Making the most of what we have: application of extrapolation approaches in radioecological transfer modelling

Nicholas A. Beresford, Michael D. Wood, Jordi Vives i Batlle, Justin E. Brown, Ali Hosseini, Tamara L. Yankovich, Clare Bradshaw & Neil Willey

STAR final Dissemination Event, Aix-en-Provence, 9-11 June 2015

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STRATEGY FOR ALLIED RADIOECOLOGY

Why?

EUROPEAN RADIOECOLOGY ALLIANCE

Making the most of what we have: application of extrapolation approaches in radiological transfer models

...... because we will never have everything we want

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- How well do ERICA extrapolation approaches work?
- Bayesian statistics
- Stoichiometry
- Transcer coefficient v's concentration ratio
- Allometry
- An alternative approach to CR for wildlife

EUROPEAN COMMISSION
Community research

STAR
(Contract Number: Fission-2010-3.5.1-269672)

DELIVERABLE (D-N°3.2)
Evaluation of extrapolation approaches to provide radioecological parameters

Editors: N.A. Beresford (NERC-CEH, UK), J.E. Brown (NRPA, Norway), J. Vives i Batlle (SCK·CEN, Belgium), A. Hosseini (NRPA, Norway), C. Bradshaw (SU, Sweden)

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Collaborators: M.D. Wood (Universtiy of Salford, UK), T.L. Yankovich (IAEA), P. Andersson (SSM, Sweden), S. Fesenko (IAEA), N. Willey (University of West of England, UK)

Journal of Environmental Radioactivity 126 (2013) 399–411
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Journal of Environmental Radioactivity
journal homepage: www.elsevier.com/locate/jenvrad

Approaches to providing missing transfer parameter values in the ERICA Tool – How well do they work?

J.E. Brown [a,*], N.A. Beresford [b], A. Hosseini [a]

Journal of Environmental Radioactivity 126 (2013) 376–387
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Application of the Bayesian approach for derivation of PDFs for concentration ratio values

A. Hosseini [a,*], K. Stenberg [b], R. Avila [b], N.A. Beresford [c], J.E. Brown [a]

Journal of Environmental Radioactivity
Volume 138, December 2014, Pages 116–121

A new simplified allometric approach for predicting the biological half-life of radionuclides in reptiles

N.A. Beresford [a, b], M.D. Wood [b]

Science of the Total Environment 463–464 (2013) 284–292
Contents lists available at SciVerse ScienceDirect
Science of the Total Environment
journal homepage: www.elsevier.com/locate/scitotenv

A new approach to predicting environmental transfer of radionuclides to wildlife: A demonstration for freshwater fish and caesium

N.A. Beresford [a,*], T.L. Yankovich [b], M.D. Wood [c], S. Fesenko [d], P. Andersson [e], M. Muikku [f], N.J. Willey [g]

DOI 10.1007/s00411-013-0481-x

ORIGINAL PAPER

Estimating the biological half-life for radionuclides in homoeothermic vertebrates: a simplified allometric approach

N. A. Beresford · J. Vives i Batlle

Journal of Environmental Radioactivity
Available online 4 April 2015
In Press, Corrected Proof — Note to users

Making the most of what we have: application of extrapolation approaches in radioecological wildlife transfer models

Nicholas A. Beresford [a, b], Michael D. Wood [b], Jordi Vives i Batlle [c], Tamara L. Yankovich [d], Clare Bradshaw [e], Neil Willey [f]

Open Access funded by Natural Environment Research Council

Concentration ratios are generic (e.g. Cs)

0.23±0.17

0.64±1.0

0.10±0.10

0.70

$$CR = \frac{Activity\ concentration\ in\ organism\ (or\ meat)(Bq\ kg^{-1}\ FM)}{Activity\ concentration\ in\ diet(Bq\ kg^{-1}\ DM)}$$

Concentration ratios are generic (e.g. Cs)


0.23±0.17


0.64±1.0


0.10±0.10


0.70


0.40-0.85


0.46


0.48±0.06


0.27±0.11


0.40±0.20


0.73±0.40


0.53

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Allometry in Radioecology

- Size affects rates of all biological processes from cellular metabolism to population dynamics
- The dependence of a biological variable Y on a body mass M is typically characterised by an allometric scaling law of the form:

$$Y = aM^b$$

where *a* and *b* are constants

Allometry in Radioecology

b most often = 'quartile values':

- mammals & birds metabolic rates scale as $M^{0.75}$ (*Kleiber's Law* 1932)
  - $M^{0.75}$ is often referred to as *metabolic live-weight*
- life-span scales as $M^{0.25}$
- food, water and inhalation rates scale as $M^{0.75}$

Allometry in Radioecology

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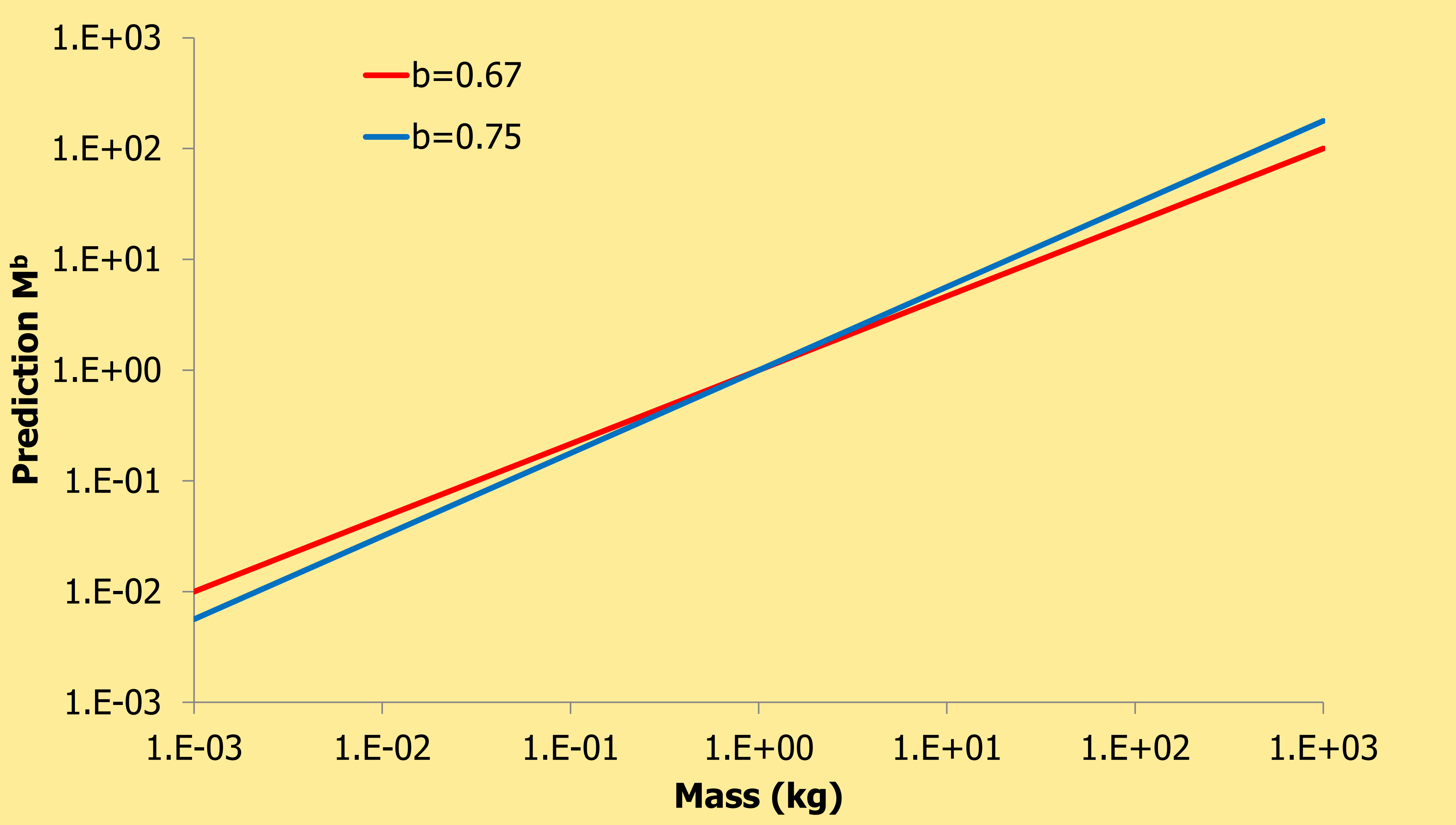
- food, water and inhalation rates scale as $M^{0.75}$

Much debate re if *b* is quartiles or tertiles (thirds)

BUT:

Allometry in Radioecology



Allometry in Radioecology

b most often = 'quartile values':

- metabolic rates scale as $M^{0.75}$ (*Kleiber's Law* 1932)
    - $M^{0.75}$ is often referred to as *metabolic live-weight*
- life-span scales as $M^{0.25}$
- food, water and inhalation rates scale as $M^{0.75}$

All potential useful for radioecological models, **but**:

Allometry in Radioecology

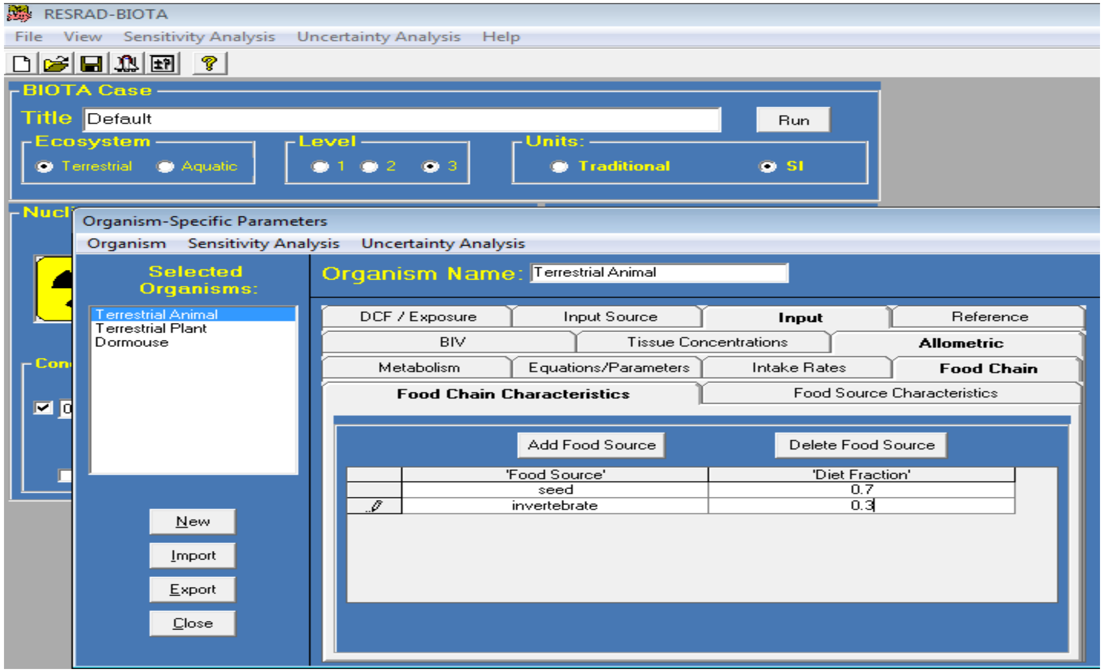
- For (some) radionuclides the biological half-life (often *c*. $M^{0.25}$) scales allometrically

