XXIV CONGRESSO
SOCIEDADE PORTUGUESA DE ESTATÍSTICA

CURRENT TRENDS IN ECOLOGICAL STATISTICS ARE DETACHED FROM ECOLOGISTS' STATISTICAL TEACHING

"…Ainda ensinamos estatística como há 20 anos atrás…" – Maria do Rosário Oliveira, 2019

TIAGO A. MARQUES

CREEM
Centre for Research into Ecological and Environmental Modelling

University of St Andrews

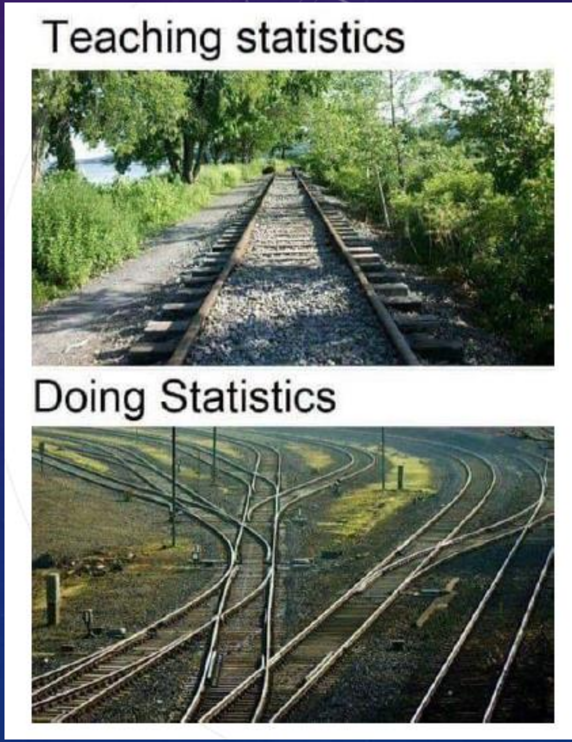
CEAUL
Centro de Estatística e Aplicações Universidade de Lisboa

Ciências ULisboa | Biologia Animal

9TH NOVEMBER 2019

ECOLOGIA NUMÉRICA @ DBA/FCUL

- Parametric statistical tests for 1, 2 or more samples
- Non-parametric equivalents
- Data transformation
- Correlation
- Regression & GLMs
- Multivariate Analysis
  - Cluster analysis
  - Dimension Reduction
  - PCA, CA, CCA, etc.
  - Discriminant Analysis



