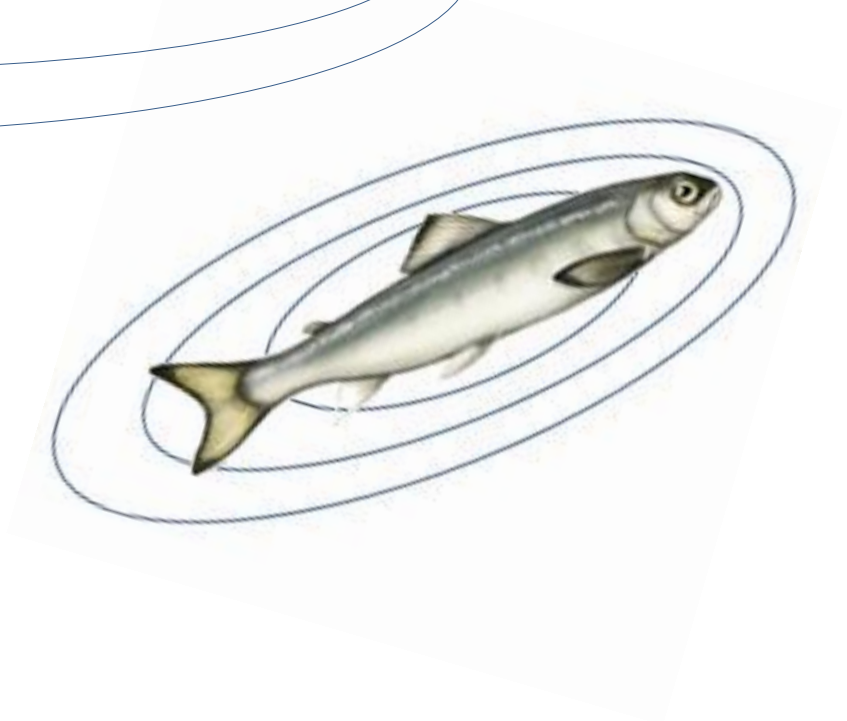
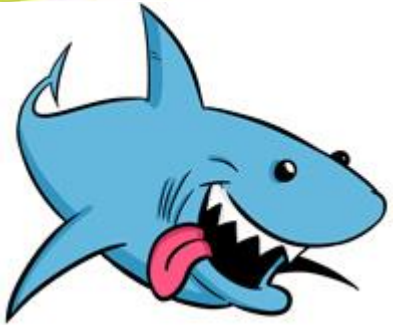
- Imperfect detection

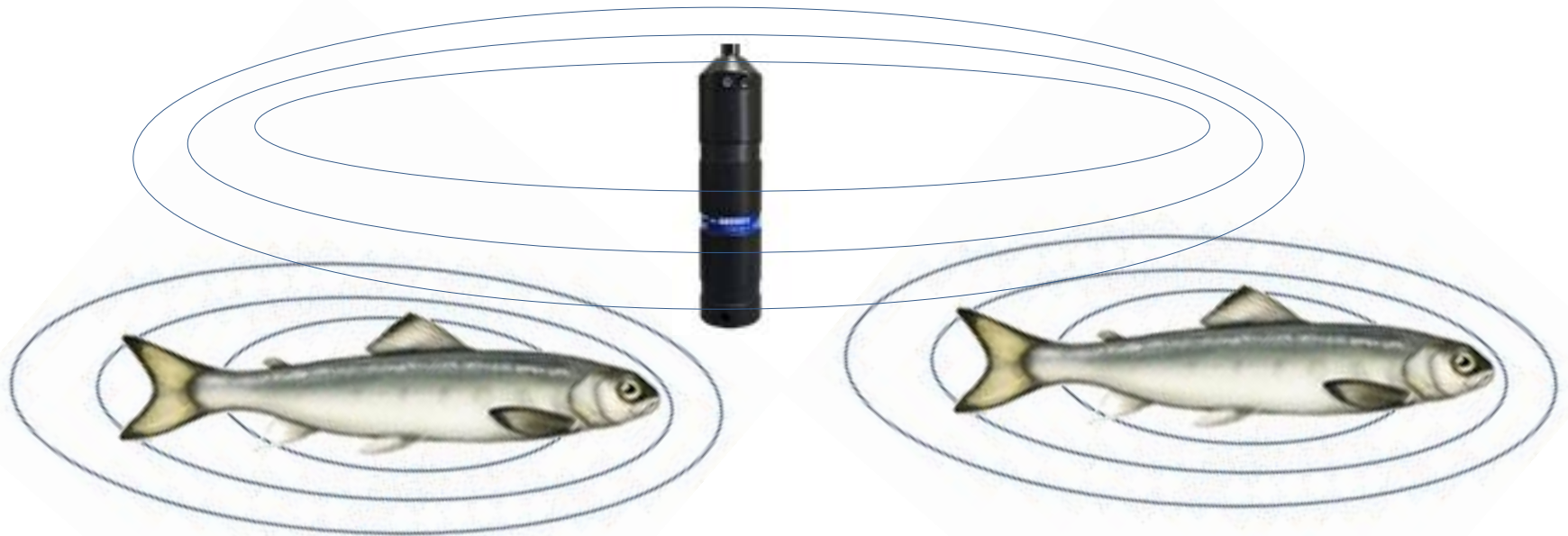
$$p < 1 < 0$$

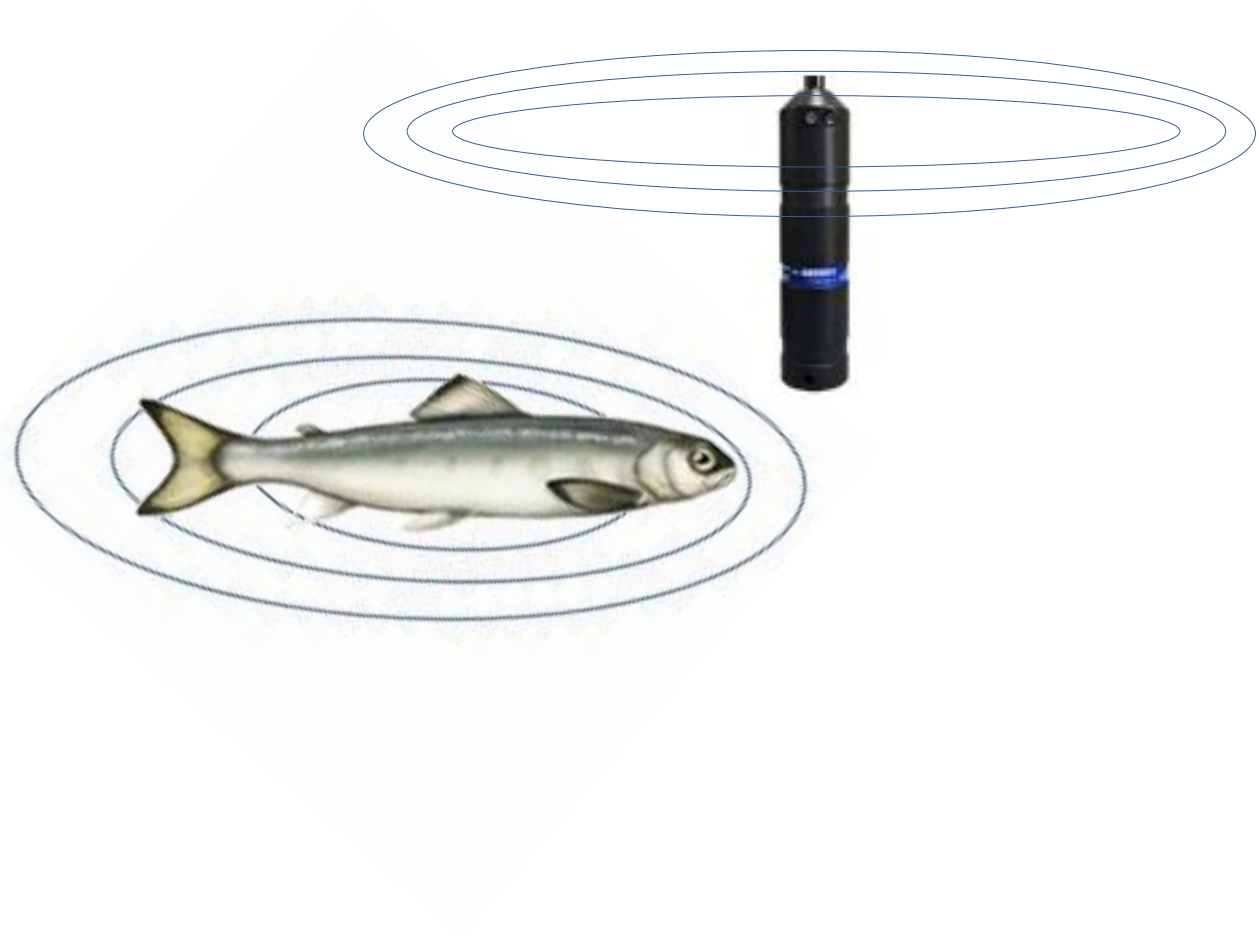
where  $p$  = probability of individual detection