Allometry in Radioecology

- For (some) radionuclides the biological half-life (often *c.* $M^{0.25}$) scales allometrically

Option to model terrestrial/riparian birds/mammals in RESRAD-BIOTA

Model performed comparable to CR model in inter-comparisons



Allometry in Radioecology

- $T_{B1/2}$ scaling to $M^{0.25}$ (for mammals & birds) **makes sense**:

$$T_{B1/2} = \frac{M \ln 2}{\varepsilon_a B_r}$$

- Kleiber's law ($B_r = aM^{0.75}$), so:

$$T_{B1/2} = \frac{\ln 2}{a\varepsilon_a} M^{0.25}$$

B_r = metabolic rate (kg d^{-1}); ε_a is a proportionality constant between the rate of biological loss of a radionuclide from the organism and the metabolic rate of the organism

Estimating 'a_B'

If $T_{B1/2}$ scales to $M^{0.25}$ then just need an estimate of a_B ($T_{B1/2}=a_B M^{0.25}$) (after Sheppard 2001)

Estimating 'a_B'

If $T_{B1/2}$ *scales to* $M^{0.25}$ *then just need an estimate of* a_B ($T_{B1/2}=a_B M^{0.25}$) (after Sheppard 2001)

GREAT!

But how do you estimate a_B*?*

The answer is:

easy

…… after four pages of algebra

The answer is:

$$a_B = \frac{\ln 2}{a_I f_1} CR_{org-diet}$$

f_1 = gastrointestinal absorption coefficient
a_I = constant on allometric relationship describing dry matter intake

$CR_{org\text{-}diet}$ and f_1 generally available & a_I values are documented for different animal types (e.g. Nagy 2001)

The answer is:

$$a_B = \frac{\ln 2}{a_I f_1} CR_{org-diet}$$

and

$$T_{B1/2} = a_B M^{0.25}$$

f_1 = gastrointestinal absorption coefficient

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The answer is:

$$a_B = \frac{\ln 2}{a_I f_1} CR_{org-diet}$$

and

$$T_{B1/2} = a_B M^{0.25}$$

so

$$T_{B1/2} = \frac{\ln 2}{a_I f_1} CR_{org-diet} M^{0.25}$$

f_1 = gastrointestinal absorption coefficient
a_I = constant on allometric relationship describing dry matter intake

$CR_{org-diet}$ and f_1 generally available & a_I values are documented for different animal types (e.g. Nagy 2001)

Is it any good?

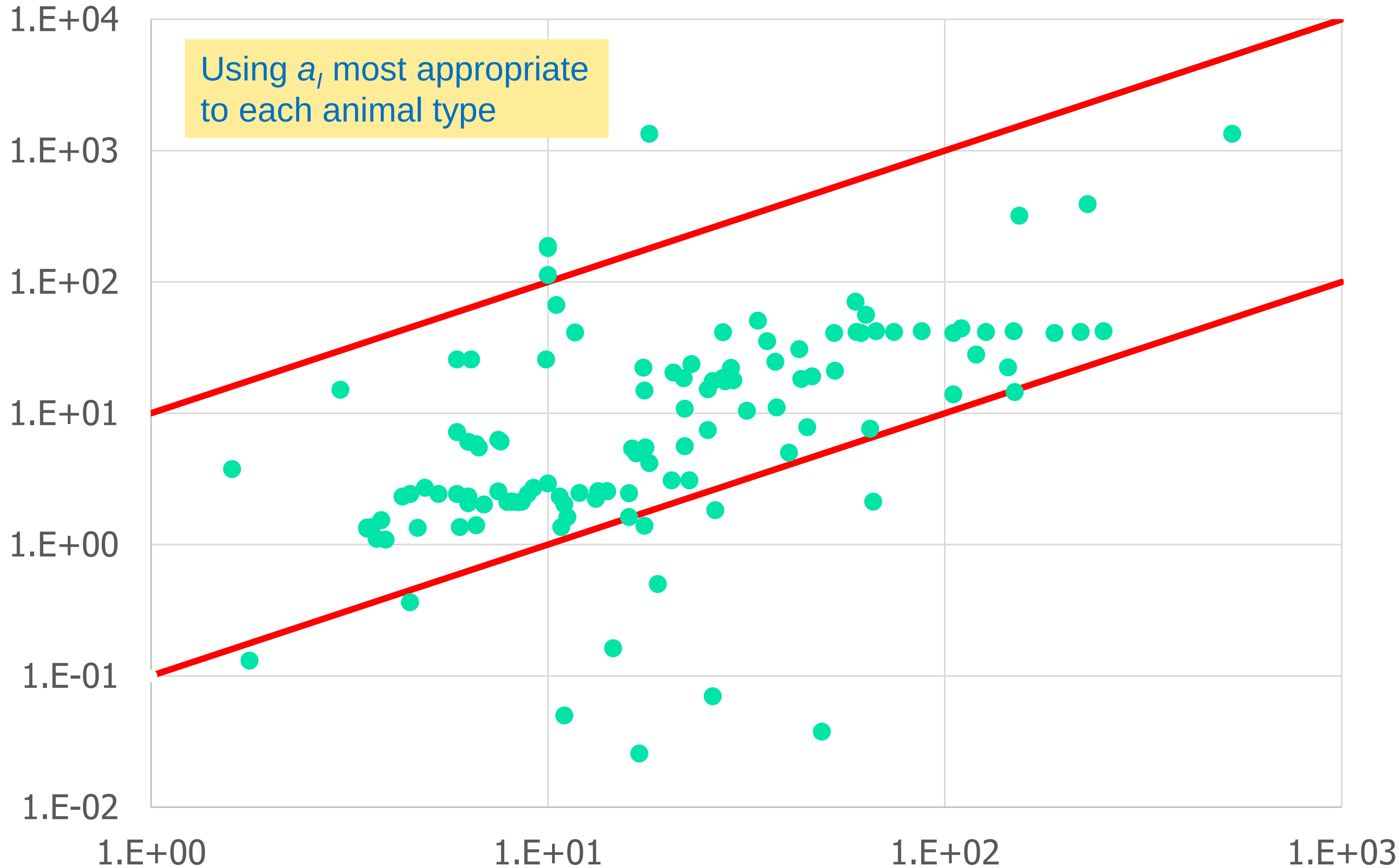
- IAEA MODARIA WG produced a database of *c*. 1900 $T_{B1/2}$ values
  - STAR partners led development for each ecosystem
- 123 values for mammals and birds used as blind test
  - Body mass 8 g to 70 kg
  - Ag, Co, Cs, I, Na, Nb, Ru, Se, Sr & Zn

Radionuclide biological half-life values for terrestrial and aquatic wildlife

Submitted J. Environ. Radioact.

N.A. Beresford[1,2], K. Beaugelin-Seiller[3], J. Burgos[4], M. Cujic[5], S. Fesenko[6], A. Kryshev[7], N. Pachal[8], A. Real[9], B.S. Su[8], K. Tagami[10], J. Vives i Batlle[11], S. Vives-Lynch[12], C. Wells[1], M.D. Wood[2]

Measured v's predicted $T_{B1/2}$



But …….

- In USDoE five elements have $T_{B1/2}$ relationships which <u>do not </u>scale to *c*. 0.25 but to *c*. 0.8
  - ➢ Am, Ce, Eu, Pu & Th
  - ➢ Why?
  - ➢ None have biological role??
- Reptiles ($B_r = aM^{0.80\text{-}0.92}$)

Alternative to CR approach for wildlife

$CR_{wo\text{-}media}$ approach

- Simple
- Widely adopted

$$CR = \frac{\text{Activity concentration in biota whole body (Bq kg}^{-1}\text{ fresh weight)}}{\text{Activity concentration media ((filtered water (Bq l}^{-1}\text{) or soil (Bq kg}^{-1}\text{ dry weight))}}$$

But ……

- Highly variable

- No data for many wildlife-radionuclide combinations

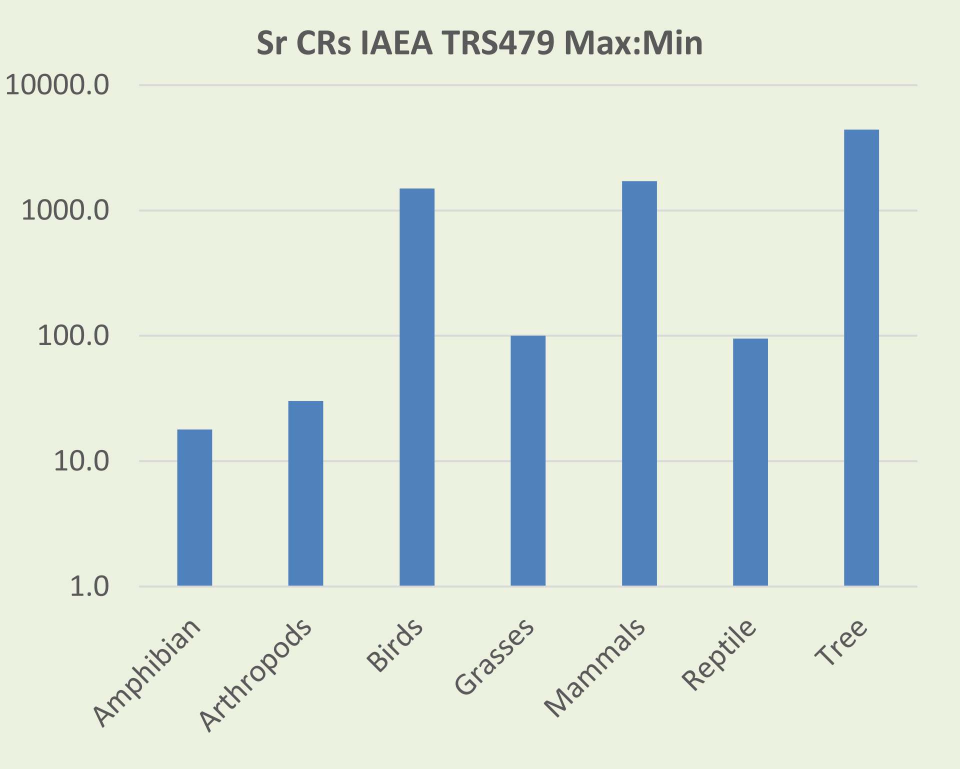


Table A.4. Bee (*Apidea*): concentration ratio values (units of Bq/kg fresh weight per Bq/kg dry weight).