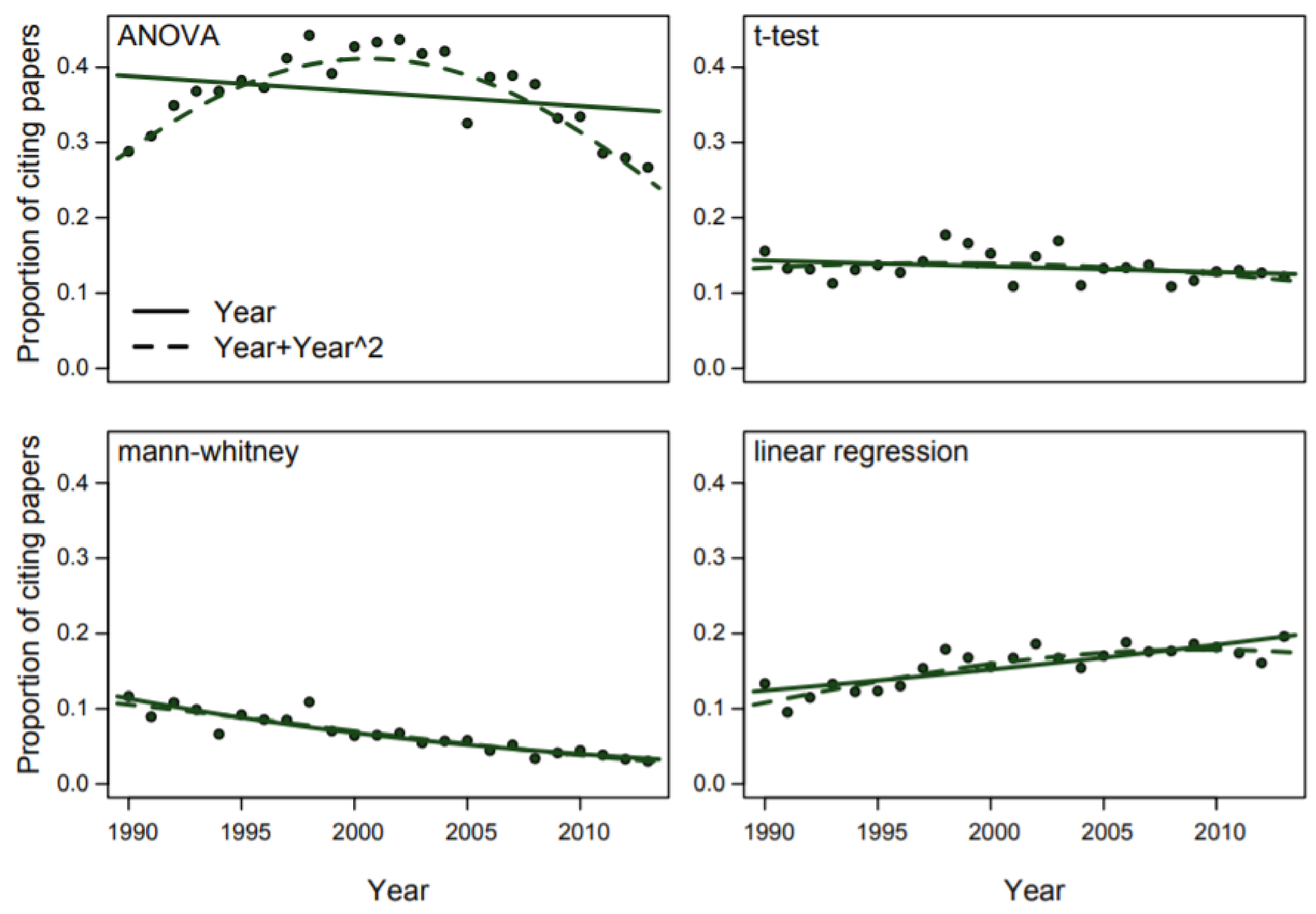
Walter J. Radermacher

WHAT STATS SHOULD WE BE TEACHING BIOLOGISTS ?

esa ECOSPHERE

The mismatch between current statistical practice and doctoral training in ecology

Justin C. Touchon[1] and Michael W. McCoy[2,†]



BIOLOGY LETTERS

rsbl.royalsocietypublishing.org

Meeting report

Cite this article: Gimenez O *et al.* 2014 Statistical ecology comes of age. *Biol. Lett.* **10**: 20140698.
http://dx.doi.org/10.1098/rsbl.2014.0698

