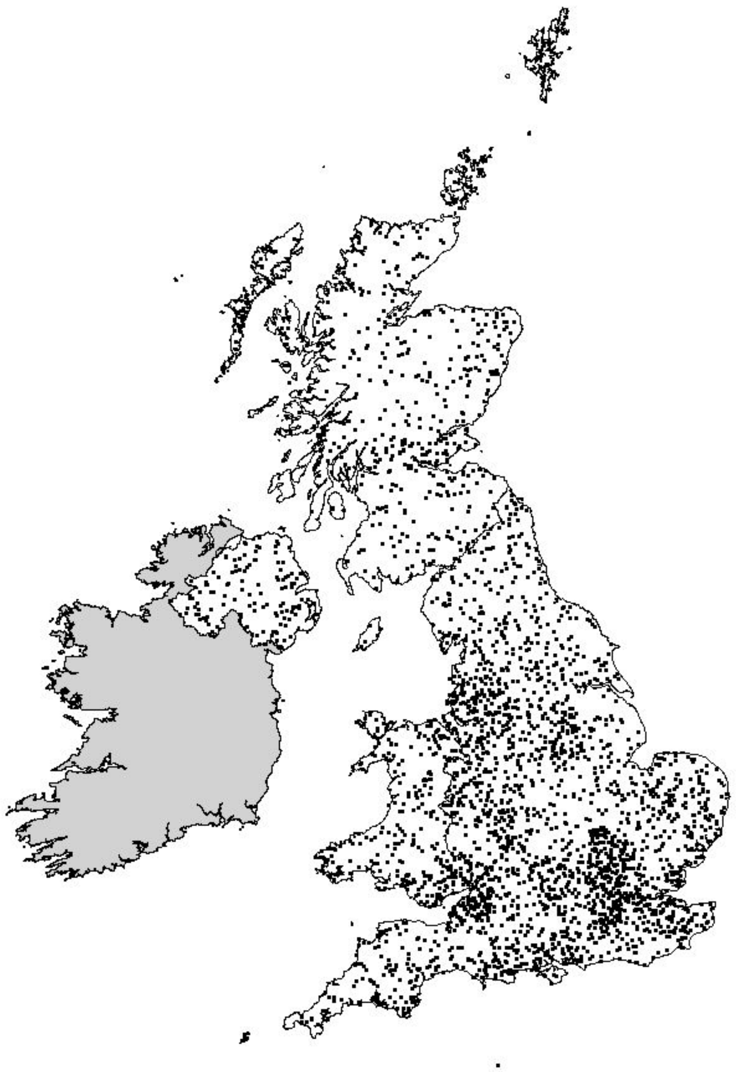
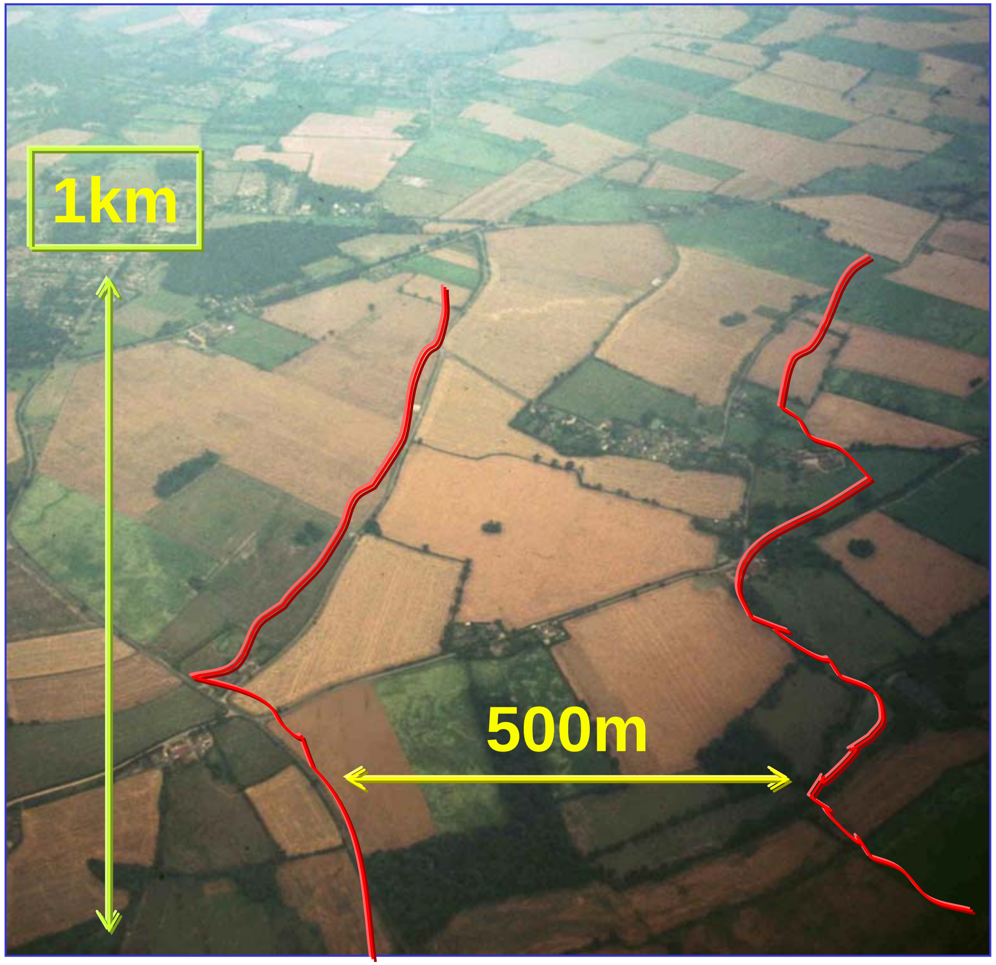
# The Breeding Bird Survey

- Volunteer-based scheme with >2000 1-km squares surveyed annually
- Stratified random design to account for differences in observer effort between regions