No empirical data.

Table A.5. Frog (*Ranidae*): concentration ratio values (units of Bq/kg fresh weight per Bq/kg dry weight).

Element	Arithmetic mean	Arithmetic standard deviation	Geometric mean	Geometric standard deviation	*n*	Ref ID
Am	1.0E−01	2.6E−02	1.0E−01	1.3E+00	7	486
Cd	1.5E−02	7.9E−03	1.3E−02	1.7E+00	5	213
Cs	5.5E−01	9.0E−01	2.8E−01	3.2E+00	105	188, 205, 256, 486
Pb	3.1E−03	2.2E−03	2.6E−03	1.9E+00	6	213
Sr	1.5E+00	1.4E+00	1.1E+00	2.2E+00	14	188, 486

ICRP Pub-114

Is there an alternative?

?

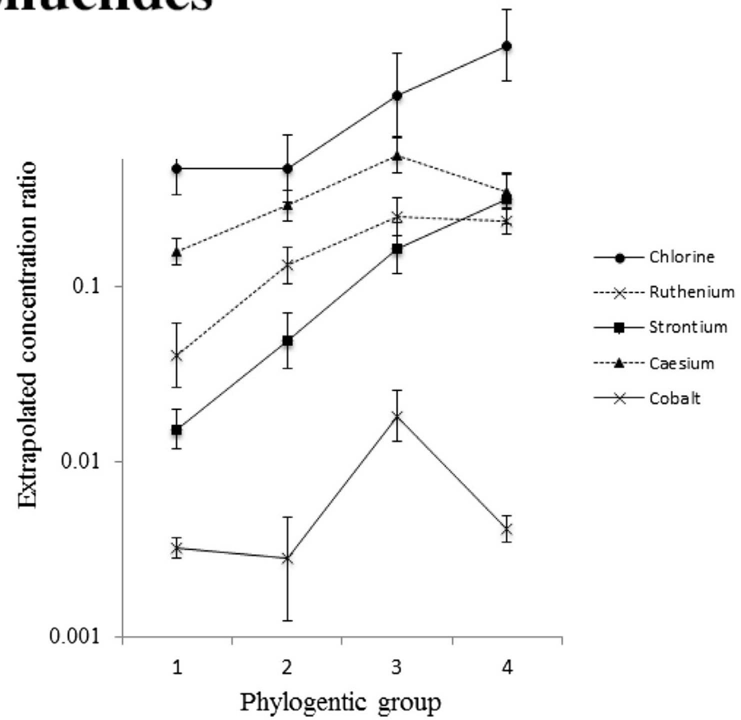
Is there an alternative?

Radiat Environ Biophys (2010) 49:613–623
DOI 10.1007/s00411-010-0320-2

ORIGINAL PAPER

Phylogeny can be used to make useful predictions of soil-to-plant transfer factors for radionuclides

Neil J. Willey



An alternative to the $CR_{wo\text{-}media}$

Radiat Environ Biophys (2010) 49:613–623
DOI 10.1007/s00411-010-0320-2

ORIGINAL PAPER

Phylogeny can be used to make useful predictions of soil-to-plant transfer factors for radionuclides

Neil J. Willey

- Can we use this approach for other organisms
- STAR - example freshwater fish and Cs

Journal of Environmental Radioactivity 126 (2013) 299–313

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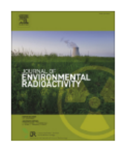
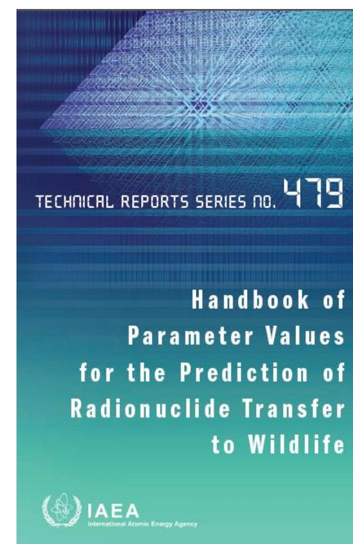


Establishing a database of radionuclide transfer parameters for freshwater wildlife

CrossMark

T. Yankovich[a,*], N.A. Beresford[b], S. Fesenko[c], J. Fesenko[d], M. Phaneuf[e], E. Dagher[f], I. Outola[g], P. Andersson[h], K. Thiessen[i], J. Ryan[j], M.D. Wood[k], A. Bollhöfer[l], C.L. Barnett[b], D. Copplestone[m]



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An alternative to the $CR_{wo\text{-}media}$

- Adapted approach used by Willey for plants
  - ➢Residual Maximum Likelihood (REML)
  - ➢Generates an adjusted mean (or relative value) taking into account inter-site variability

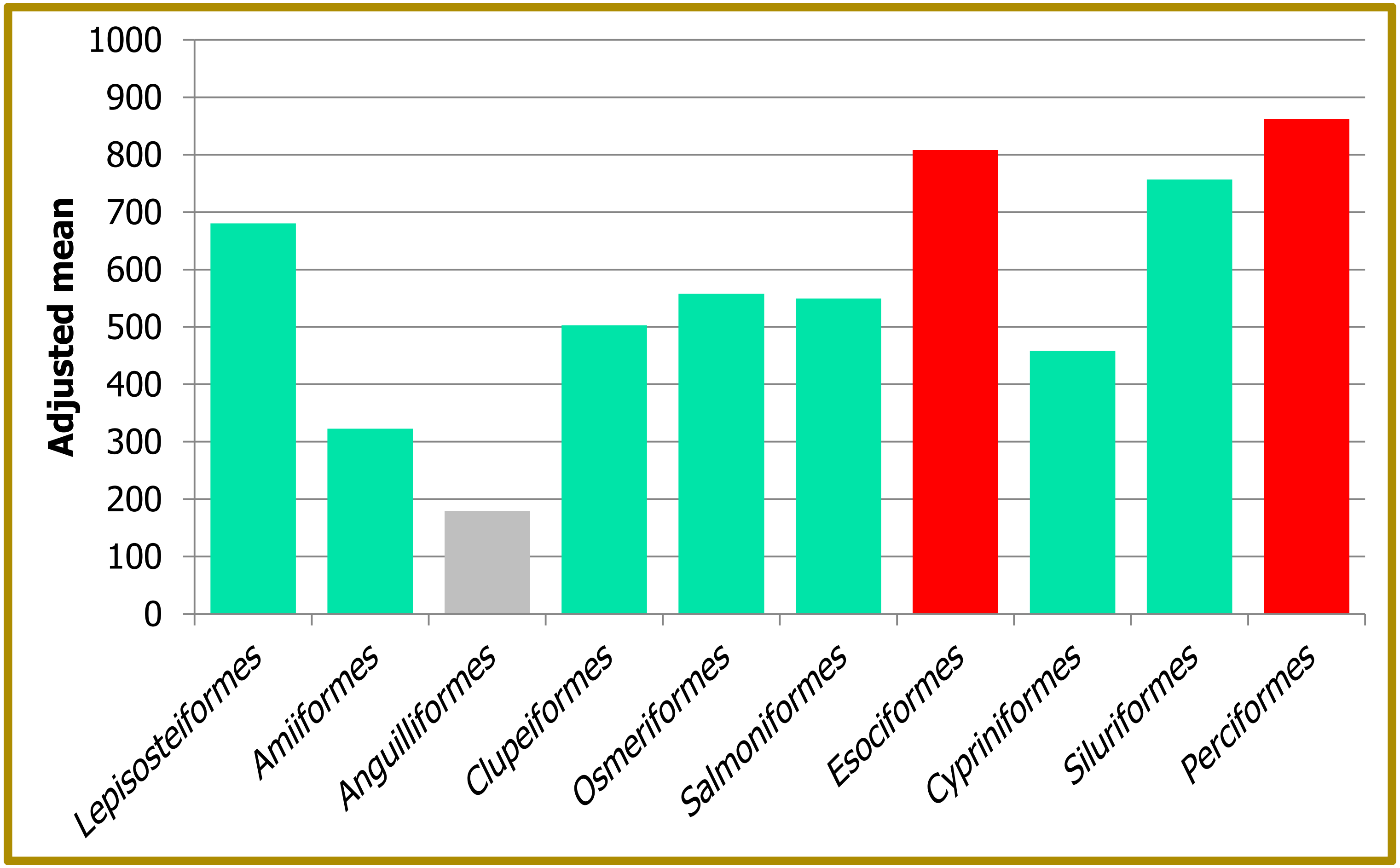
An alternative to the $CR_{wo\text{-}media}$

- Adapted approach used by Willey for plants
  - ➢Residual Maximum Likelihood (REML)
  - ➢Generates an adjusted mean (or relative value) taking into account inter-site variability
- Initial data source Yankovich et al (2013)
  - ➢REML requires site/study contains more than one species (one of which must occur at another site)
  - ➢Supplemented with additional data (can mix CR and activity concentration data)
  - ➢597 data entries including 10 orders, 14 families, 33 genera & 53 species

Output

Generates *adjusted mean* (or relative value) – taking into account inter-site variability

Output (by order)



Ignore the number ...... it's all relative

A hypothesis!