Population ecology

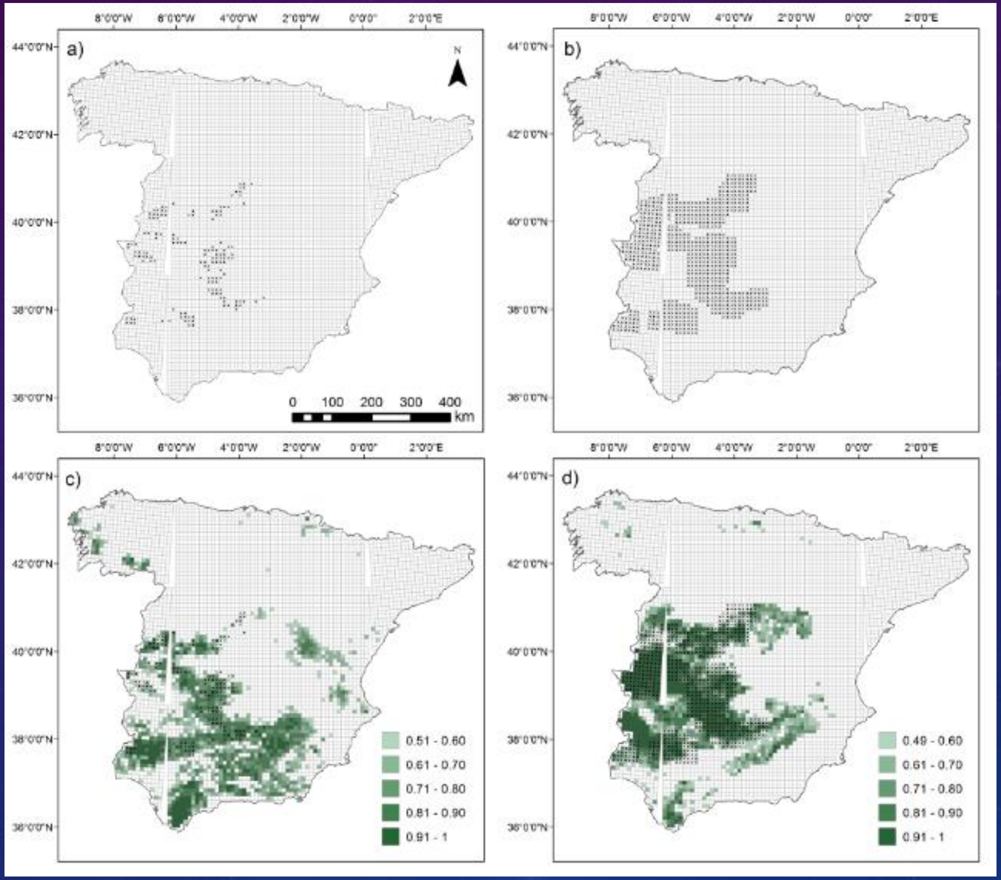
Statistical ecology comes of age

Olivier Gimenez[1], Stephen T. Buckland[2], Byron J. T. Morgan[3], Nicolas Bez[4], Sophie Bertrand[4], Rémi Choquet[1], Stéphane Dray[5], Marie-Pierre Etienne[6], Rachel Fewster[7], Frédéric Gosselin[8], Bastien Mérigot[9], Pascal Monestiez[10], Juan M. Morales[11], Frédéric Mortier[12], François Munoz[13], Otso Ovaskainen[14], Sandrine Pavoine[15,16], Roger Pradel[1], Frank M. Schurr[17], Len Thomas[2], Wilfried Thuiller[18], Verena Trenkel[19], Perry de Valpine[20] and Eric Rexstad[2]

[1]CEFE UMR 5175, CNRS, Université de Montpellier, Université Paul-Valéry Montpellier, EPHE, 1919 Route de Mende, 34293 Montpellier Cedex 5, France
[2]Centre for Research into Ecological and Environmental Modelling, University of St Andrews,

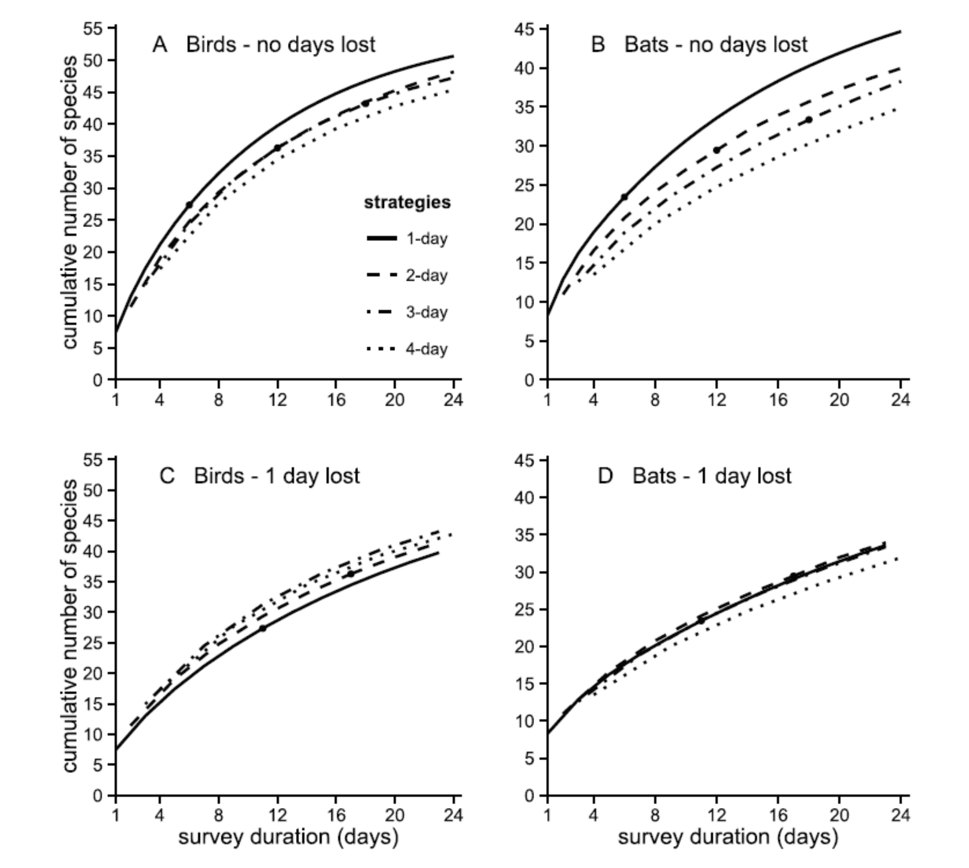
The desire to predict the consequences of global environmental change has been the driver towards more realistic models embracing the variability and uncertainties inherent in ecology. Statistical ecology has gelled over the past decade as a discipline that moves away from describing patterns towards modelling the ecological processes that generate these patterns. Following the fourth International Statistical Ecology Conference (1–4 July 2014) in Montpellier, France, we analyse current trends in statistical ecology. Important advances in the analysis of individual movement, and in the modelling of population dynamics and species distributions, are made possible by the increasing use of hierarchical and hidden process models. Exciting research perspectives include the development of methods to interpret citizen science data and of efficient, flexible computational algorithms for model fitting. Statistical ecology has come of age: it now provides a general and mathematically rigorous framework linking ecological theory and empirical data.