# Field methods




**Line Transect method**

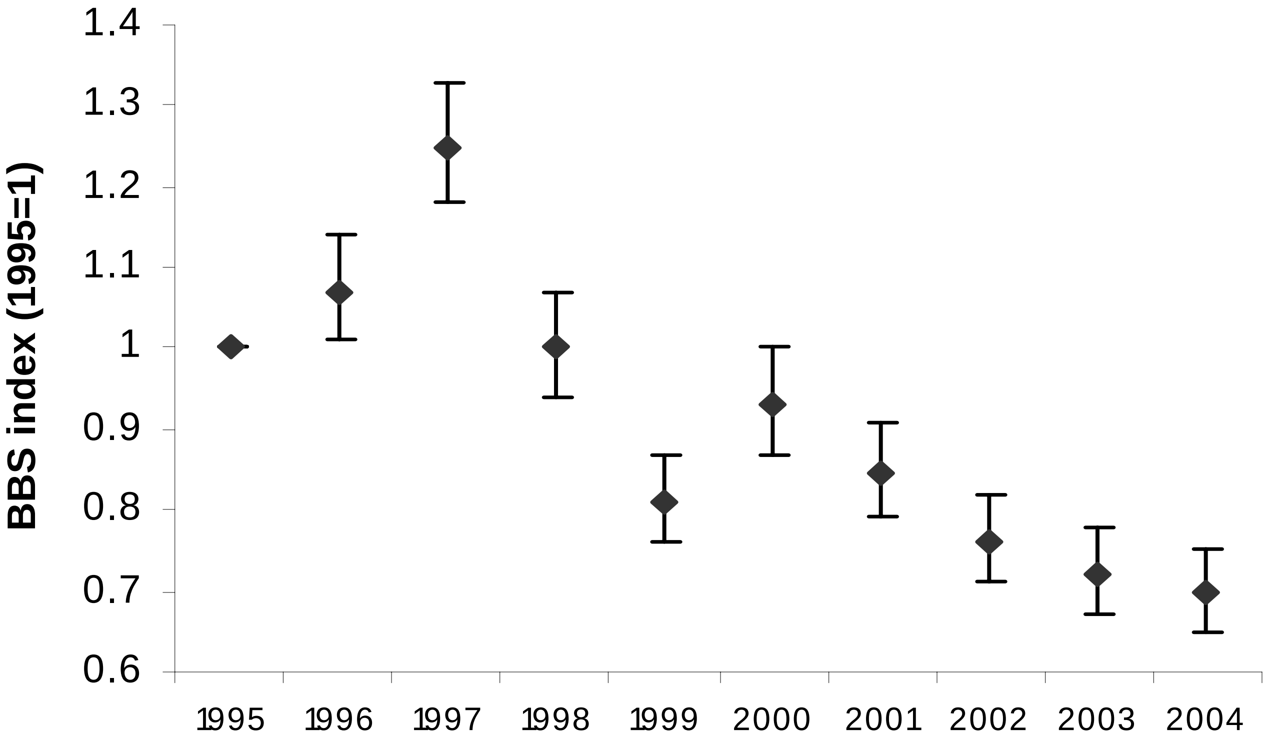
**Two 1-km transects**

ONE visit to record habitat

TWO visits to count mammals seen or record presence based on field signs, dead animals, local knowledge for that season

# Temporal trends in relative abundance

- Log-linear Poisson regression to model site counts, with site and year effects
- Trends only produced for species occurring on a mean of 40 or more squares in two or more years

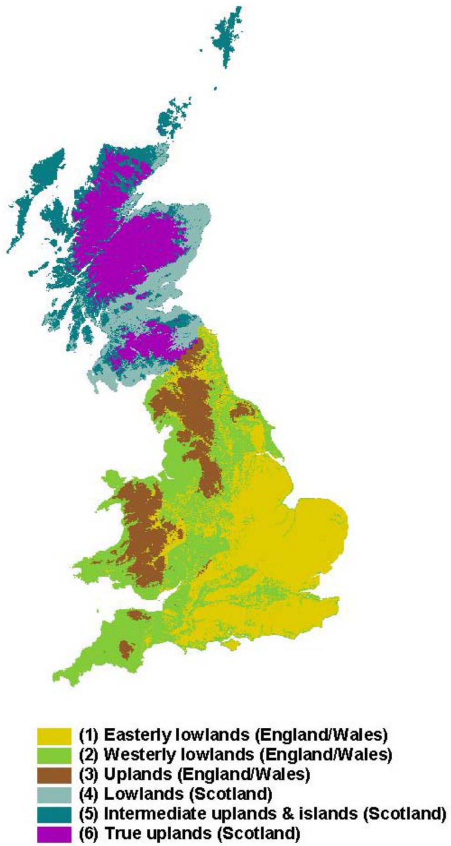



# Temporal trends in relative abundance

- Corrections for over-dispersion made using the ‘dscale’ option in SAS
- Model estimated using observed counts to predict missing counts
- Counts are weighted to account for the stratified sampling design
- Significance examined by making a comparison between first and last years. Non-overlapping of 95% confidence intervals used to assess significance at 5% level

# Temporal trends in relative abundance

- Where sample size is adequate, trends are produced at UK level, Country, GOR's and for environmental zones

# Temporal trends in relative presence

- For species that leave obvious field signs, or are known to be present on a BBS square
- Includes counts of live animals, dead animals, field signs or local knowledge of presence (e.g. gamekeeper)

# Temporal trends in relative presence

- Presence/absence is modelled as a function of site and year using logistic regression
- Year effect is the relative odds ratio i.e the odds of being present on a particular square in a particular year relative to the odds of being present in the first year

# Temporal trends in relative presence

- EXAMPLE

If in first year, probability of being present = 0.2 (absent = 0.8)

odds of being present = (0.2 / 0.8) = 0.25

If five years later the odds of being present = 0.8 (absent =0.2)

odds of being present = (0.8 / 0.2) = 4

Therefore: the odds ratio relative to the first year would be

4 / 0.25 = 16

# Temporal trends in relative presence

- Because we are measuring a change in ratio, it is not possible to ascribe a percent change measure to the probability of presence at all sites (as with the count data)
- However, it is essential to model the data in this way, to ensure that estimated probability of presence remains in the range 0-1
- The odds-ratio is a convenient means of dealing with this problem; the log of the odds can be multiplied by any constant rate of increase and yet probabilities remain sensible
- However, interpretation is not as intuitive as analyses of count data