The REML model outputs can be used to predict the radionuclide (Cs) activity concentrations in unknown species from the results of a species which has been sampled at a specific site

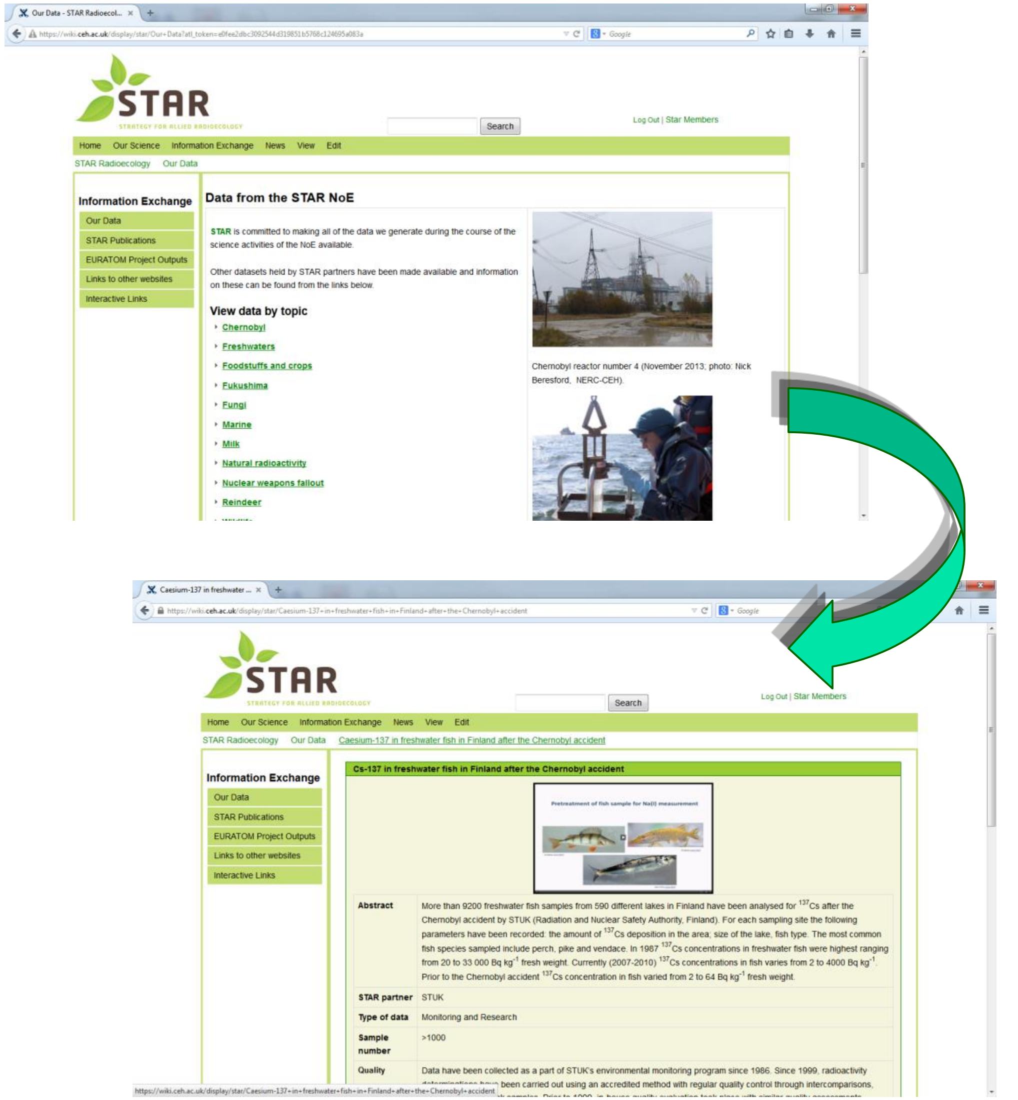
Does it work?

STUK had made data available from lakes monitoring programme through STAR

Not used within REML analyses

Used data from 1988 to test:

- 27 lakes
- 11 species



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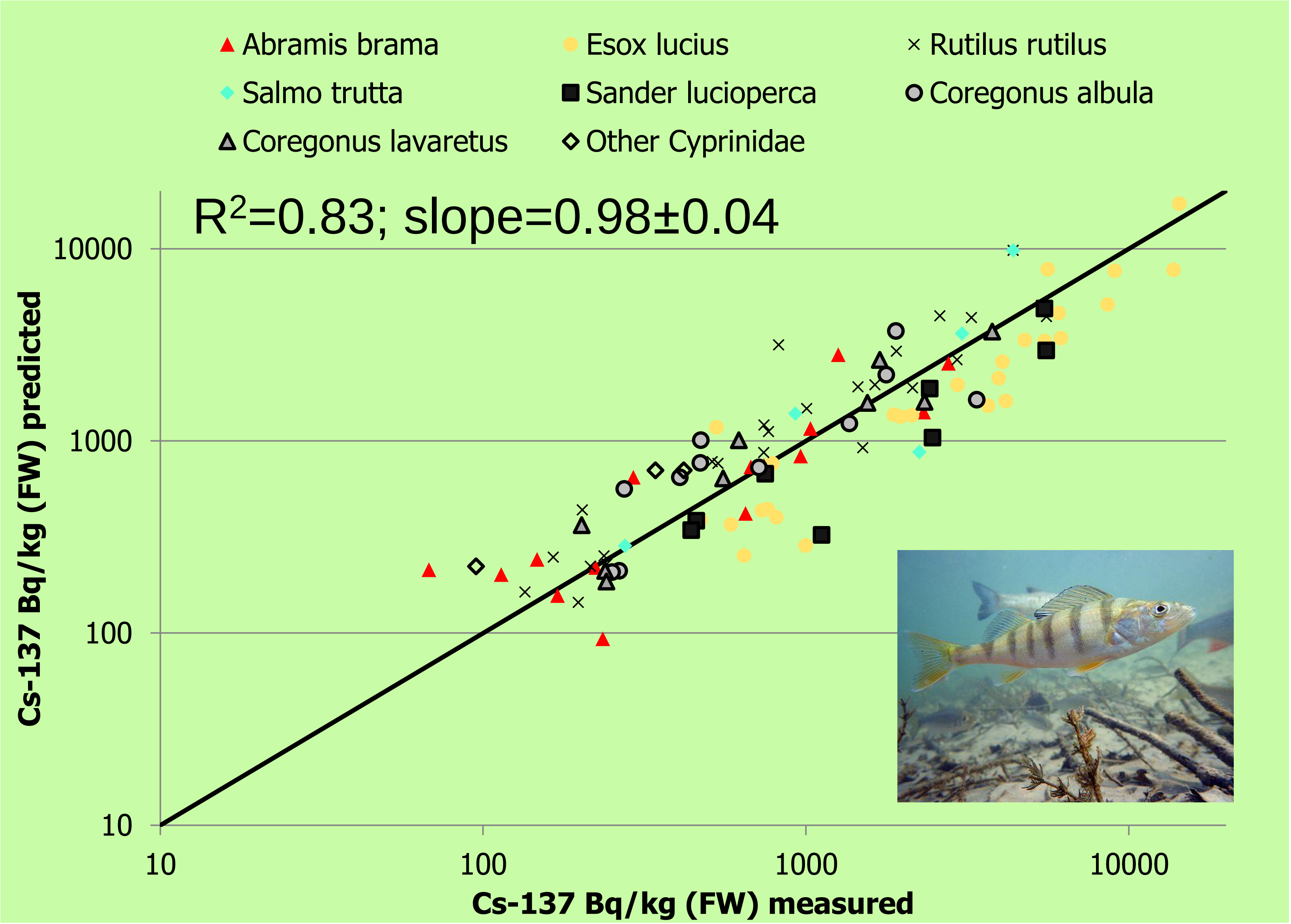
Approach

- *Perca fluviatilis* present at all 27 sites
- Assumed to be the ‘known’ species

- Concentrations in all other species estimated as:

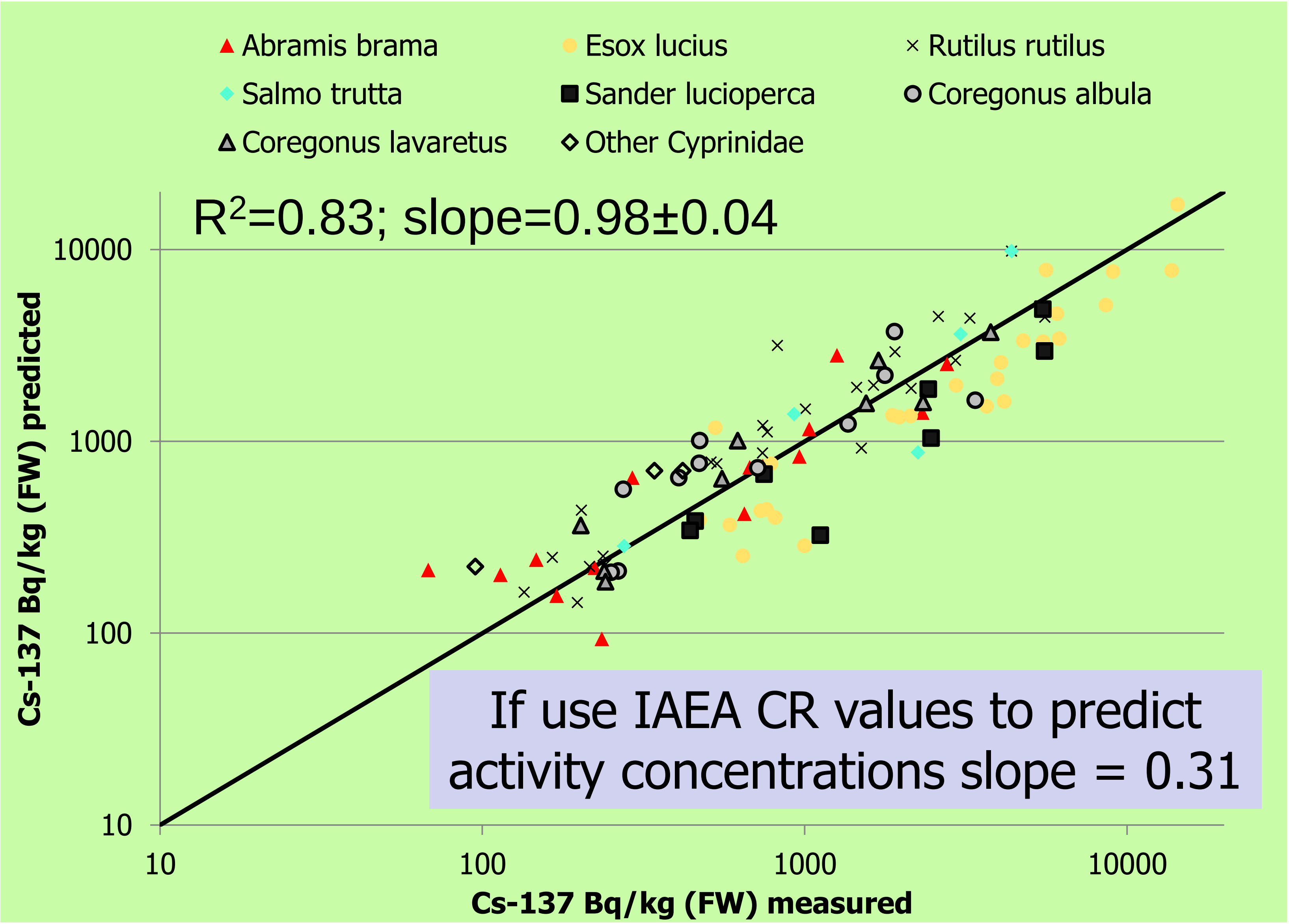
$$Cs137\ \ activity\ conc.in\ perch\ \times\ \frac{REML\ value\ species\ X}{REML\ value\ perch}$$