SPECIES DISTRIBUTION MODELLING



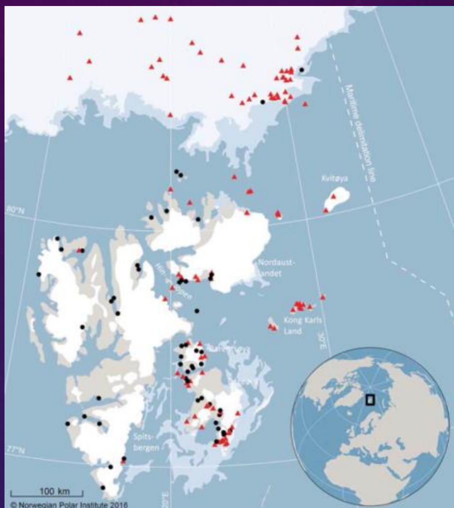
García-Barón, I., Cortés-Avizanda, A., Verburg, P. H., Marques, T. A., Moreno-Opo, R., Pereira, H. M. & J. A. Donázar 2018 How to fit the distribution of apex scavengers into land-abandonment scenarios? The Cinereous vulture in the Mediterranean biome. *Diversity and Distributions **24**: 1018-1031*

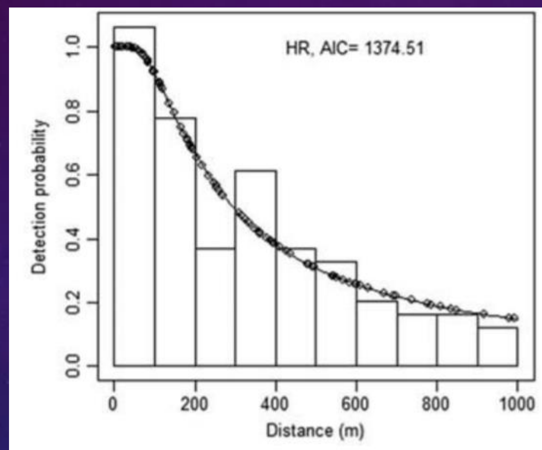
MEASURING BIODIVERSITY

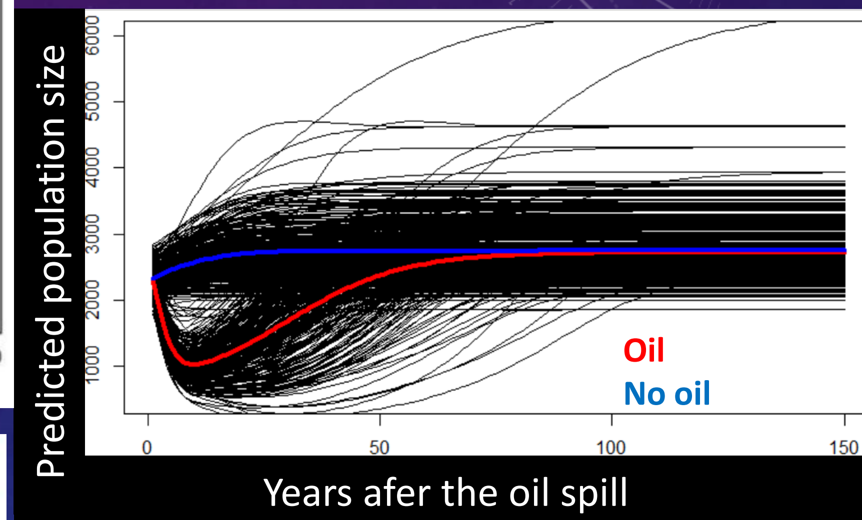


Marques, J. T. , Pereira, M. R., Marques, T. A., Santos, C. D., Santana, J., Beja, P. & Palmeirim, J. M. 2013 Optimizing sampling design to deal with mist-net avoidance in Amazonian birds and bats. *PLoS One*, **8**:e74505.