# GLMs versus GAMs

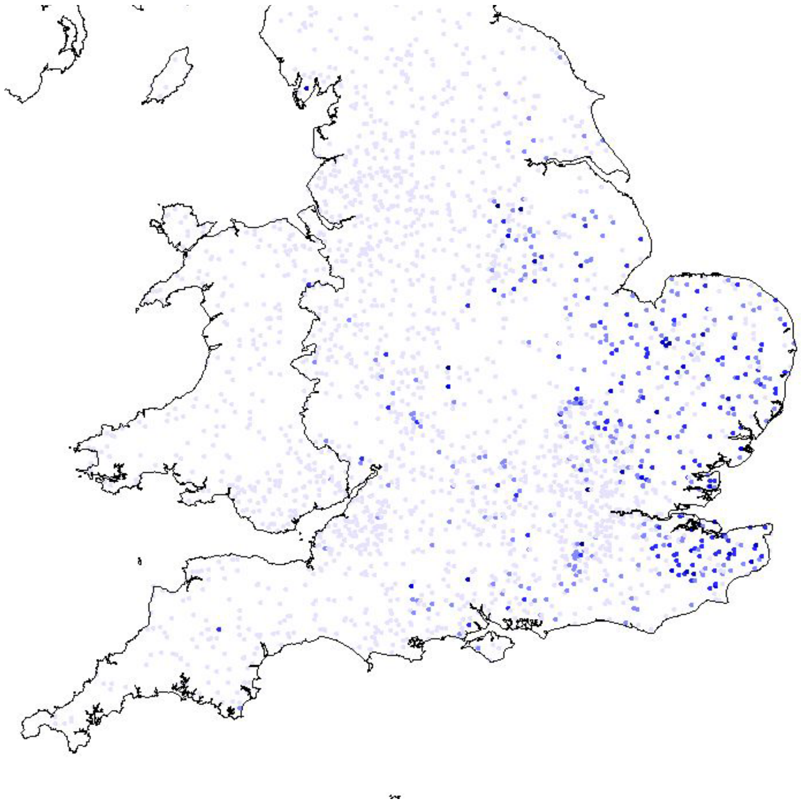
- Unlike conventional GLMs, which allow change in mean abundance over time to follow a smooth linear form or sequence of unrelated estimates, GAMs allow mean abundance to follow a more arbitrary smooth function
- Before the trend is estimated, a level of smoothing is chosen that is appropriate to the objective of the study (e.g. determine important features, whilst ignoring fine-scale fluctuations)
- Bootstrapping to produce confidence intervals
- Can be used to determine significant turning points in the index series
- Need a ‘sufficient’ run of years

# Spatial Interpolation

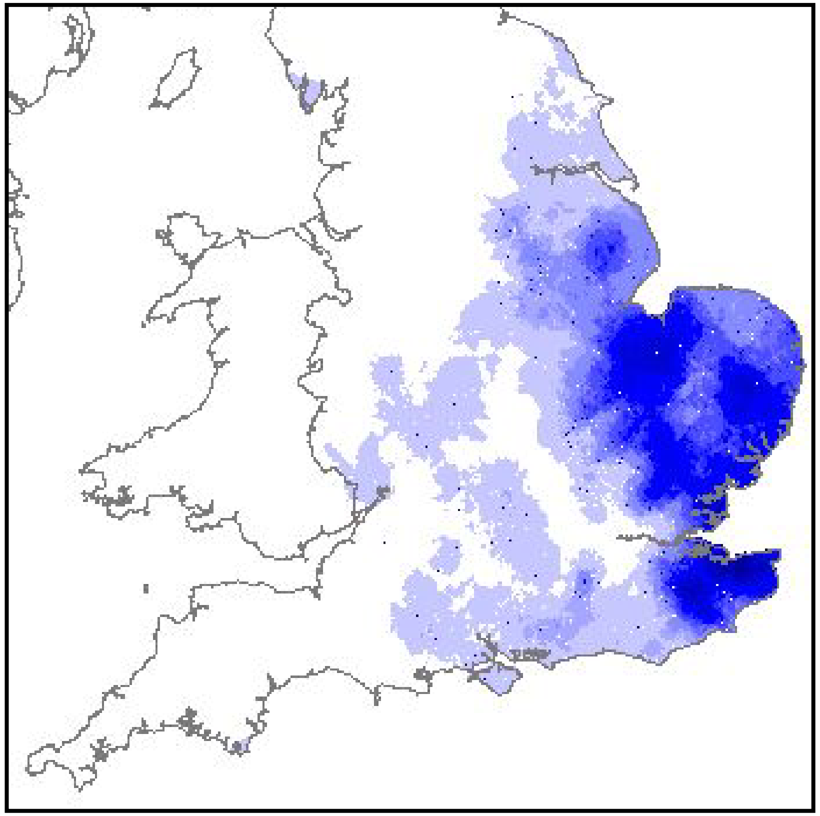
Process of using counts at surveyed sites
to estimate counts at unsurveyed sites