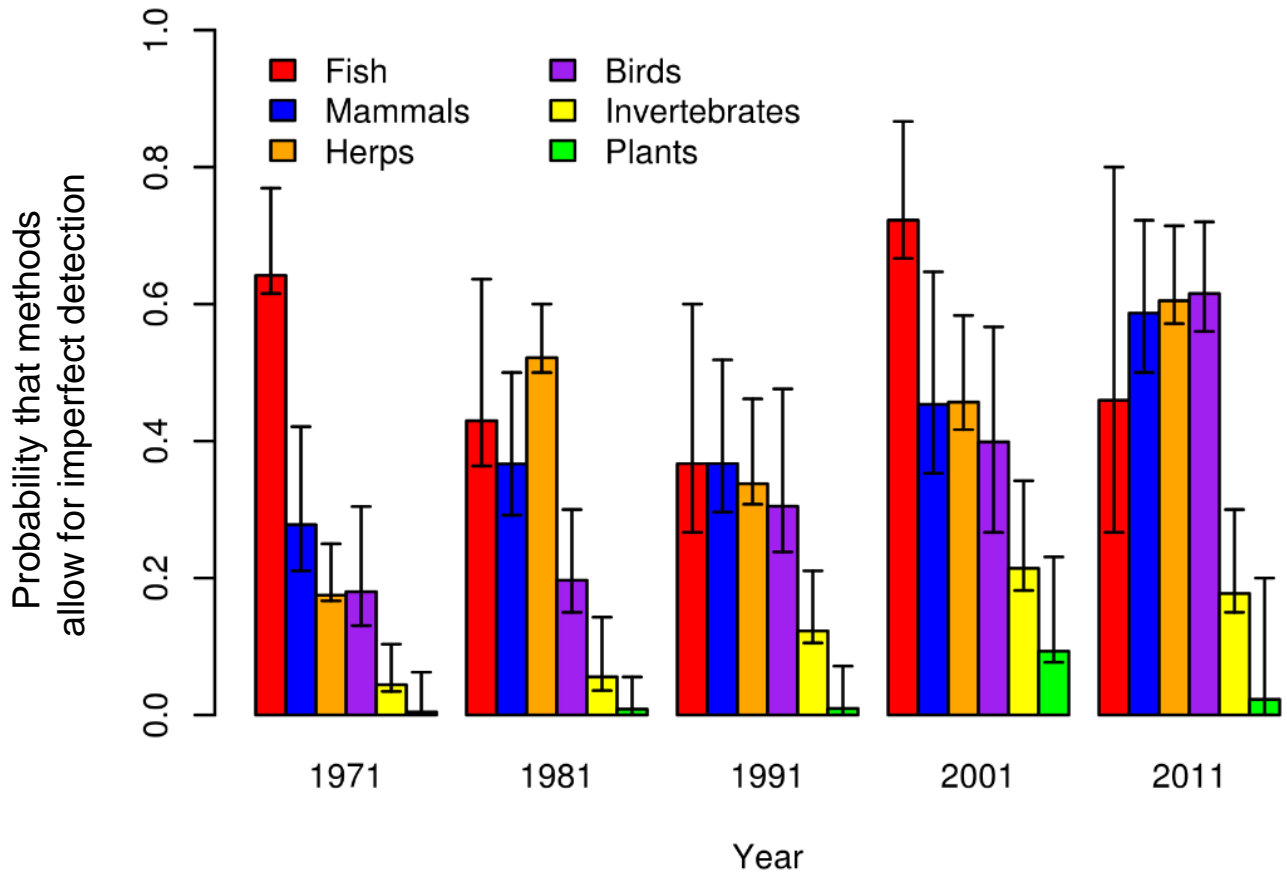












Overall: 23%

- Alternatives:

  - $p = 1$ : under-estimate survival

  - $p = x$ : over- and under-estimate survival

- Usually assumed that  $p$  is temporally invariant

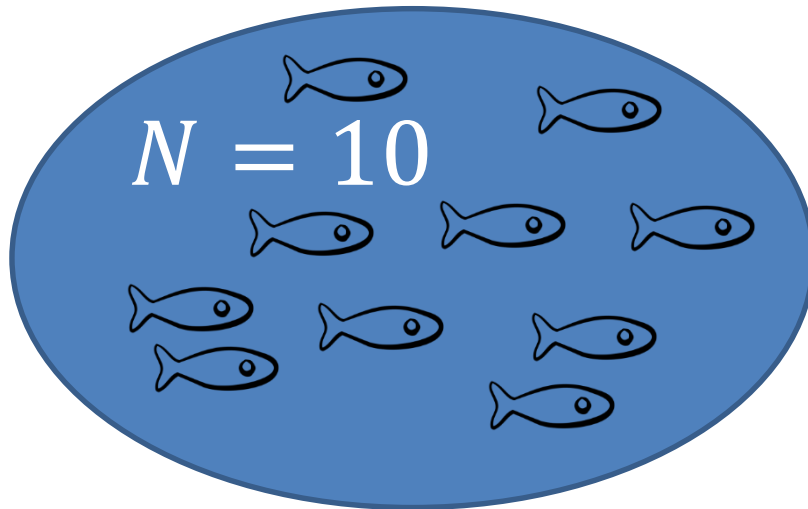


Example:

Estimate:

$$p = ?$$

$$n = ?$$



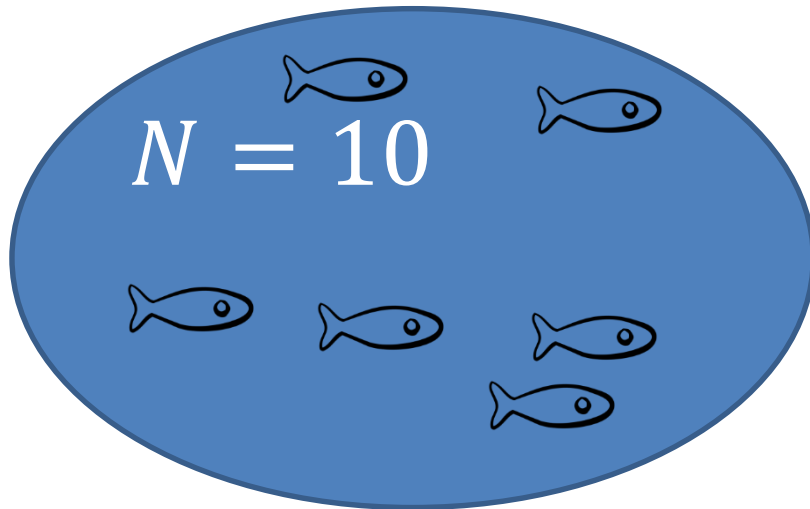
$$N = n \times \frac{1}{p} = ?$$



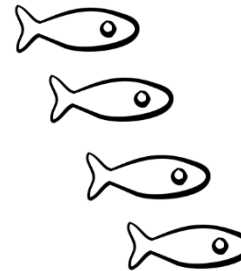
Example:

Estimate:

$$p = 0.4$$



$$n = 4$$



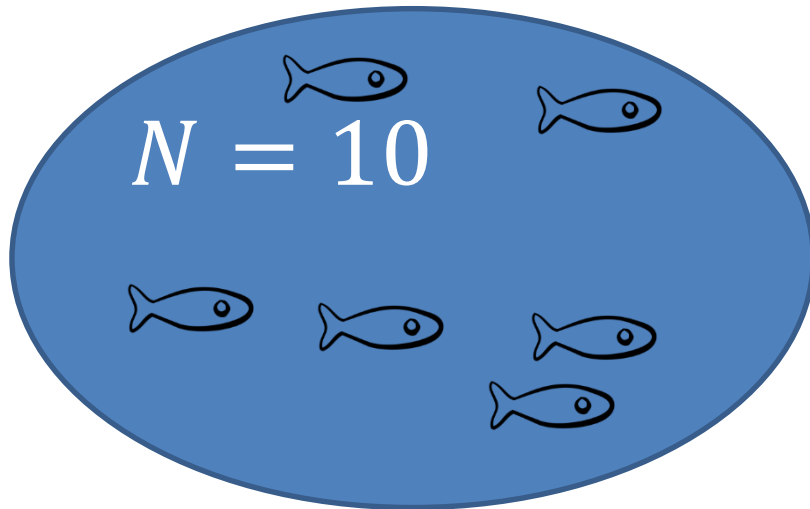
$$N = n \times \frac{1}{p} = 10$$



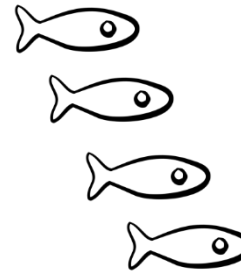
Example:

Assume:

$$p = 1$$



$$n = 4$$



$$N = n \times \frac{1}{p} = 4$$



# Telemetry data: challenges

- Imperfect detection





# Telemetry data: challenges

- Imperfect detection
- Small sample sizes
  - Increased probability of inaccurate estimate
  - Increased uncertainty about estimate
  - Usually due to \$\$\$\$





# Telemetry data: challenges

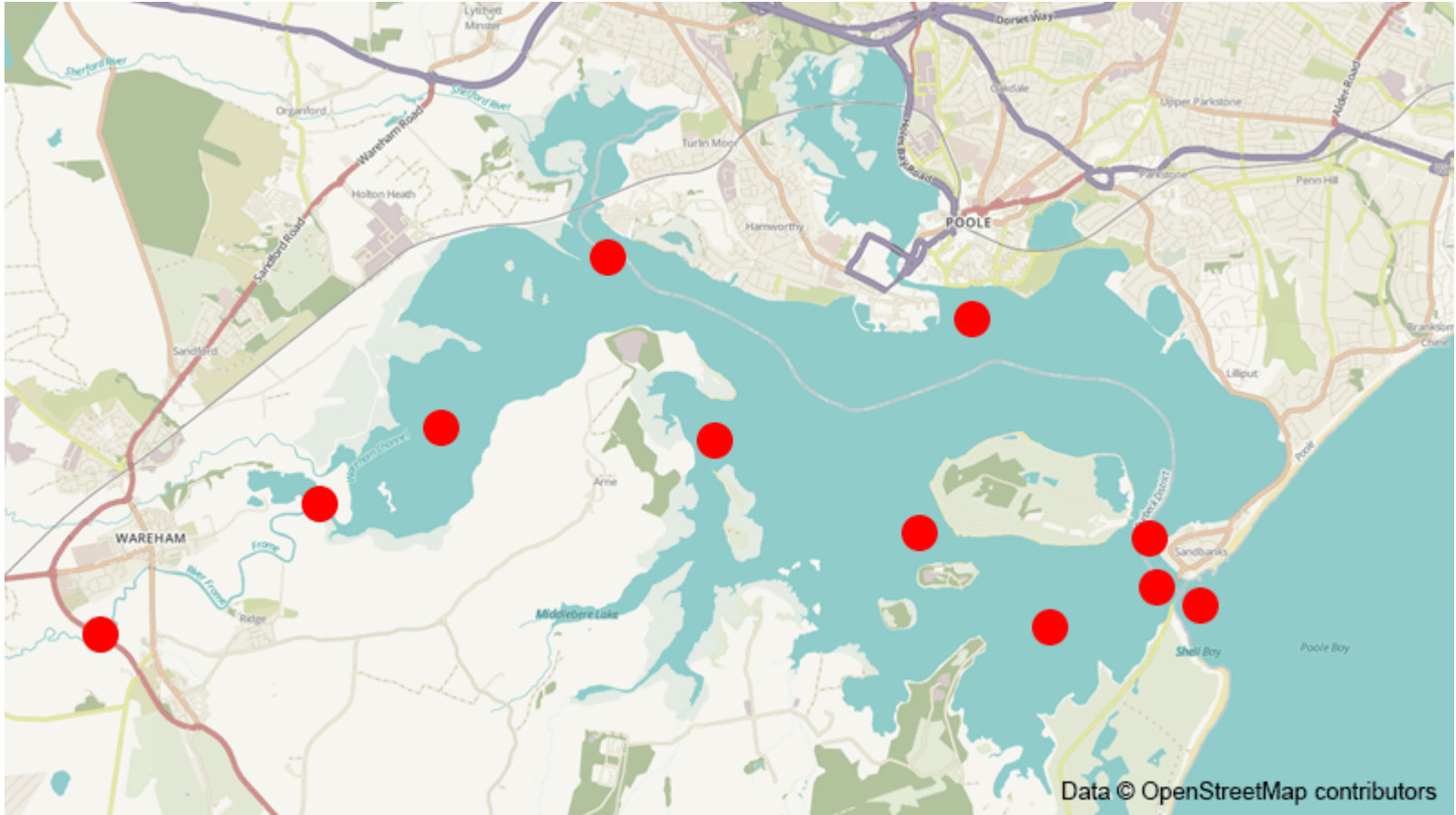
- Imperfect detection
- Small sample sizes
- Experimental design



# Telemetry data: challenges

- Imperfect detection
- Small sample sizes
- Experimental design
  - Receiver locations