Result



Abramis brama
Esox lucius
Rutilus rutilus
Salmo trutta
Sander lucioperca
Coregonus albula
Coregonus lavaretus
Other Cyprinidae
R2=0.83; slope=0.98±0.04
10000
1000
100
10
10
100
1000
10000
Cs-137 Bq/kg (FW) predicted
Cs-137 Bq/kg (FW) measured

Result


Abramis brama
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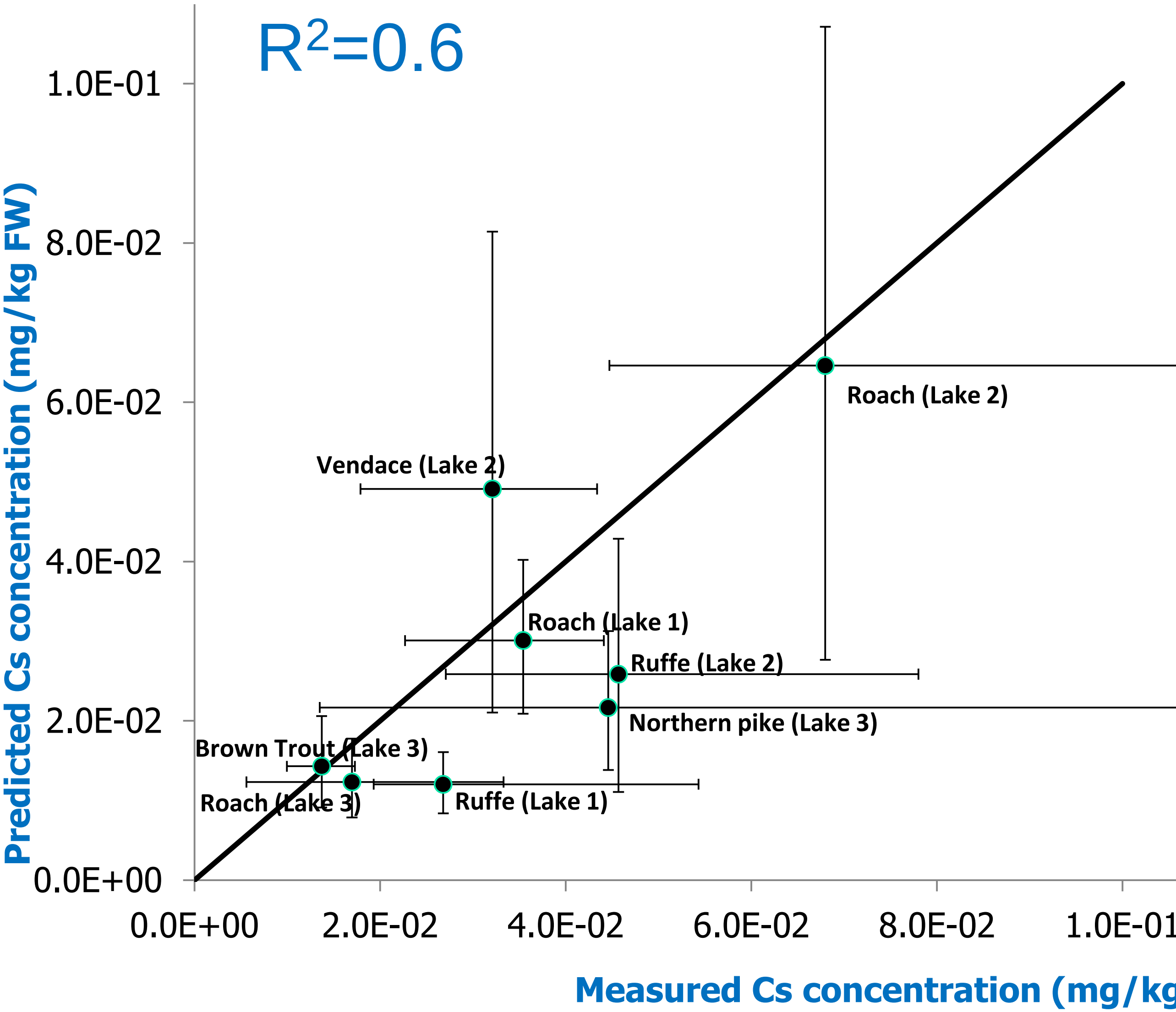
10000
1000
100
10
10
100
1000
10000
Cs-137 Bq/kg (FW) predicted
Cs-137 Bq/kg (FW) measured
If use IAEA CR values to predict activity concentrations slope = 0.31

Stable Cs English lakes




Terrestrial?

Disclaimer

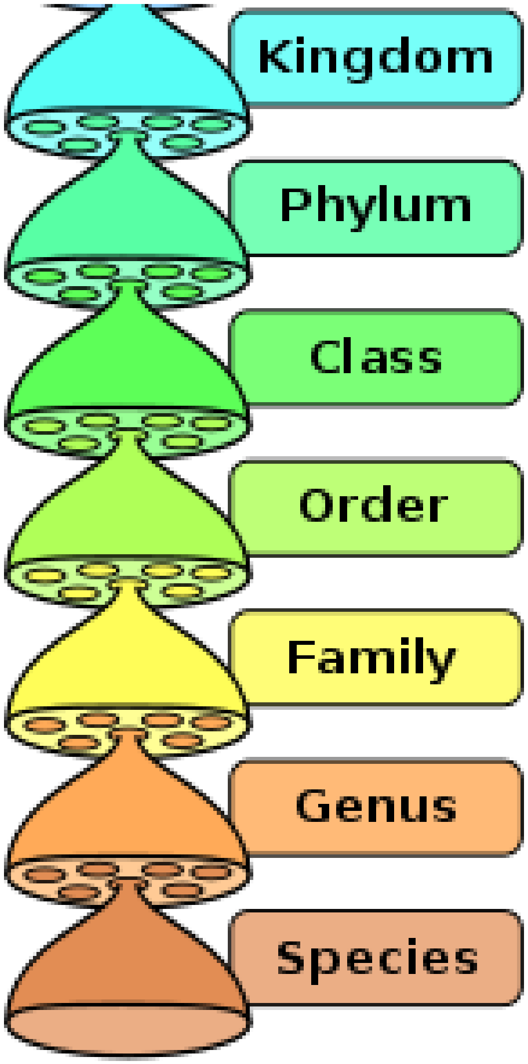
We've tried it, but

all that follows is provisional!