Basically a means of converting point data
to surface data

# Example: Turtle Dove

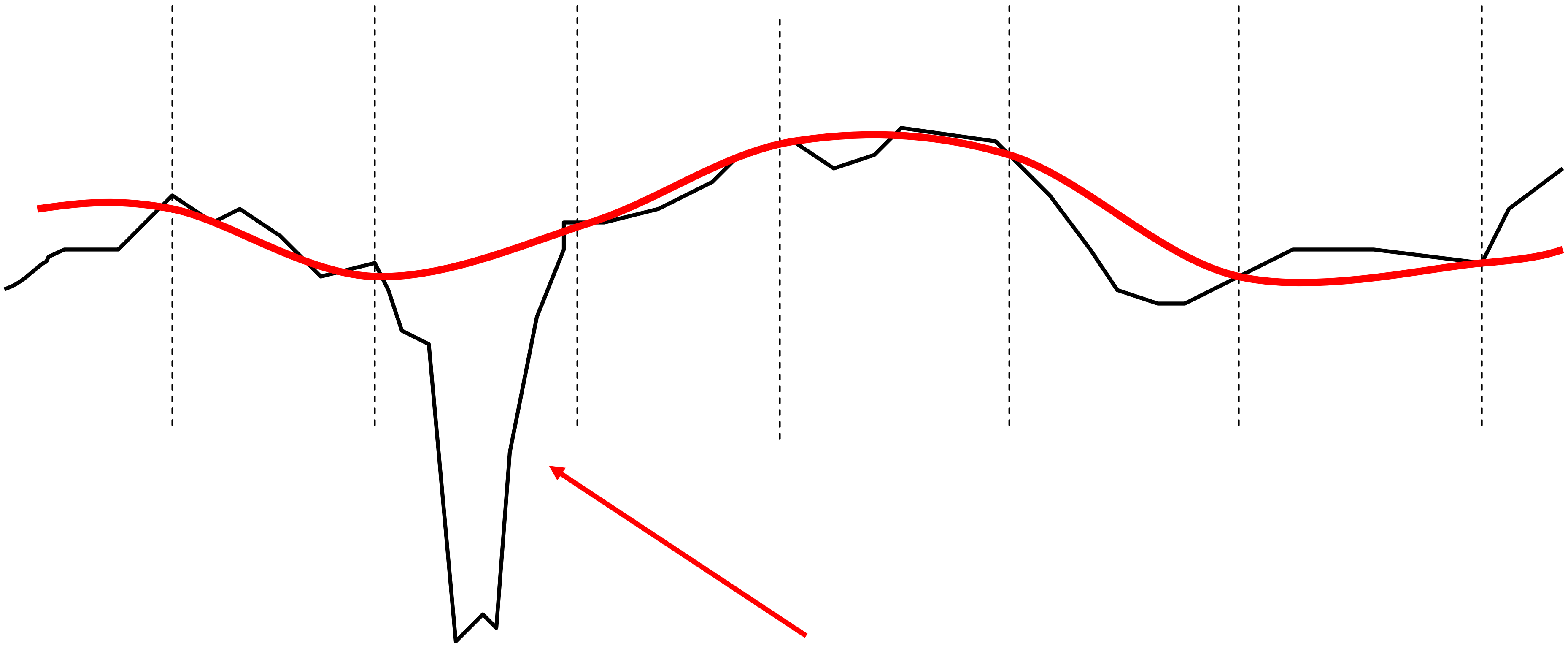


BBS squares surveyed in 2003



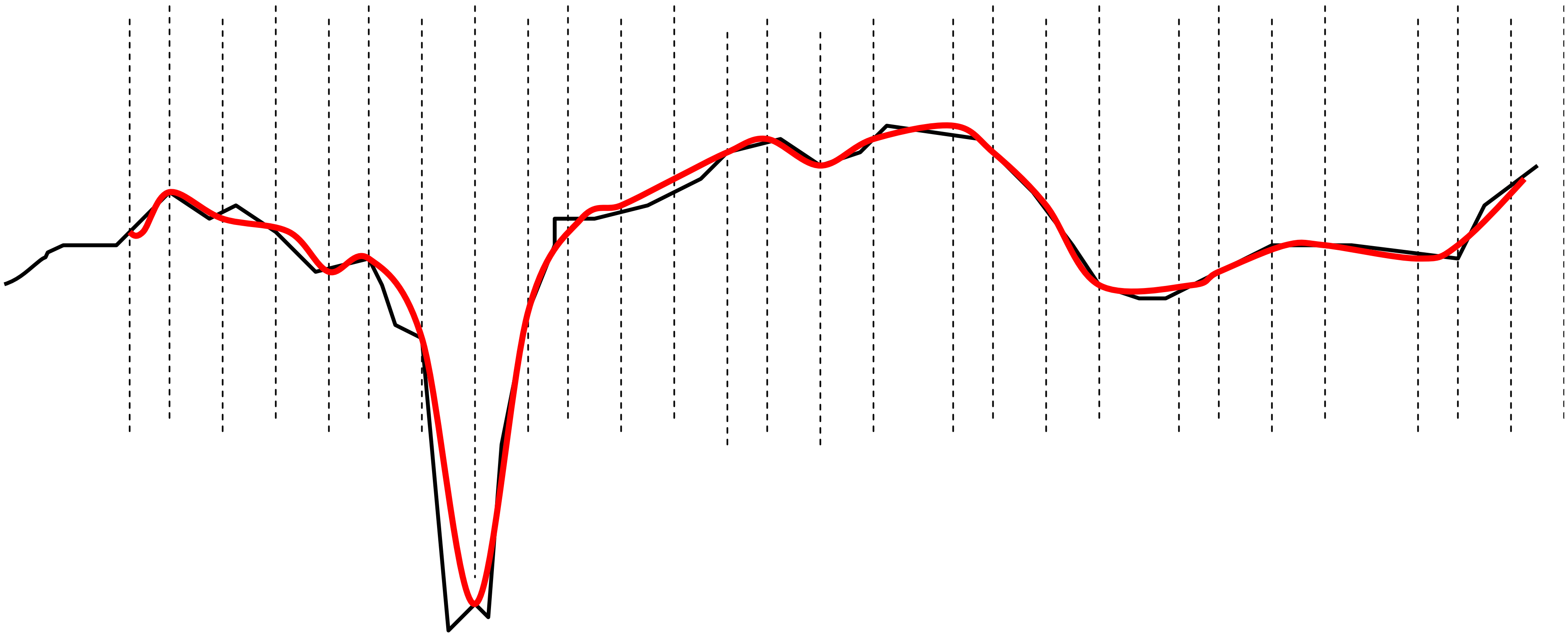
# How reliable are these maps?

Imagine this cross section represents abundance: If each dashed line represents a BBS square, this spacing would miss major local sources of variation, like the dip