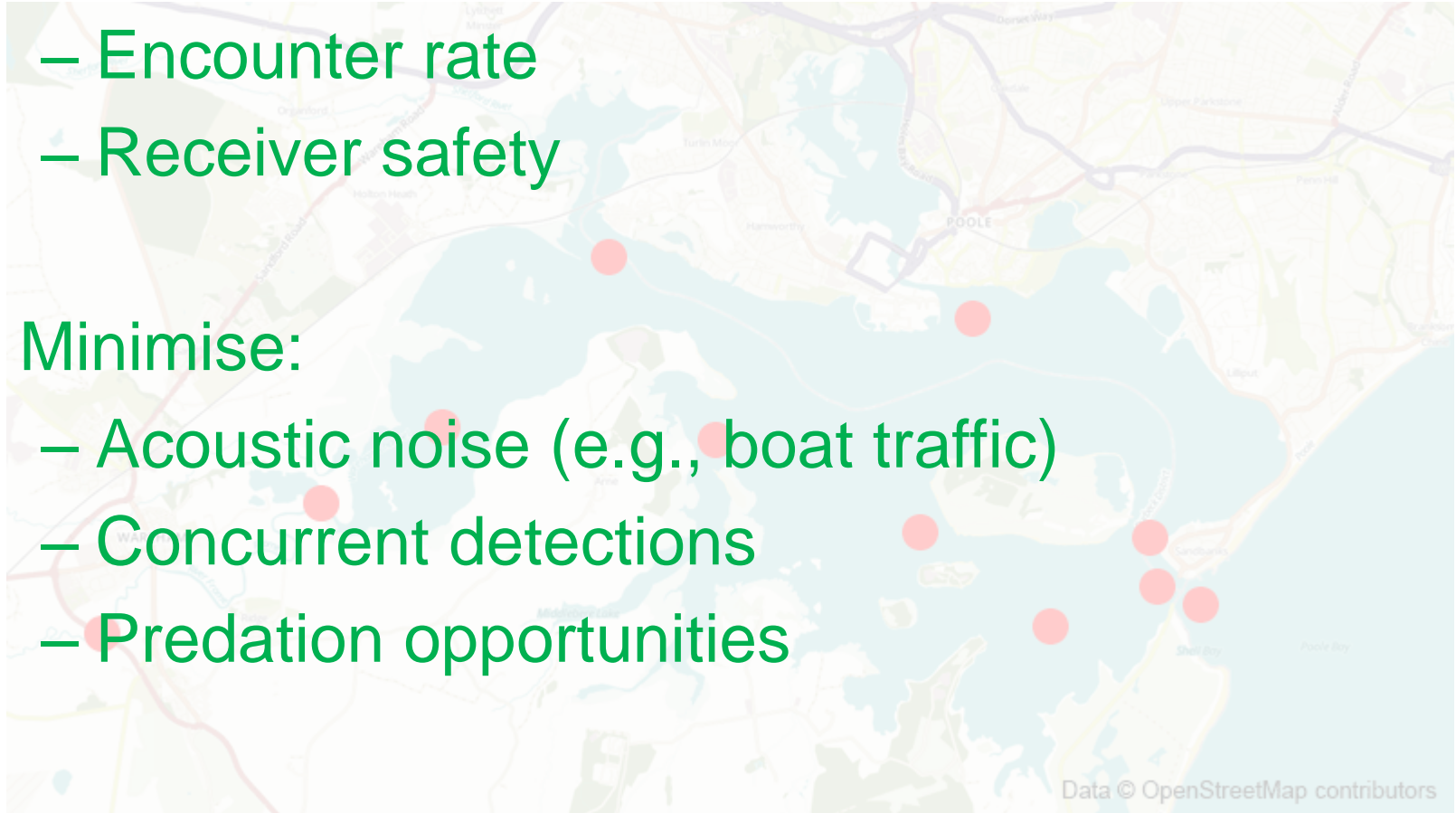


- Maximise:

- Encounter rate
- Receiver safety

- Minimise:

- Acoustic noise (e.g., boat traffic)
- Concurrent detections
- Predation opportunities