INVESTIGATING POPULATION DYNAMICS





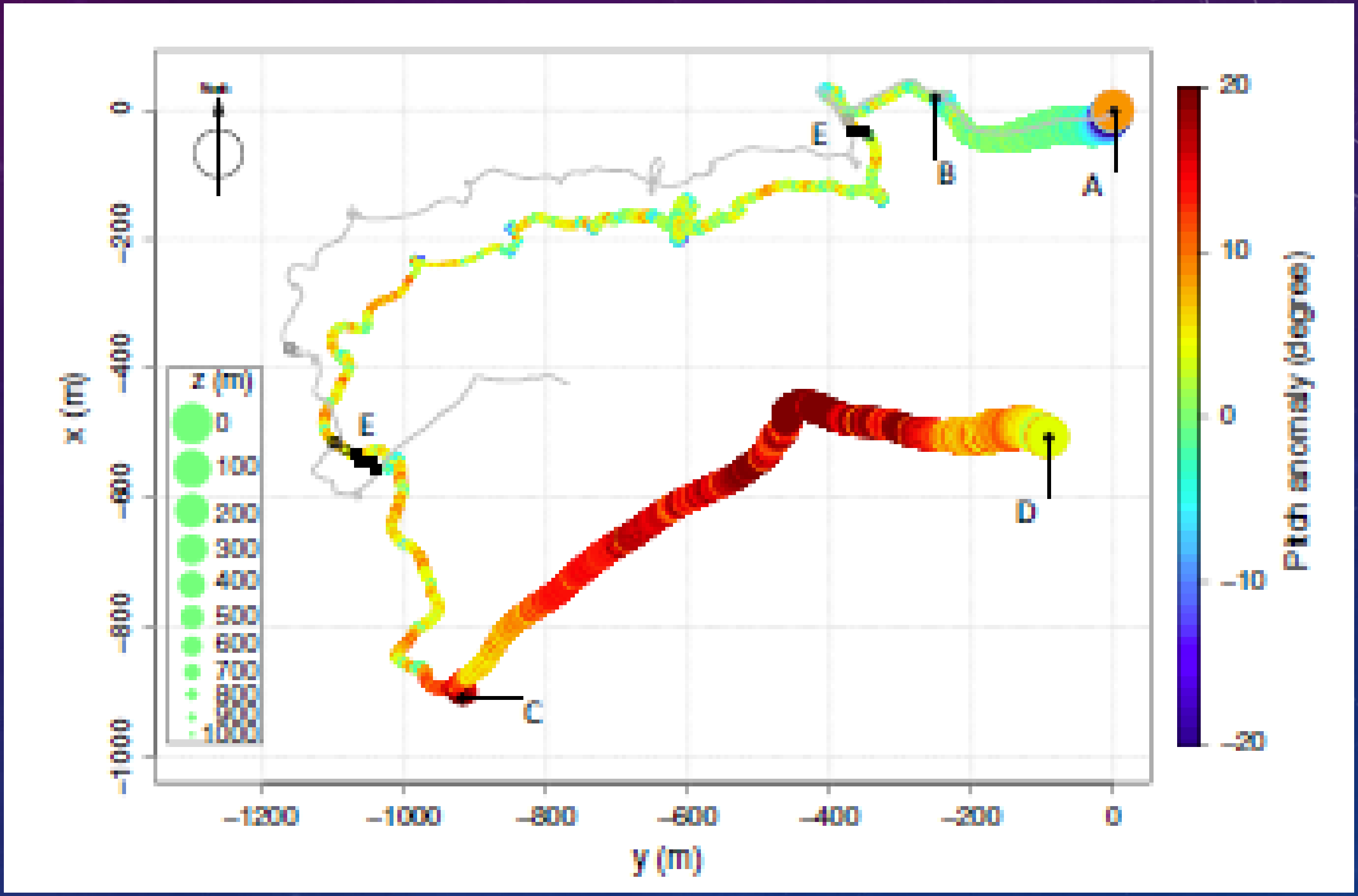


	2004		2015		Change, 2004 to 2015	
	$\hat{N}$	$\hat{N}$ 95% CI	$\hat{N}$	$\hat{N}$ 95% CI	$\Delta \hat{N}$	$\Delta \hat{N}$ 95% CI
Svalbard	241	(153, 329)	264	(199, 363)	23	(−97, 143)
Pack Ice	444	(282, 606)	709	(334, 1026)	265	(−117, 647)
Total	685	(501, 869)	973	(665, 1884)	288	(−349, 925)

Ongoing CARMMHA work
(dolphins in the Gulf of Mexico after the deepwater Horizon Oil spill)

Aars, J.; Marques, T.; Lone, K.; Andersen, M.; Wiig, Ø.; Fløystad, I. M. B.; Hagen, S. B. & Buckland, S. T. 2017 The number and distribution of polar bears in the western Barents Sea area. *Polar Biology*. **36**: 1374125

UNDERSTANDING ANIMAL MOVEMENTS



Laplanche, C., Marques, T. A. & Thomas, L. 2015 Tracking marine mammals in 3D using electronic tag data. *Methods in Ecology and Evolution*. **6**: 987–996