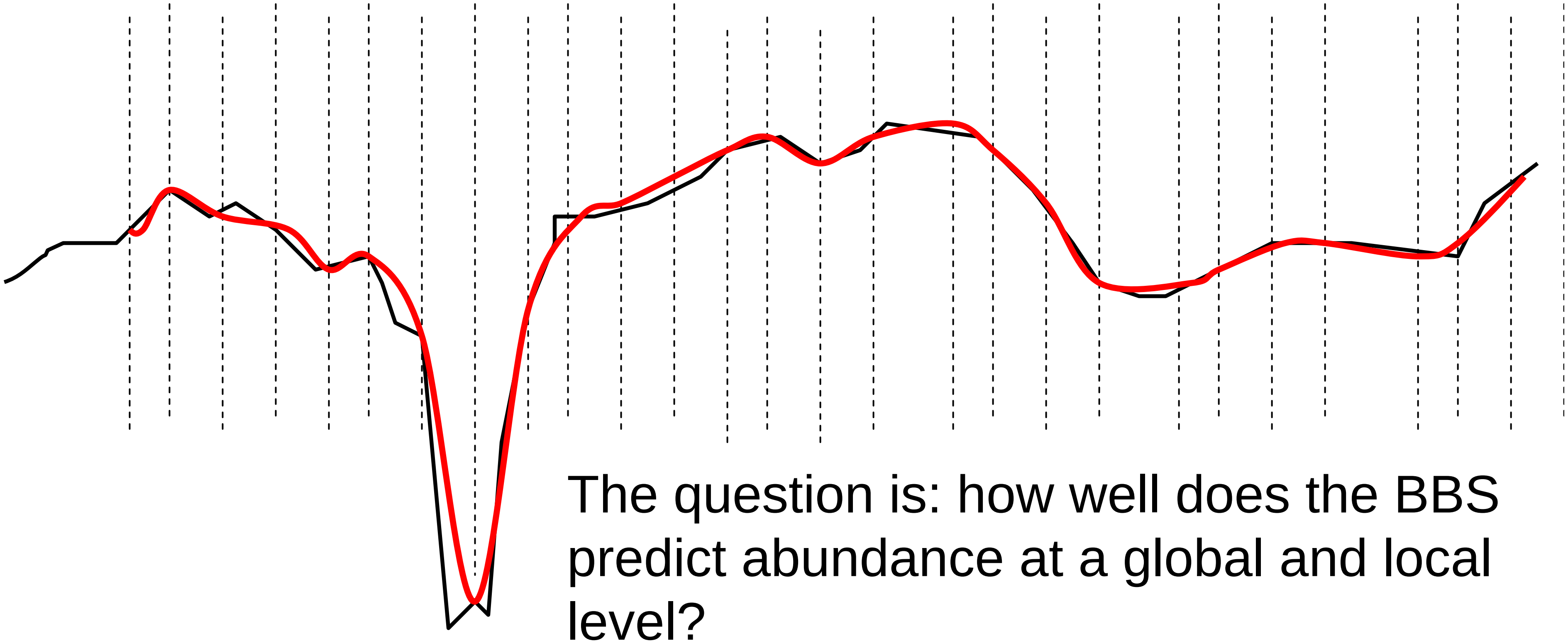
# Survey coverage

If you increase the survey coverage, the local variation will be more accurately captured



# Survey coverage

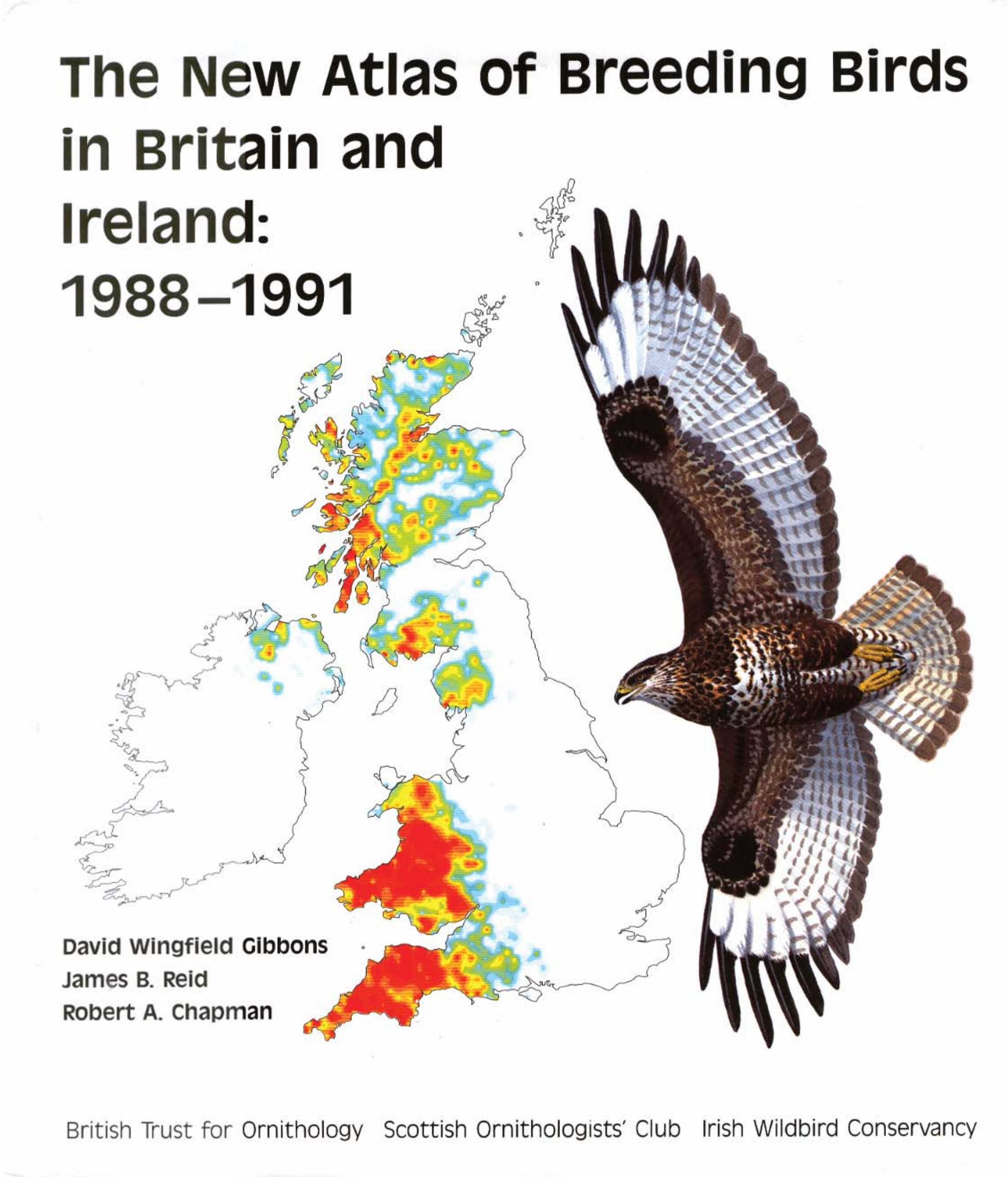
Interpolated surface is now much closer to reality at the local level, but we pay for this in the form of greater survey effort:



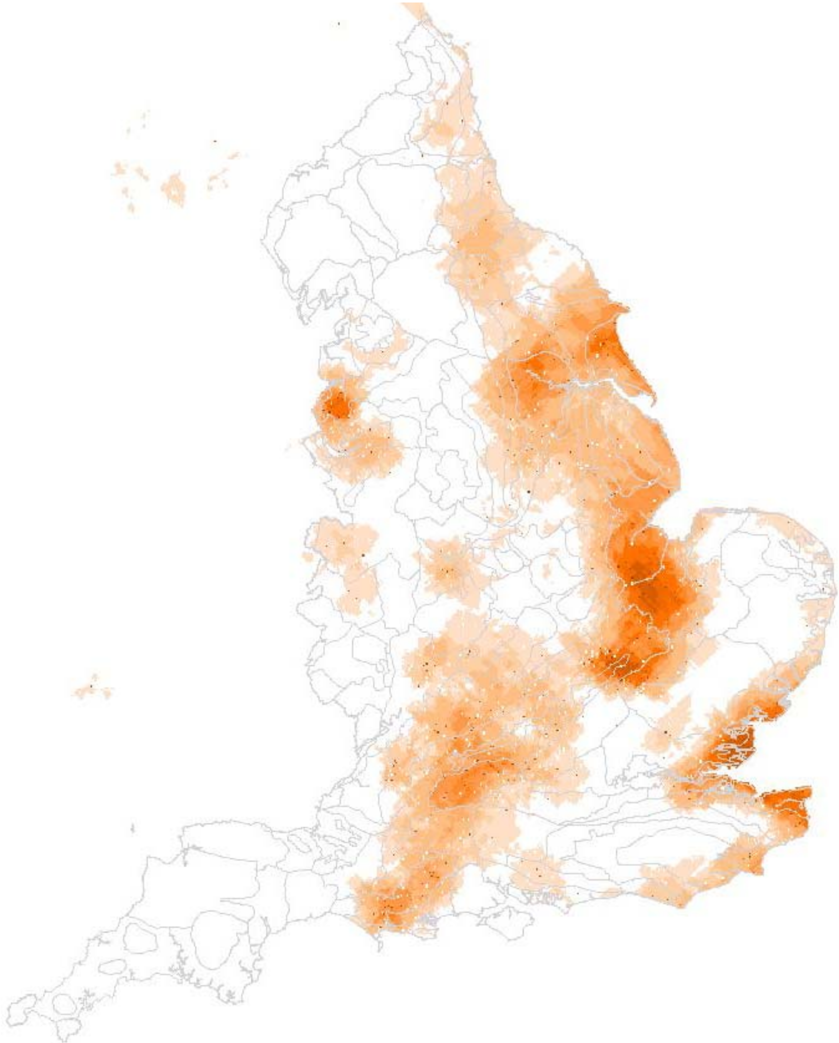
The question is: how well does the BBS predict abundance at a global and local level?

# BBS versus last breeding Atlas

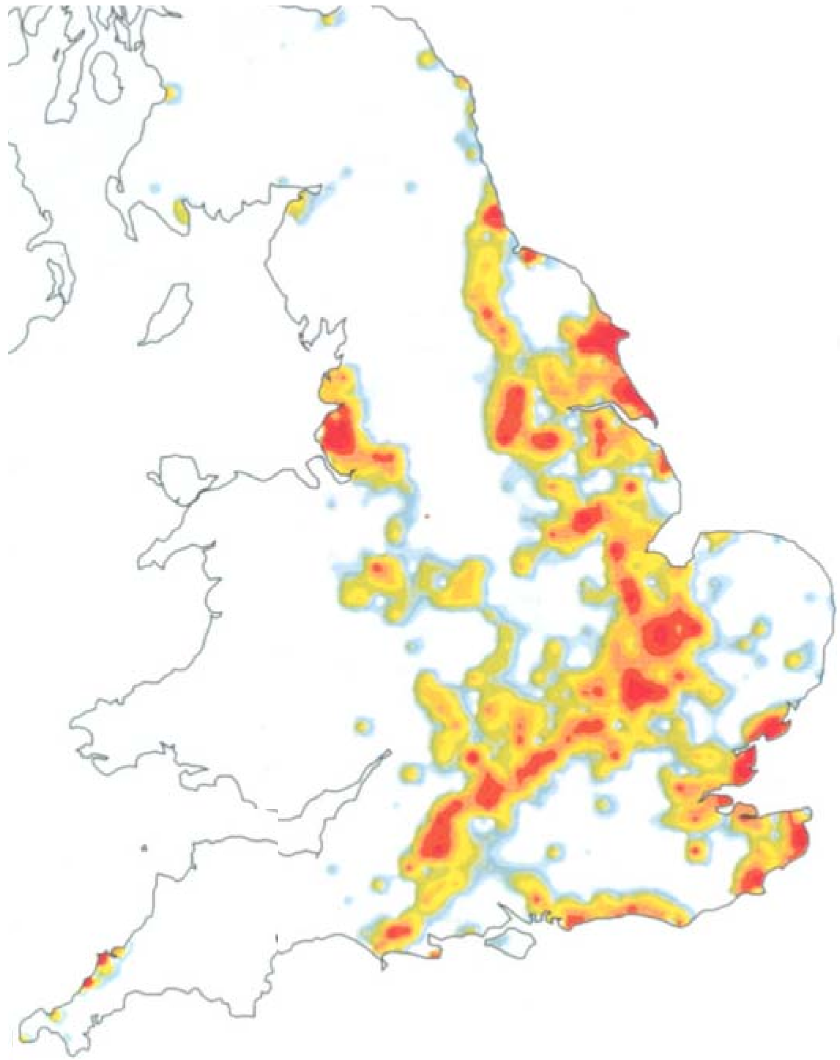
- Large survey effort > 42,000 4-km squares surveyed
- Abundance maps produced for all abundant and widespread species