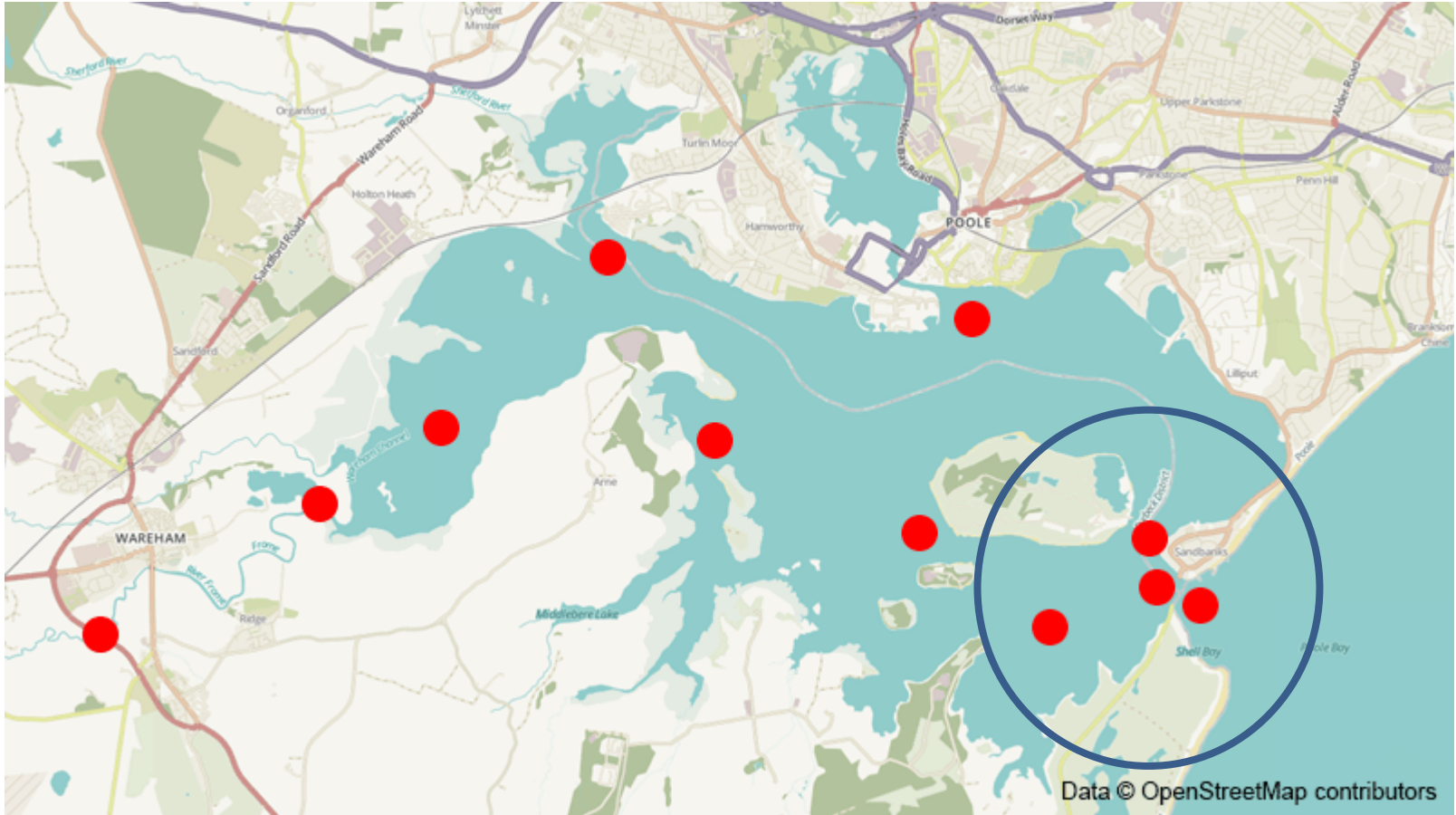


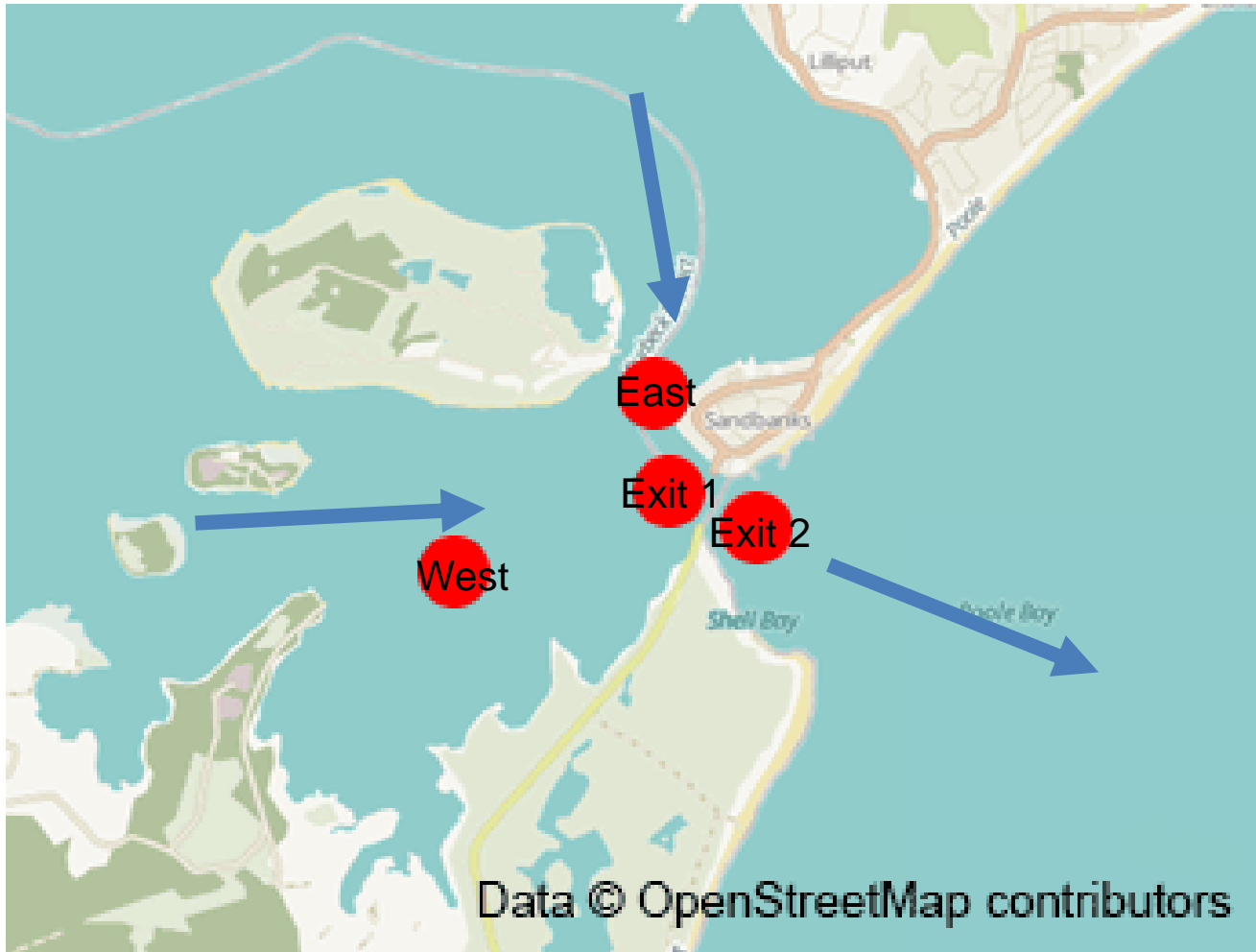
# Telemetry data: challenges

- Imperfect detection
- Small sample sizes
- Experimental design
  - Receiver locations
  - Last receiver









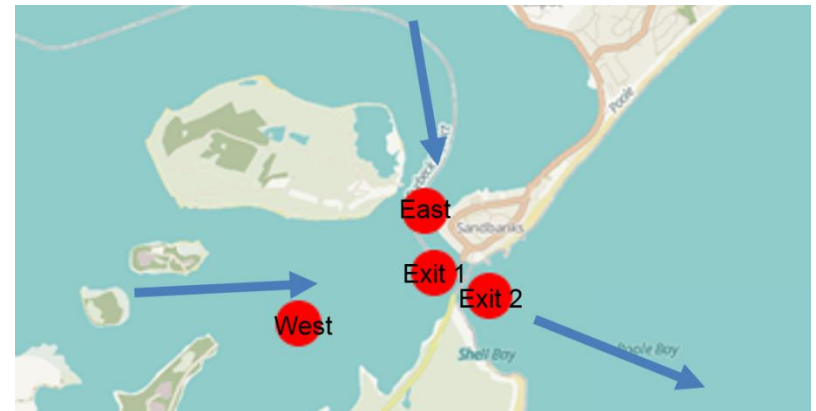
- Detection probabilities ( $p$ ) only estimable with detection information farther up- / down- stream!
- % detections at receiver 2 detected at receiver 1

$$n_{r1} \sim \text{Binomial}(n_{r2}, p_{r1})$$

East and West receivers efficiencies estimated from Exit 1

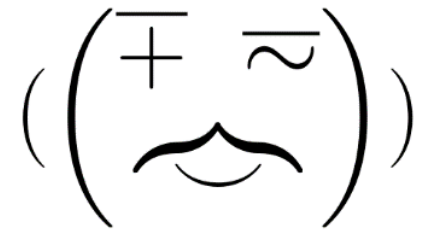
Exit 1 receiver efficiency estimated from Exit 2

No efficiency estimate for Exit 2





# Outline



- Telemetry data: challenges
- **State-Space modelling**
- Examples (from the Dorset Frome):
  - Poole harbour sea trout
  - Frome PIT tag movements
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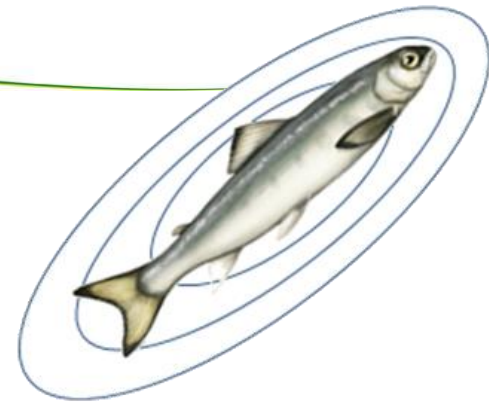


# State-Space modelling

- Separates nuisance parameter (detection probability  $p$ ) from parameter of interest (transition probability  $\phi$ )
- Goal: estimate State when not detected and thus detection and transition probabilities
- Explained in Gimenez et al. 2007, *Ecological Modelling*, 206, 431-438



# State-Space modelling



State matrix of individual  $i$

$$z_i = [A, ?, B, ?]$$

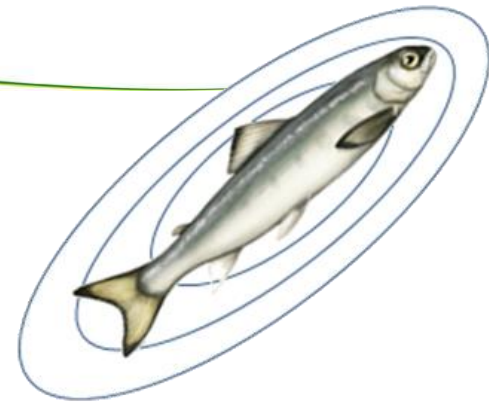
Space matrix of individual  $i$

$$w_i = [1, 0, 1, 0]$$

Individual  $i$  observed in state  $k = A$  at time  $t = 1$ , was unobserved at  $t = 2$ , was observed in  $k = B$  at  $t = 3$  and was unobserved at  $t = 4$ .