- Reference assumed = site
- Maybe some data to remove

http://www.ceh.ac.uk/tree

Terrestrial

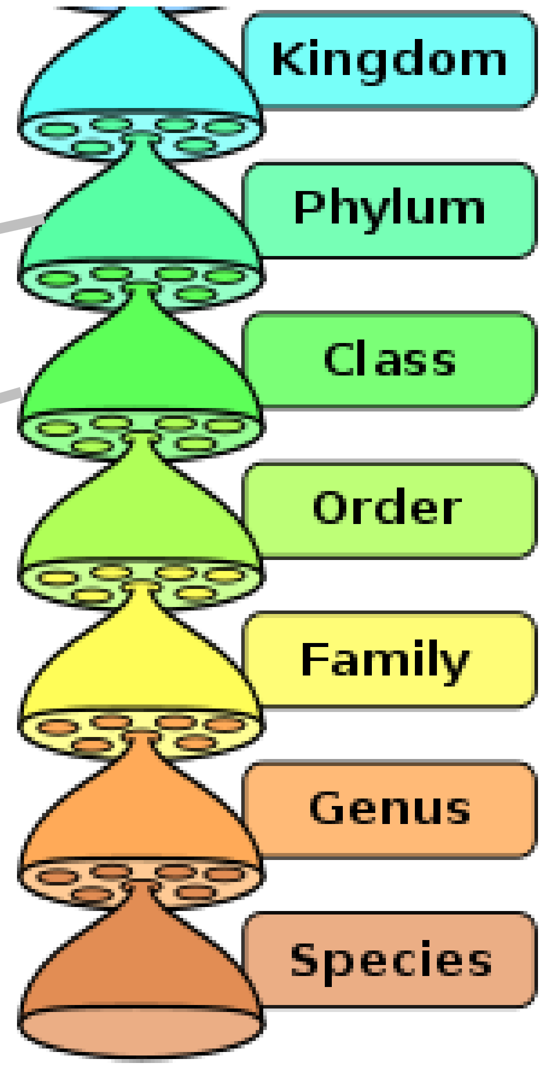


Terrestrial - plants

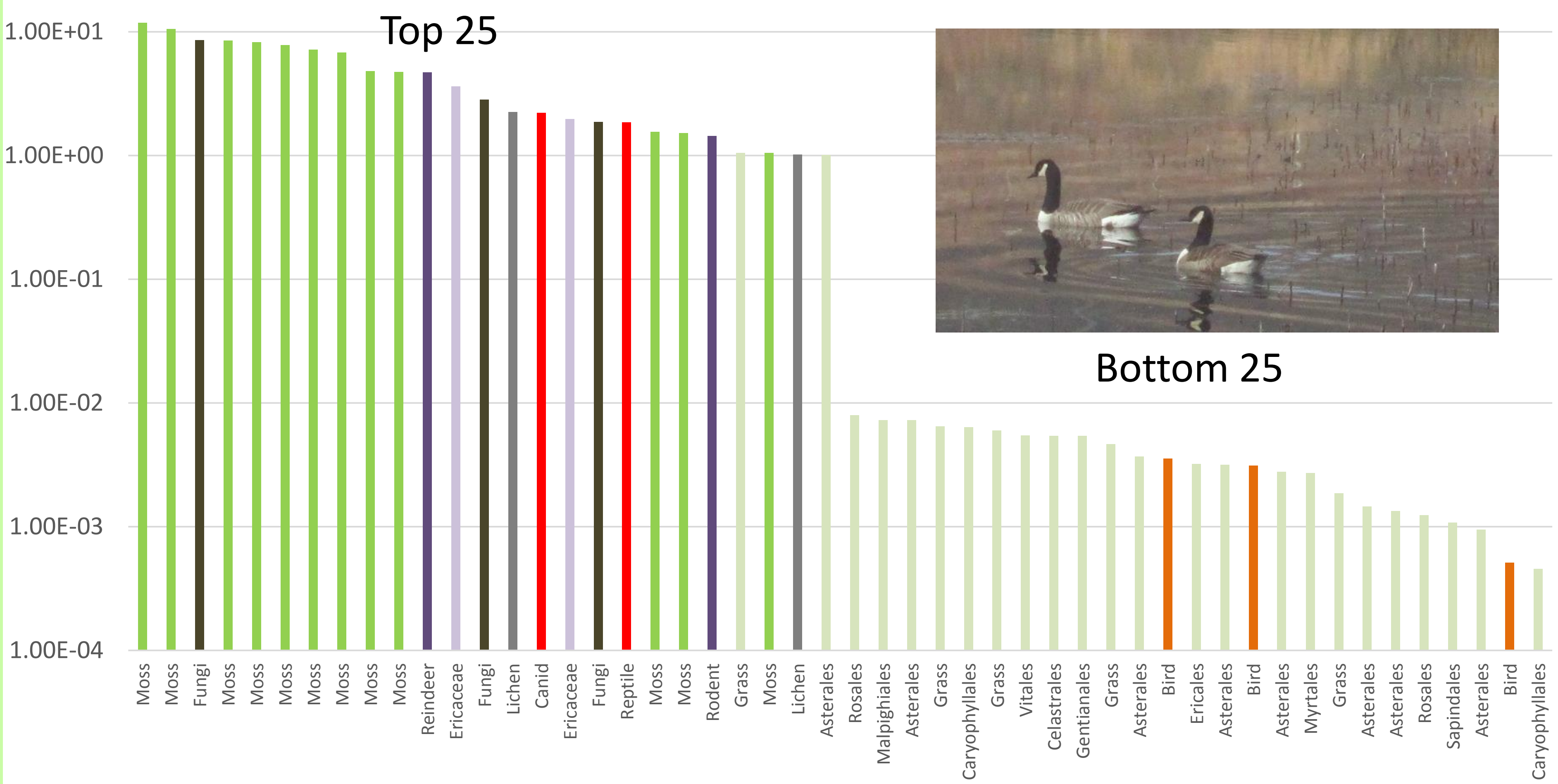
‘Cladistic’ system

e.g. Angiosperm

e.g. Eudicot



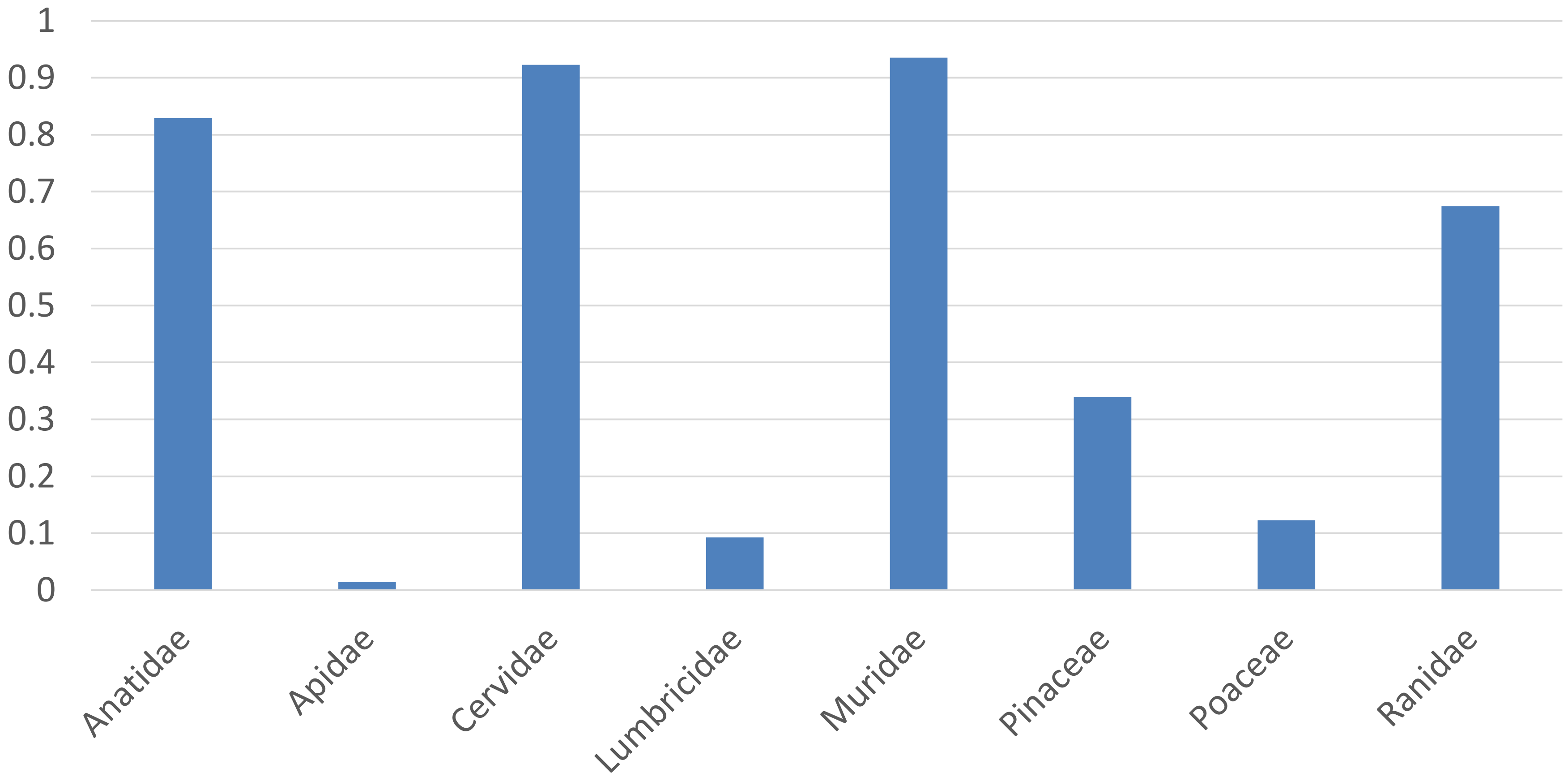
Example output: Cs by genus



REML adjusted mean

202 Genus

Sr at Family level: ICRP RAPs



REML adjusted mean

Predictions v measurements

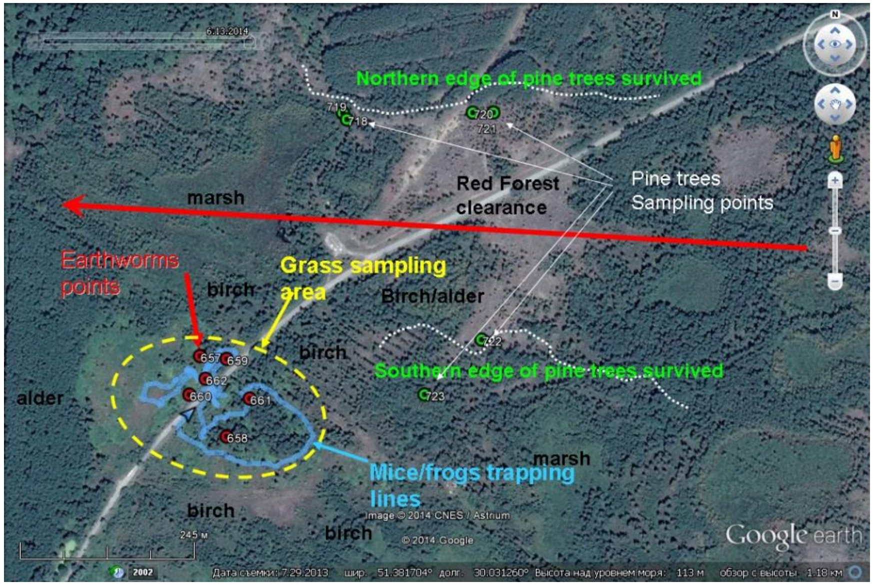
COMET
COordination and iMplementation
of a pan European instrumenT for Radioecology

Radiat Environ Biophys (2014) 53:125–149
DOI 10.1007/s00411-013-0493-6

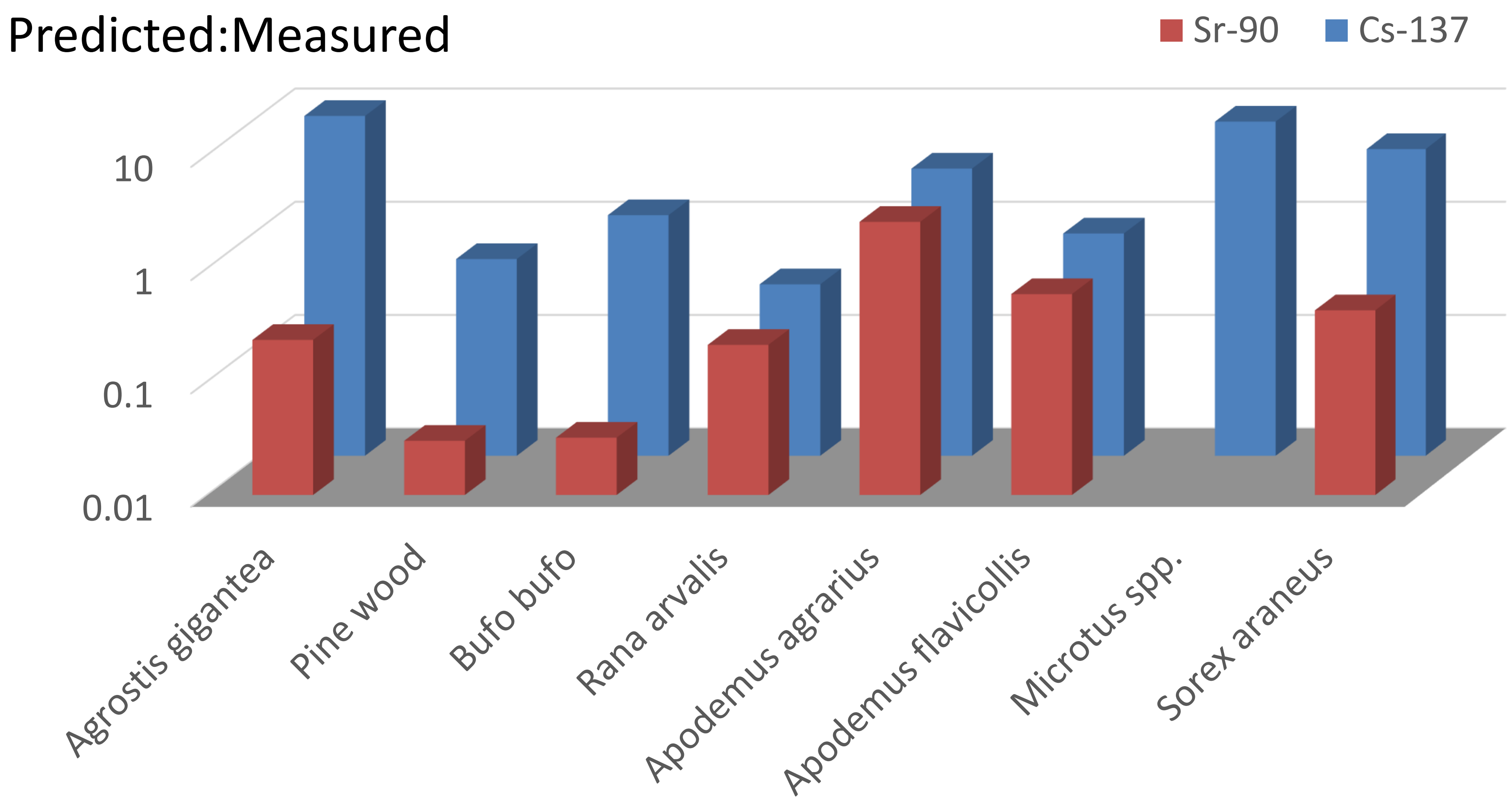
ORIGINAL PAPER

Transfer parameters for ICRP reference animals and plants collected from a forest ecosystem