**BBS (2002)**



**Last Atlas (88-91)**



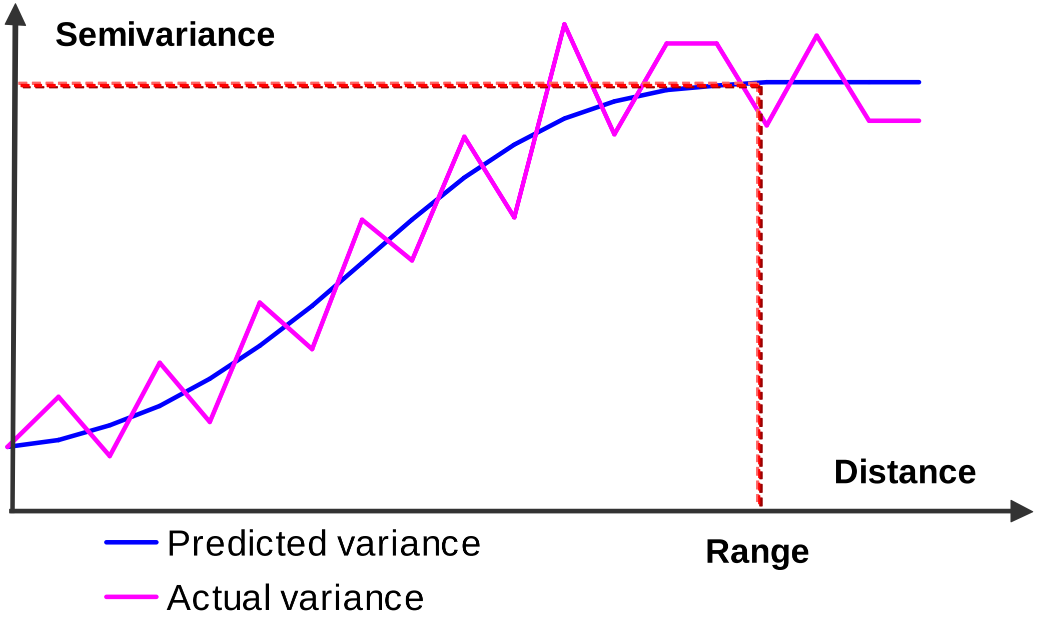
# Improving predictions


- Independent landscape data and **Cokriging** may improve predictions (e.g. CEH landcover data)
- Importance of other variables e.g. climate, food supply and altitude could be examined in a similar way

# How is the prediction surface created?

- The method (kriging) uses information on the degree of spatial correlation between counts at surveyed sites (semi-variance)
- Strength of the semi-variance depends on the distance between surveyed sites
(small distance = small semivariance)

- **Semivariance** increases with distance until a point is reached at which there is no further increase




- Within the range, locations are related to each other and all must be considered when estimating an unknown point within this range

To estimate abundance at an unsurveyed site, all known counts within range are assigned weights using the semivariogram

General equation for estimating the unknown count at a point is:

$$z_0 = \sum_{i=1}^{s} z_x W_x$$

$z_0$ is the unknown count
$z_x$ are counts at surveyed points
$W_x$ are weights associated with each surveyed point
$s$ is number of sampled points used in estimation

# Choosing between models

**1. Cross validation repeats the following**

i) Removes a known point from the data set

ii) Uses the remaining points to estimate the value at the point removed

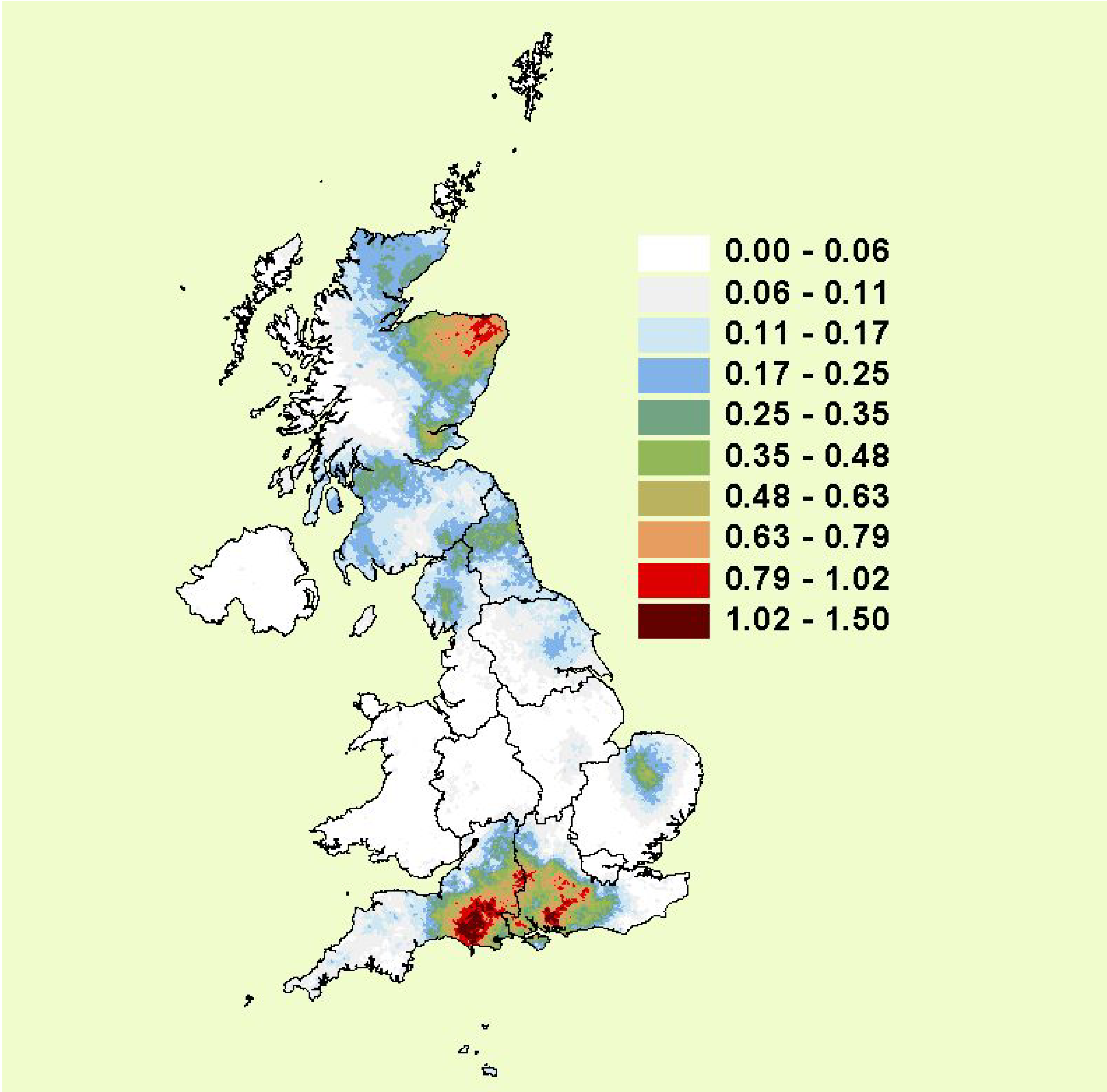
iii) Calculates the predicted error of the estimation by comparing the estimated count with the known count