# State-Space modelling



## State

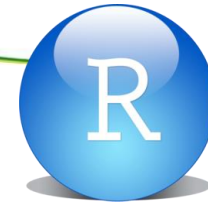
- Survived
- Died
- Stopped migrating
- Etc.

## Space

- Time
- Location
- Time & Location
- Etc.



# State-Space modelling

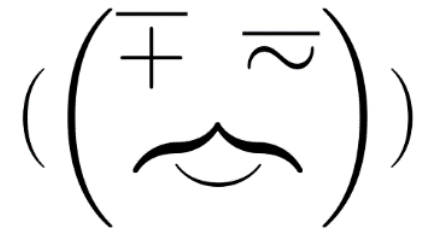


**JAGS**

- Parameter estimates by MCMC (Monte Carlo Markov Chains)
- Estimates joint probability of parameters given the data
- Bayesian inference (but can use frequentist methods)



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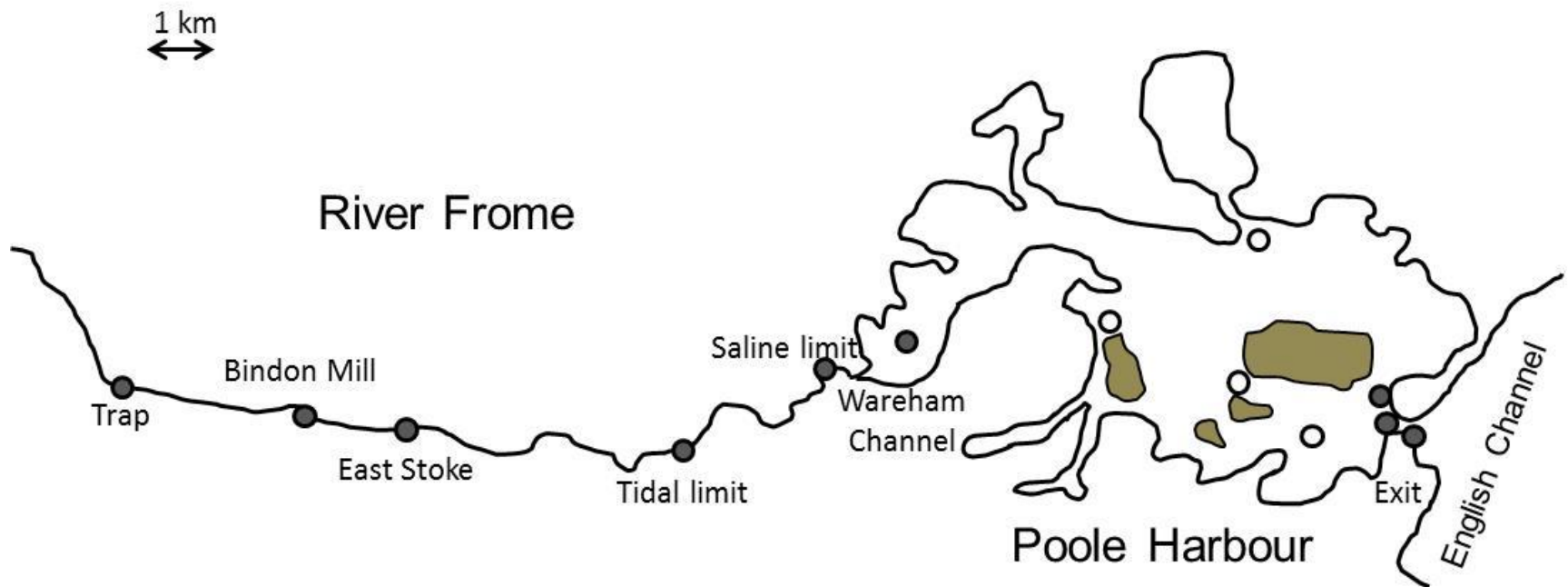


# Example: Poole harbour sea trout

- Aim: estimate relative risks to sea trout smolts of migration in freshwater and estuarine zones
- Assume:
  - Physical or behavioural differences between individuals were unimportant
  - Individuals travelled independently
- More details: <http://stephendavidgregory.github.io/tracking/Holbrook>



# Example: Poole harbour sea trout





# Example: Poole harbour sea trout



2013: 30 smolts ( $\bar{x}$  length = 182mm [123-247mm];  $\bar{x}$  weight = 70g [19-177g])

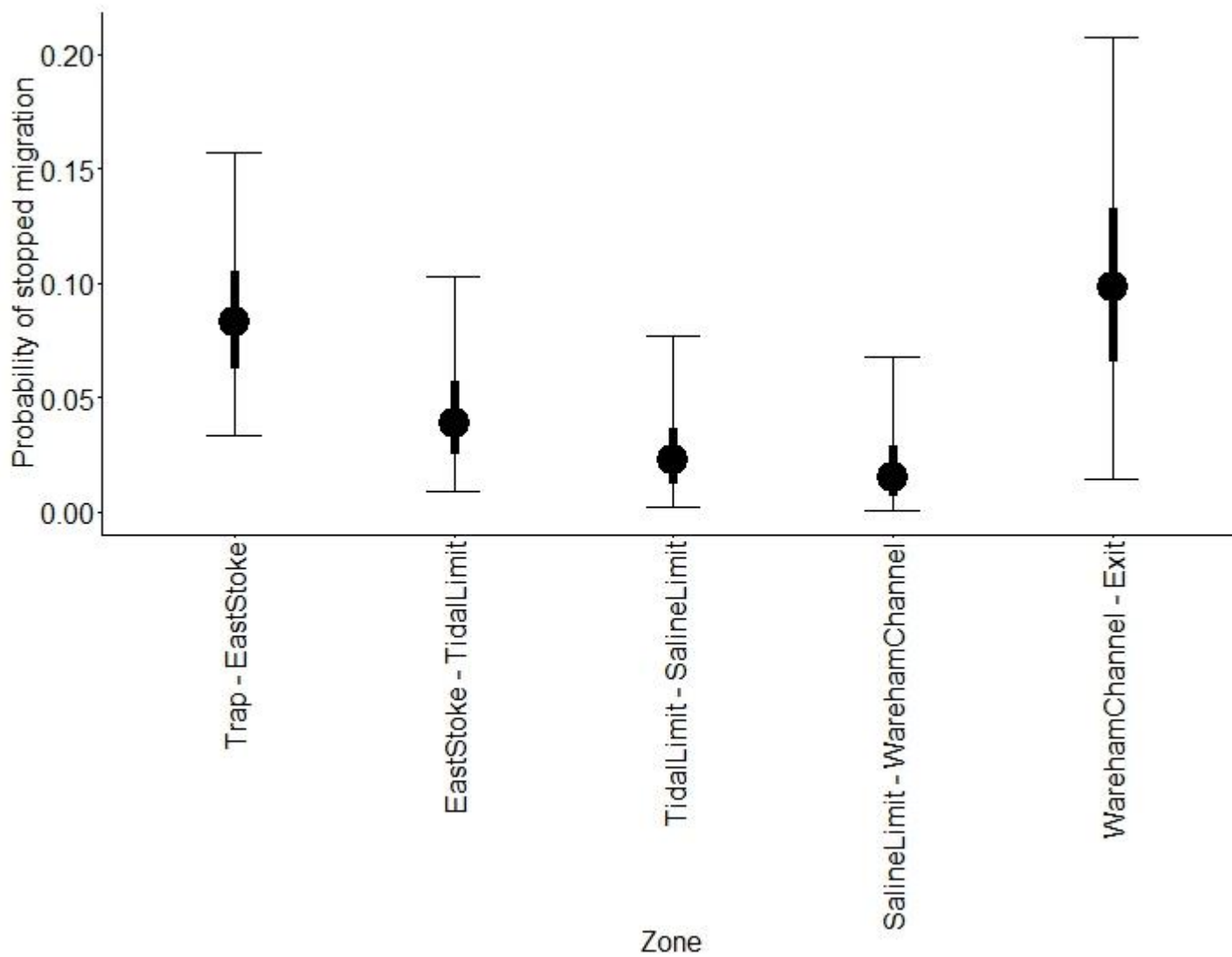
2014: 51 smolts ( $\bar{x}$  length = 213mm [163-273mm];  $\bar{x}$  weight = 105g [44-199g])