C. L. Barnett · N. A. Beresford · L. A. Walker ·
M. Baxter · C. Wells · D. Copplestone



Chernobyl: TREE-COMET site

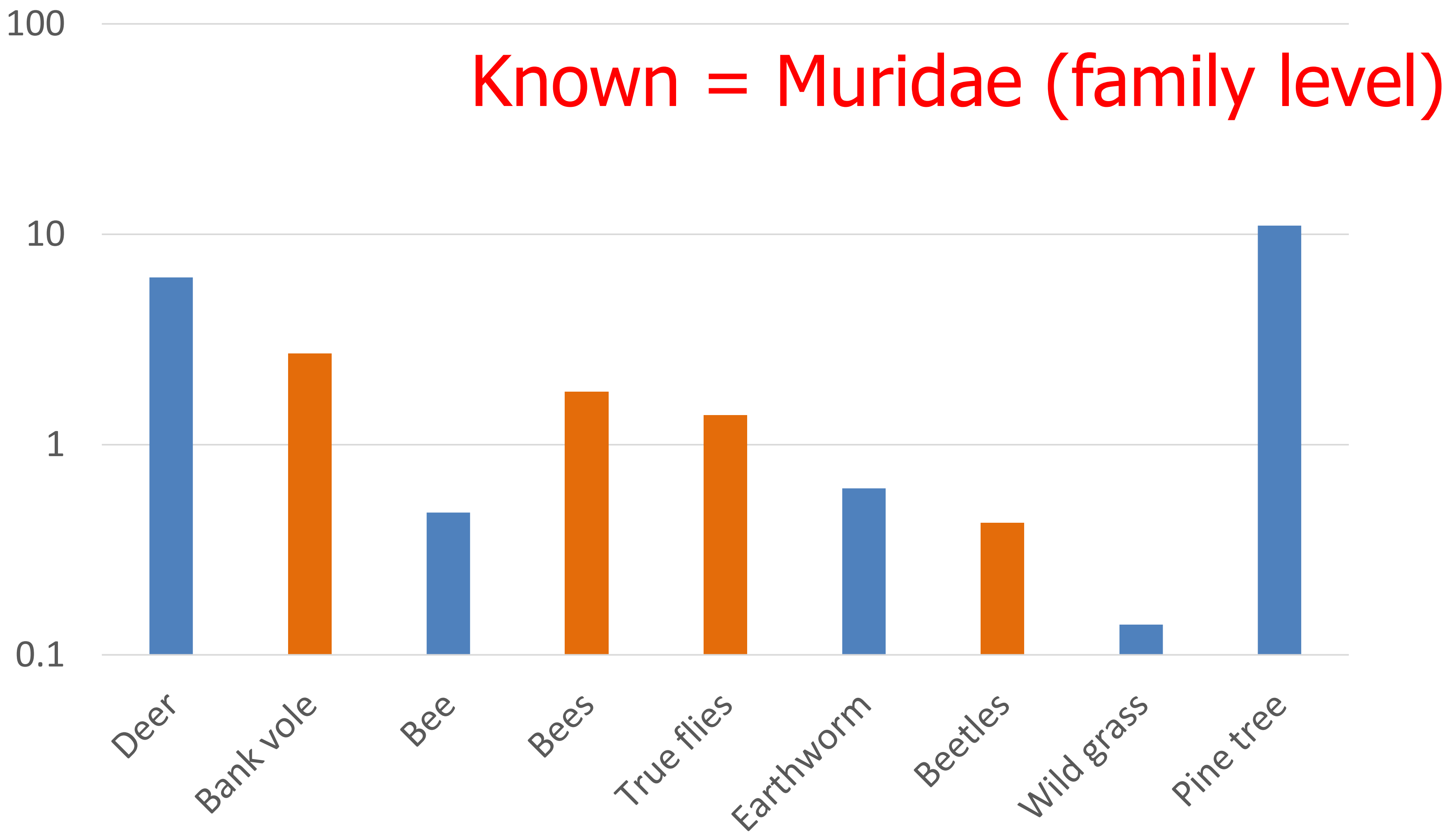


Cs known = Myodes (genus level)

Sr known = Cricetidae (family level)

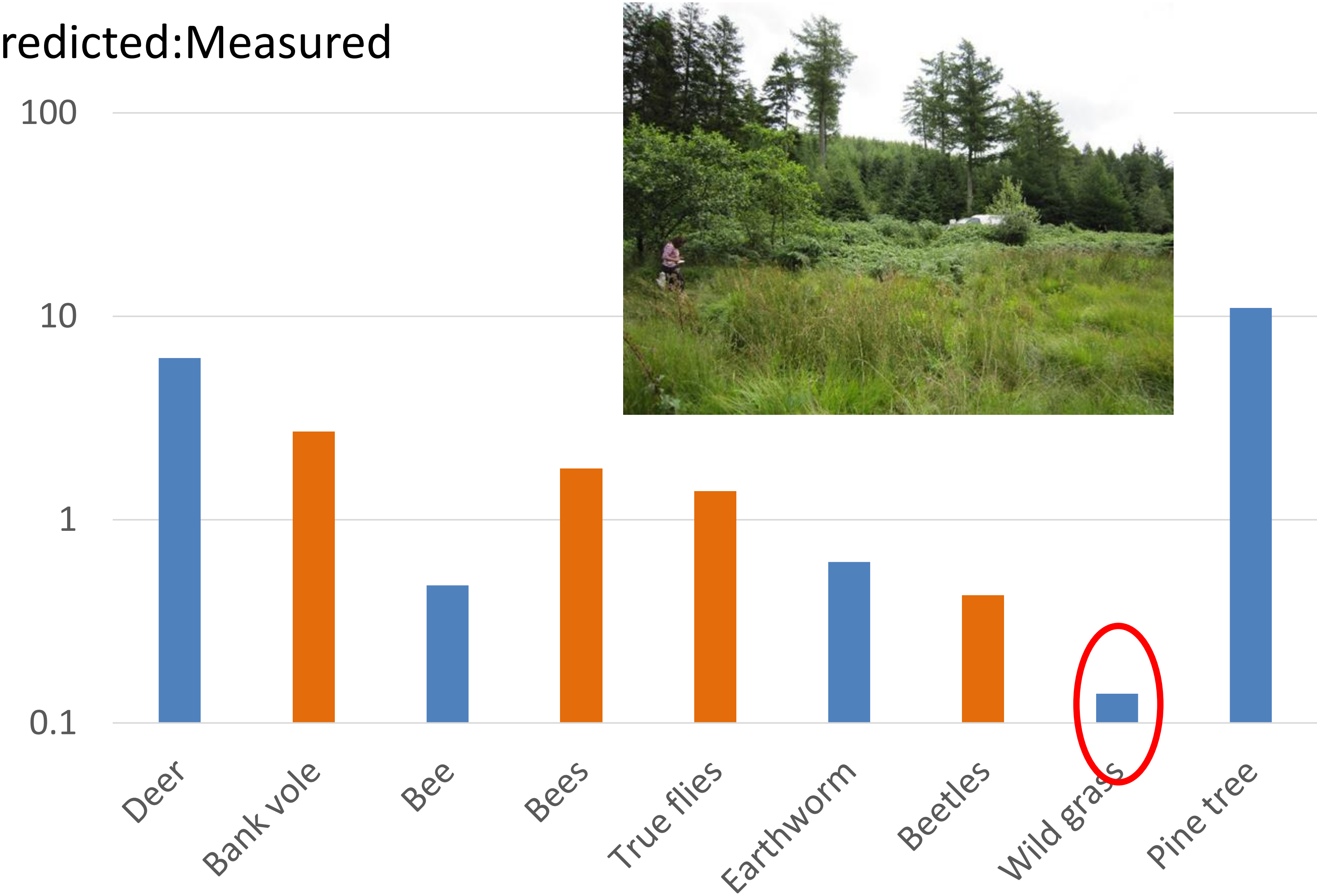
UK Barnett *et al.* site Cs

Predicted:Measured



UK Barnett *et al.* site Cs

Predicted:Measured



Photos: http://www.ceh.ac.uk/tree

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EURATOM

Allometry of transfer parameters in marine biota

Jordi Vives i Batlle, Belgian Nuclear Research Centre, SCK•CEN, Mol, Belgium. E-mail: jvibatll@sckcen.be
N.A. Beresford, NERC Centre for Ecology & Hydrology, CEH Lancaster, UK. E-mail: nab@ceh.ac.uk

Introduction

Exchange rate and bioaccumulation of radionuclides in biota are commonly represented by two simple parameters: the biological half-life of elimination ($T_{B1/2}$) and the concentration ratio (CR). This study presents an interpolation method to calculate these parameters for radionuclides in marine biota based on allometric scaling.

Objective

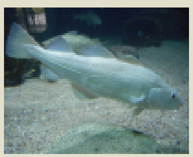
Investigate the hypothesis that, for marine biota, *b* would be close to the slope of −¼ frequently found in allometric relationships in biology, and that *a* would depend on the individual properties of compounds formed by radionuclides in the marine environment.

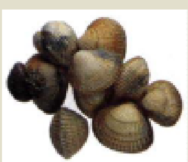
Materials and methods

Power relationships of the type $Y = a \times M^b$ were fitted to a CR and $T_{B1/2}$ database for Tc, I, Cs, Pu and Am in fish, crustaceans, molluscs, plants and plankton reported in Vives i Batlle *et al.* (2007). To this was added data for 29 additional elements. To discriminate potentially significant relationships, we used the criteria $r^2 > 0.7$, p-value of 2-tailed Student T-test < 0.05 and N > 2.

Results

For CR, the mean value of b for statistically valid relationships was -0.26 ± 0.09. For those radionuclides we also found a significant linear relationship between $\log_{10}(a)$ and $\log_{10}(K_d)$ (Figure 1), showing particle-reactive (or sediment seeking) radionuclides to have the highest $\log_{10}(a)$ values. These relationships present an opportunity to estimate CR when data are lacking, from M and K_d. The mean value of b for the 4 elements with valid $T_{1/2B}$ relationships (R^2 value > 0.7) was 0.16 ± 0.03.