**2. Validation** splits surveyed sites into two samples: one to develop the model and other to test the accuracy of the model

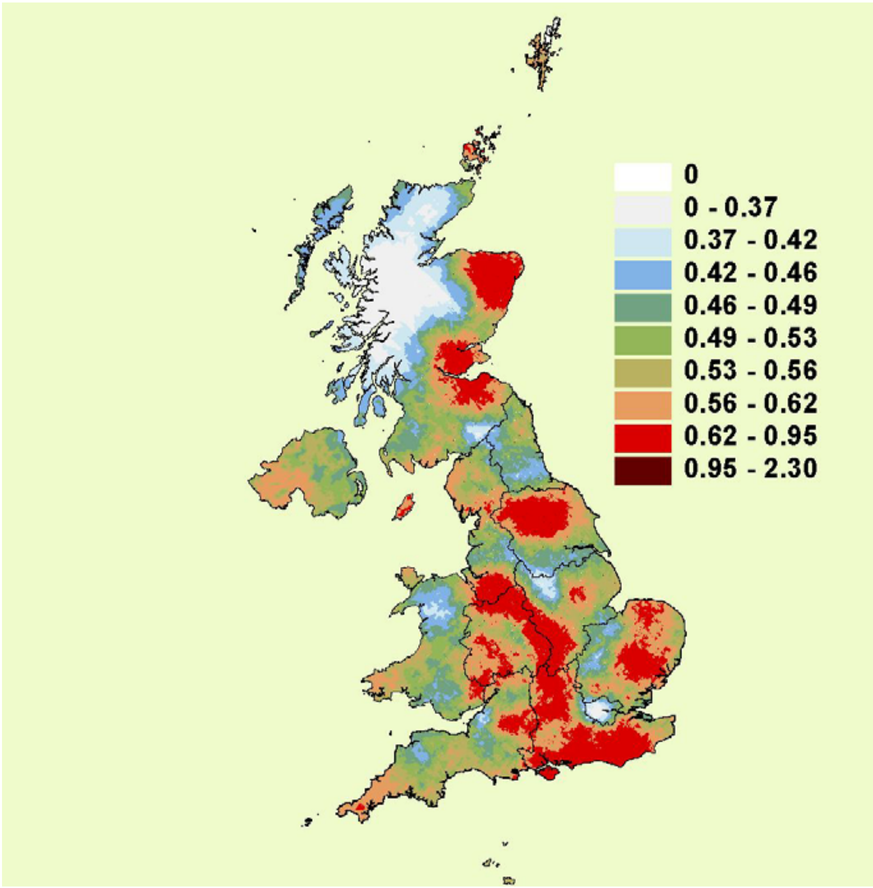
# Relative abundance

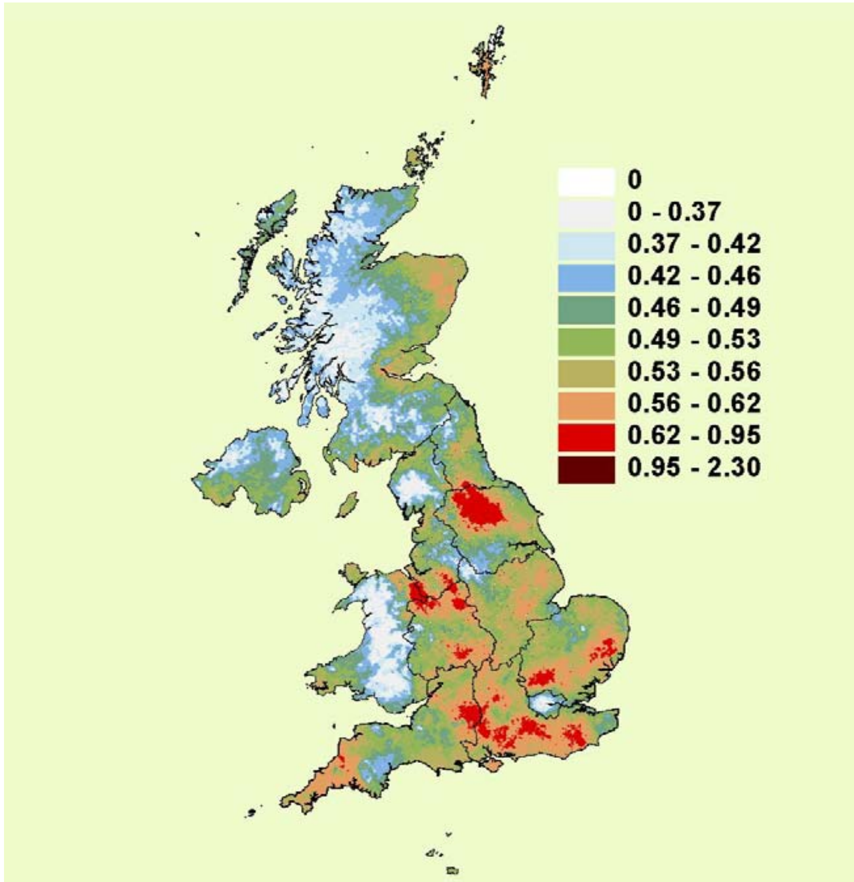
**e.g. Roe Deer**

**(2003)**



# e.g. Rabbit 1995 and 2004



# Limitations of this methodology

- For count data that are clearly non-normal, there is little theory to suggest that a kriging predictor is reasonable
- One can transform the data to get round some of the problems
- However, there is a need to develop our expertise in model-based procedures for count data to produce accurate predictions and associated measures of prediction uncertainty, while imposing realistic distribution assumptions on the data

# Alternative approaches??

- <u>Neural networks</u> perhaps most reliable species distribution/relative abundance maps, although computer intensive, interactive in nature, and not well placed to examine which factors have the strongest influence on distribution/relative abundance
- <u>'Autologistic' models</u> e.g. Augustin, Buckland & Mugglestone (J. Appl. Ecol. '96) and developments on this theme e.g. incorporating the relationship between presence/absence and abundance, difference between 'absence' and 'non-detection'. However, are complex, requiring high programming language (and expertise)