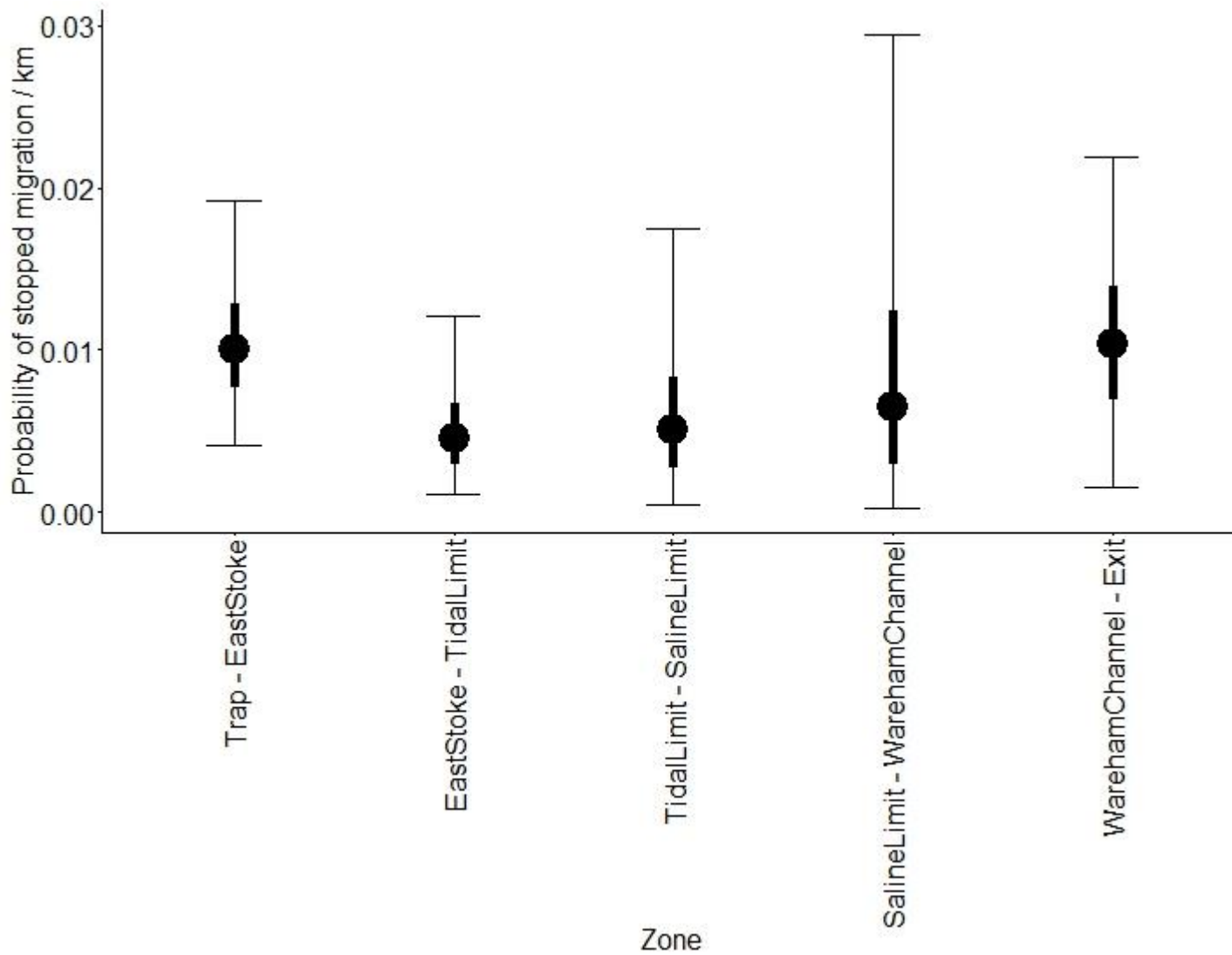
# Example: Poole harbour sea trout

<i>Station</i>	<i>Distance from trap (km)</i>	<i>Year</i>	<i>No. Tags detected *</i>	<i>Detection probability (95% CI)</i>	<i>Day time obs.</i>	<i>Night time obs.</i>
Bindon Mill	5.4	2013	20	N/A	0%	100%
		2014	36		14%	86%
East Stoke	8.2	2013	25	0.93	0%	100%
		2014	42	(0.86-0.95)	10%	90%
Tidal Limit	16.7	2013	24	0.99	8%	92%
		2014	45	(0.95-1.00)	18%	82%
Saline Limit	21.1	2013	21	0.96	43%	57%
		2014	42	(0.90-0.99)	48%	52%
Wareham Channel	23.4	2013	20	0.81	40%	60%
		2014	37	(0.70-0.84)	62%	38%
Exit	32.9	2013	22	0.84	68%	32%
		2014	36	(0.72-0.87)	56%	44%

# Example: Poole harbour sea trout



# Example: Poole harbour sea trout



# Estimating sea trout smolt migration risks

*Estimating transition probabilities with Bayesian State Space models*

28 Jan 2016 in Tracking © 7 minutes read



<http://stephendavidgregory.github.io/>



Game & Wildlife CONSERVATION TRUST

# Example: Frome PIT tag movements

- Aim: describe smolt freshwater migration behaviour in relation to individual characteristics
  - Transition probability ~ River characteristics
    - ~ Smolt characteristics
    - ~ Temporal variables