Item	Parameters for $T_{B1/2}$ (d)				Parameters for CR (L kg^{-1})												
	Tc	Cs	Pu	Am	Pu	Am	Ru	Co	Pm/Eu	Ra	Th	Cm	Mn	Zr	Po	Ac	Pa
a	90	34	631	231	239	231	29	460	1949	55	362	363	4063	269	3495	300	35
b	0.15	0.17	0.20	0.13	-0.39	-0.28	-0.46	-0.25	-0.38	-0.31	-0.27	-0.27	-0.13	-0.30	-0.17	-0.30	-0.17
R^2	0.72	0.92	0.91	0.76	0.80	0.70	0.75	0.72	0.72	0.79	0.89	0.85	0.46	0.60	0.84	0.58	0.32
p	0.03	0.04	0.2	0.03	0.001	0.002	0.002	0.004	0.004	0.001	0.0002	0.0004	0.04	0.007	0.01	0.02	0.02

Table 1: Calculated allometric constants (a) and exponents (b) for CR and $T_{B1/2}$

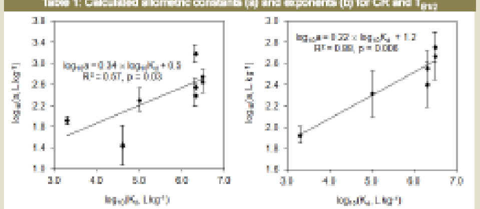
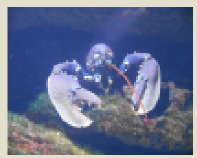
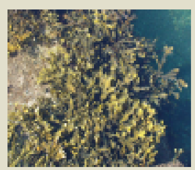


Figure 1: $\log_{10}(a)$ for the CR and $\log_{10}(Kd)$ with (left) and without (right) Ru, Eu and Pm





An anomaly for the allometric relationships for marine organisms with respect to those for terrestrial organisms is that the actinides and lanthanides scale with an exponent similar to other elements for marine organisms, unlike the case for terrestrial biota.

Conclusions

The observed scaling of the CR to $M^{-0.26 \pm 0.09}$ is compatible with metabolic theory scaling to to $M^{-¼}$, given that the CR is an activity concentration relative to mass and to activity in the medium. The observed scaling of $T_{B1/2}$ to $M^{+0.16 \pm 0.03}$ is slightly outside theory predictions that turnover rates scale with $M^{-¼}$, but compatible with the range +0.15 to +0.30 quoted in USDoE (2002). The elements for which the CR scales allometrically are mostly lanthanides and actinides. Association of *a* with the K_d is strongest for particle-seeking elements, most likely binding to biological / organic matter (e.g. food). As food ingestion relates to metabolism, and hence, to body mass via Kleiber's law, the resultant CR will scale allometrically (Beresford et al., 2015).

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Application of Bayesian statistics in radioecology

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INTRODUCTION

Quantification of risk to wildlife as a consequence of releases of radioactivity to the environment requires the determination of activity concentrations in various environmental media and selected plants and animals. A simple and widely used method to model radionuclide transfer from soil and water to biota is through the application of concentration ratios (CR).

A common step in data collations required to populate CR (and other) databases is the pooling or combining of data to produce more robust estimates for the parameters of interest. However, the combined data are usually extracted from different studies with variable sample sizes and different measures of averages and variation. Another common issue is the application of different extrapolation approaches to derive missing transfer parameter values.

BAYESIAN APPROACH

The procedure for assigning a probability distribution to a model parameter, such as CR, can be divided into two main steps:

i) selection of a probability model or distribution type and
ii) estimation of the distribution parameters.

It is usually assume that the CRs are log-normally distributed. Now what remains is to discuss how to estimate the distribution parameters, i.e. the geometric mean (GM) and geometric standard deviation (GSD). For this purpose, below we introduce three methods regarding utilisation of the various related datasets/information in order to generate more robust estimates of GM and GSD, all based on the application of Bayes' theorem (Bayes, 1763):

$$p(\theta \mid y) = \frac{p(y \mid \theta)p(\theta)}{\int p(y \mid \theta)p(\theta)d\theta} \quad \text{or} \quad \text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\int (\text{likelihood} \times \text{prior})d\theta}$$

Here, the posterior distribution describes our state of knowledge about the desired parameter θ (i.e. GM or GSD) after considering the data. The likelihood function describes how probable the current data are given the parameter θ. The prior represents the present state of our knowledge based on an initial consideration of the parameter θ.

A JOINT PRIOR DISTRIBUTION FOR THE MEAN AND VARIANCE

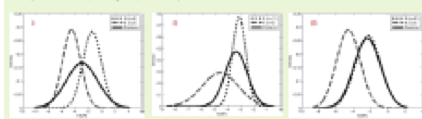
This Bayesian inference method is based on the assumption that the available empirical data for the case of interest and the existing historical (literature) data are exchangeable and can be considered as being from the same population. In this case, the other data carries information on both the mean and variance of the distribution and can be used to define a joint prior distribution (Gelman et al. 2004).

CR data for 8 species of bat are used here to illustrate a typical situation where we can apply this approach.

Table 1. Data for eight bat species sampled in the Chernobyl exclusion zone (from Gaschak et al., 2010)

Code	Species	N	GM	GSD
A	Brown long-eared	5	0.11	3.1
B	Common Noctule	20	0.10	2.7
X	Daubenton	2	0.01	3.9
C	Lesser Noctule	5	0.04	1.6
D	Nathusius' Pipistrelle	51	0.10	4.4
E	Parti-coloured	11	0.04	1.7
F	Serotine	17	0.26	4.0
G	Soprano Pipistrelle	2	0.23	4.1

Let us assume that our aim is to derive a PDF for the CR of the Daubenton species of bat (Code X in Table 1). Since only 2 data points are available for this species, maximum likelihood estimates (e.g. sample mean and variance) will not work well. However, there are data available for other 7 bat species that can be considered more or less representative (analogues) for the species of interest.



Graphs above show three different cases where Daubenton's data (X) is combined with data of three various analogues: i) species G (N=2) as analogue leads to the largest posterior GSD among all tried analogues because of the total few observations, ii) species E (N=11) as an analogue has a smaller GSD than data and leads to smaller posterior median GSD, iii) species D with N=51 is used as analogue and almost completely dominates the data (N=2).

HIERARCHICAL MODEL: PRIOR IMPLICITLY DERIVED FROM DATA OF SEVERAL SIMILAR UNITS

The second approach is applicable when considering a number of related units (such as species or elements which share some common traits) or groups of measurements that are believed to be similar with regards to the parameter of interest. The approach is called hierarchical updating and can be used to obtain estimates for all unit/groups simultaneously, letting the units borrow strength from the overall dataset (Morris, 1983). The method offers an alternative to using either separate estimates or a complete pooled estimate and the estimates from hierarchical models are therefore sometimes called partially pooled estimates (Gelman et al., 2004).

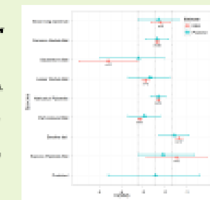


Figure. The posterior logarithmic mean from the hierarchical model assuming a common variance for the bat species given in Table 1. The Maximum Likelihood Estimate (MLE) is shown with 95% confidence interval.

The vertical dotted lines show the posterior median and 95% probability interval of the population mean.

The posterior mean of the species of interest, Daubenton bat, is heavily influenced by population, but the 95% probability interval still includes the observed mean.

The last bar shows the median and 95% probability interval of the predicted mean of a new species belonging to the same population.

INDEPENDENT PRIOR DISTRIBUTIONS FOR THE MEAN AND VARIANCE

The third Bayesian updating technique considered is applicable to situations where, in addition to data for the case of interest, there is available either relevant historical data or information, but these do not tell us anything about the variance of the case of interest. In such a situation, the prior distributions of mean and variance are specified independently and these are often referred to as semi-conjugate prior distributions. If no prior information is available for the variance, a so called non-informative prior for the variance can be used.

Using Bayesian statistics to revise the ERICA Tool

The first major update of ERICA Tool (Brown et al. 2008) released November 2014 (http://www.erica-tool.eu/). Upon updating the ERICA Tool CR databases some decisions had to be made in dealing with cases where available data were limited. To improve the situation in terms of deriving more robust parameter estimates the Bayesian semi-conjugate approach was applied. The approach was as follows: after identifications of cases where N≤5, the updated gap-filling options, available in the ERICA Tool, were consulted to discern which analogues would have been used if no data were available for these cases. In this way a surrogate organism or radionuclide has been assigned for each case where possible and further these have been used as priors in the process of updating.

Table 1. Some examples from the revised ERICA Tool marine CR database where new parameter estimates have been derived based on the application of the Bayesian semi-conjugate method.

Radion.	Species	N Prior	N Data	Mean	SD	New estimates Mean	New estimates SD
Co	fish	[illegible]	3	[illegible]	[illegible]	[illegible]	[illegible]
Sr	fish	115	[illegible]	[illegible]	[illegible]		
Cd	Crustacean	[illegible]	5	[illegible]	[illegible]	[illegible]	[illegible]
Cd	Mollusc - Bivalve	24	[illegible]	[illegible]	[illegible]		
Co	Polychaete worm	[illegible]	3	[illegible]	[illegible]	[illegible]	[illegible]
Co	Mollusc - Bivalve	42	[illegible]	[illegible]	[illegible]		
Ru	Macroalgae	[illegible]	4	[illegible]	[illegible]	[illegible]	[illegible]
Ru	Phytoplankton	11	[illegible]	[illegible]	[illegible]		
Pu	Polychaete worm	[illegible]	3	[illegible]	[illegible]	[illegible]	[illegible]
Pu	Mollusc - Bivalve	166	[illegible]	[illegible]	[illegible]		

CONCLUSION

Bayesian approaches require specification of prior distributions for parameter values. In the context of the work discussed here, priors have been used to take into account the existing external information/data and also to describe our 'belief' about the relevancy of these data for our case of interest. As priors represent additional knowledge which would not be considered if we were only using likelihood function, considering them is not only a necessary step in the process of learning and acquiring knowledge, but also a crucial element for coming to the right conclusion (Kruschke, 2010). Given that the prior knowledge (external data/information) is valid, this approach provides more robust parameter estimates as compared to when only limited site or study specific empirical data are used. Bayesian approaches have a much wider applicability to radioecological problems and are being considered within the COMET (www.comet-radioecology.org) project.

A full description of the methodology presented here, and discussion of its application within radioecology can be found in Hosseini et al. (2013).

REFERENCES

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Bayesian