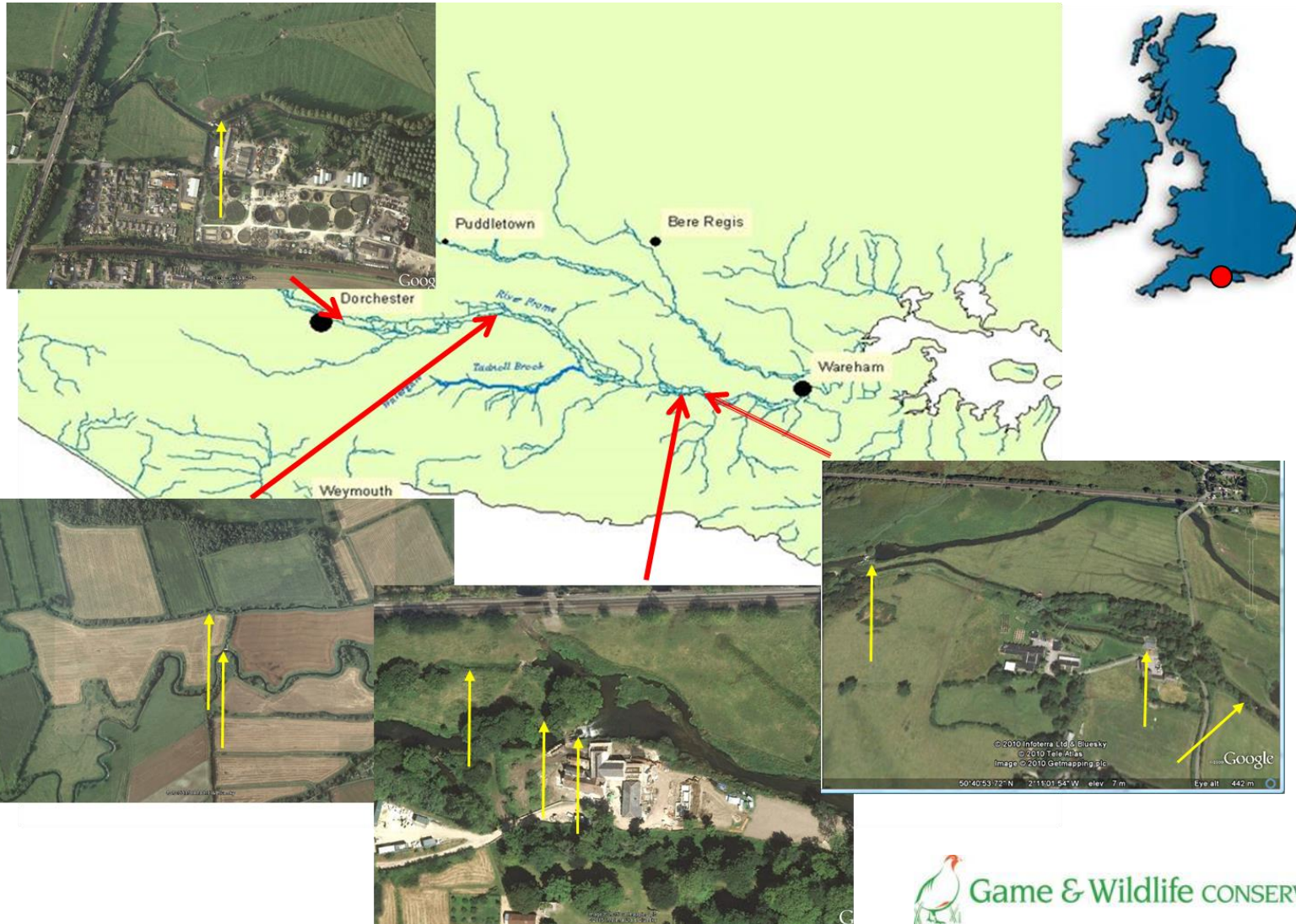


# Example: Frome PIT tag movements

- Up to 10,000 salmon parr tagged per year
- Up to 50 locations throughout the catchment



# Example: Frome PIT tag movements





# Example: From PIT tag movements

- Uninformative prior on transition probability

$$\phi \sim \text{Beta}(1, 1)$$

- Informative prior, allowing for covariates

$$\text{logit}(\phi) \sim \alpha + \beta X$$

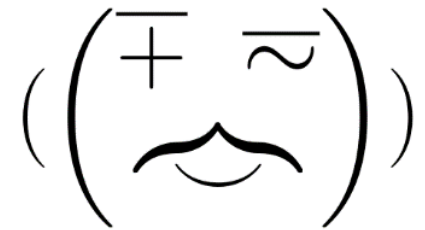


# Example: From PIT tag movements

- Example questions
  - How is the probability and speed of transition related to smolt size?
  - How is the probability and speed of transition related to flow?
  - How is the probability of transition related to shoaling behaviour?
  - ...



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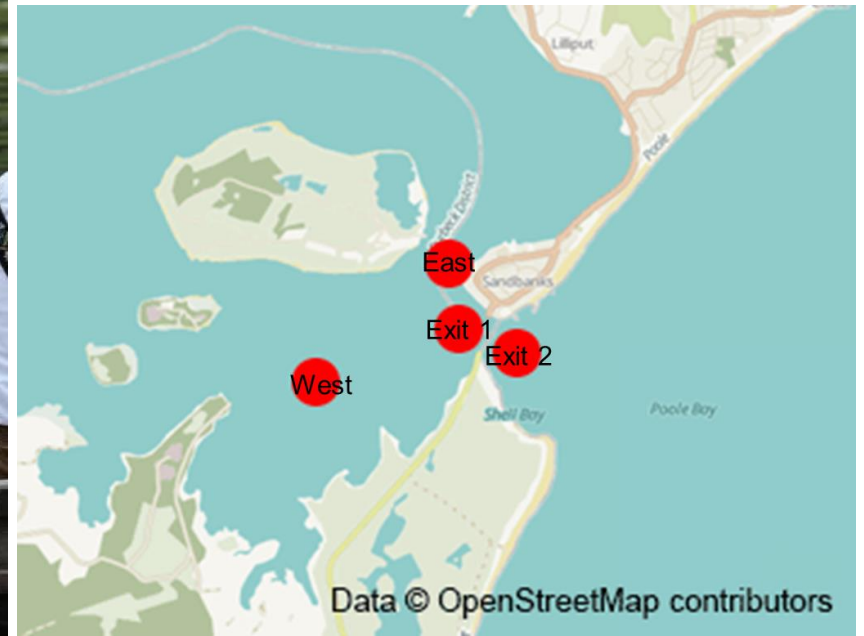
# Take away points

- Experimental design (last receiver) is important!



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# Take away points

- Experimental design (last receiver) is important!



# Take away points

- Experimental design (last receiver) is important!
- State-Space modelling: efficient use of data
  - Fewer assumptions
  - [Probably] better accuracy
  - Better accounting of uncertainty





# Take away points

- Experimental design (last receiver important!)
- State-Space modelling: efficient use of data
- New studies:

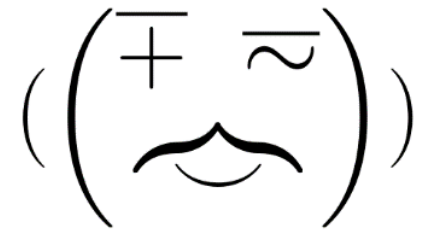


*Tracking technology + State-Space modelling = exciting opportunities*





# Thanks

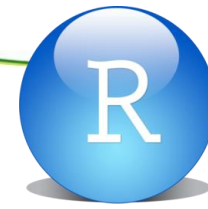


[sgregory@gwct.org.uk](mailto:sgregory@gwct.org.uk)

<http://stephendavidgregory.github.io/>



# State-Space modelling



**JAGS**

- Parameter estimates by MCMC (Monte Carlo Markov Chains)
- Estimates joint probability:

$$\pi(\phi, p | z, w) \propto \pi(z, w | \phi, p) \pi(\phi) \pi(p)$$

where:

$\pi(\phi, p | z, w)$  = posterior parameter probabilities

$\pi(z, w | \phi, p)$  = product of the likelihood of the data given the parameters

$\pi(\phi)$  = prior probabilities of transition

$\pi(p)$  = prior probabilities of detection