INTERPRETING CITIZEN SCIENCE DATA

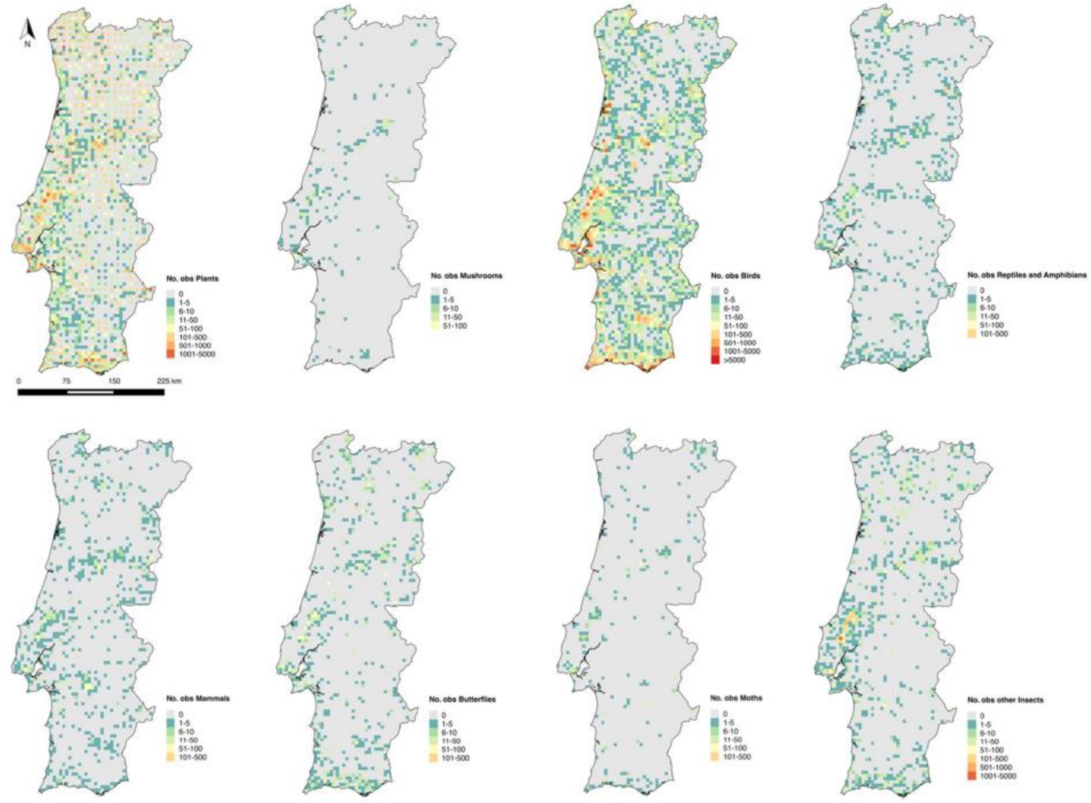


Figure 4. Number of citizen science species observations in mainland Portugal per grid cell, for each of the eight taxonomic groups analyzed. Figure created with QGis. 2014. Quantum GIS Geographic Information System. Open Source Geospatial Foundation Project. http://www.qgis.org/en/site/.

Tiago, P., Ceia-Hasse, A. Marques, T. A., Capinha, C. & Pereira, H. M. (2017) Spatial distribution of citizen science casuistic observations for different taxonomic groups. *Scientific Reports*. **7**: 12832

METHODS

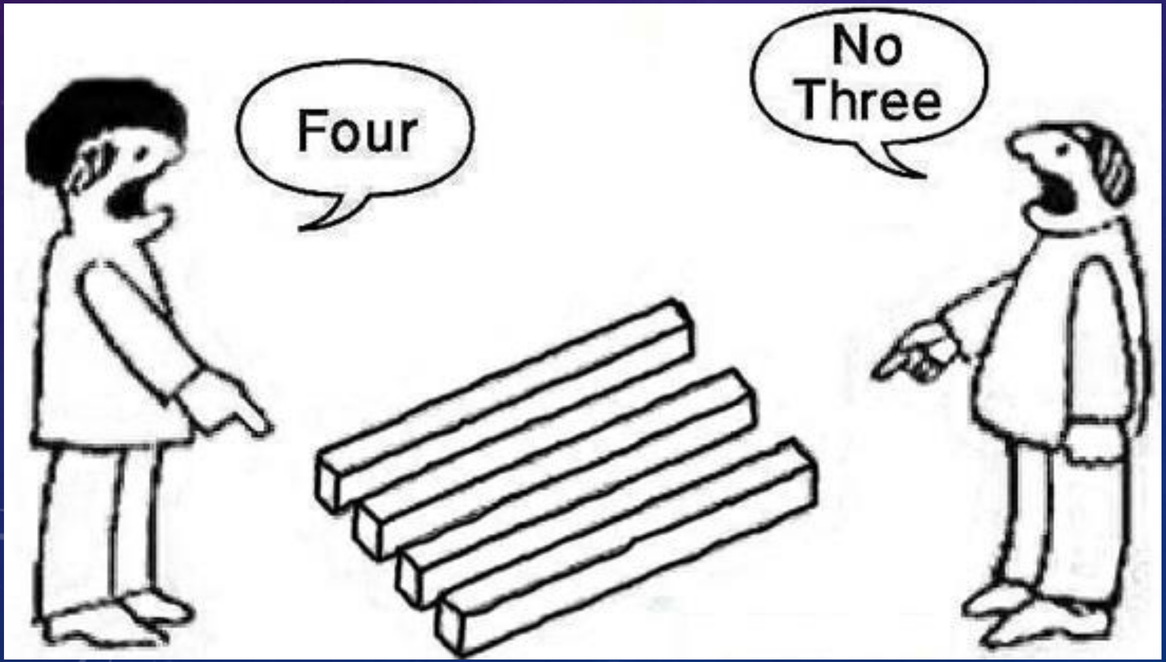
- None of the above can be addressed with a t-test or an ANOVA
- Ecological statistics is moving away from modelling spatio-temporal patterns per se and towards modelling the ecological processes that generate those patterns.
- Hidden Process Models – Underlying latent states with observations
  - Hidden Markov Models
  - State Space Models
  - Hierarchical models

REALITY, NATURE & FILTERS

WE WANT TO MAKE INFERENCES ABOUT REALITY

But really…

can you really say what is in fact reality?



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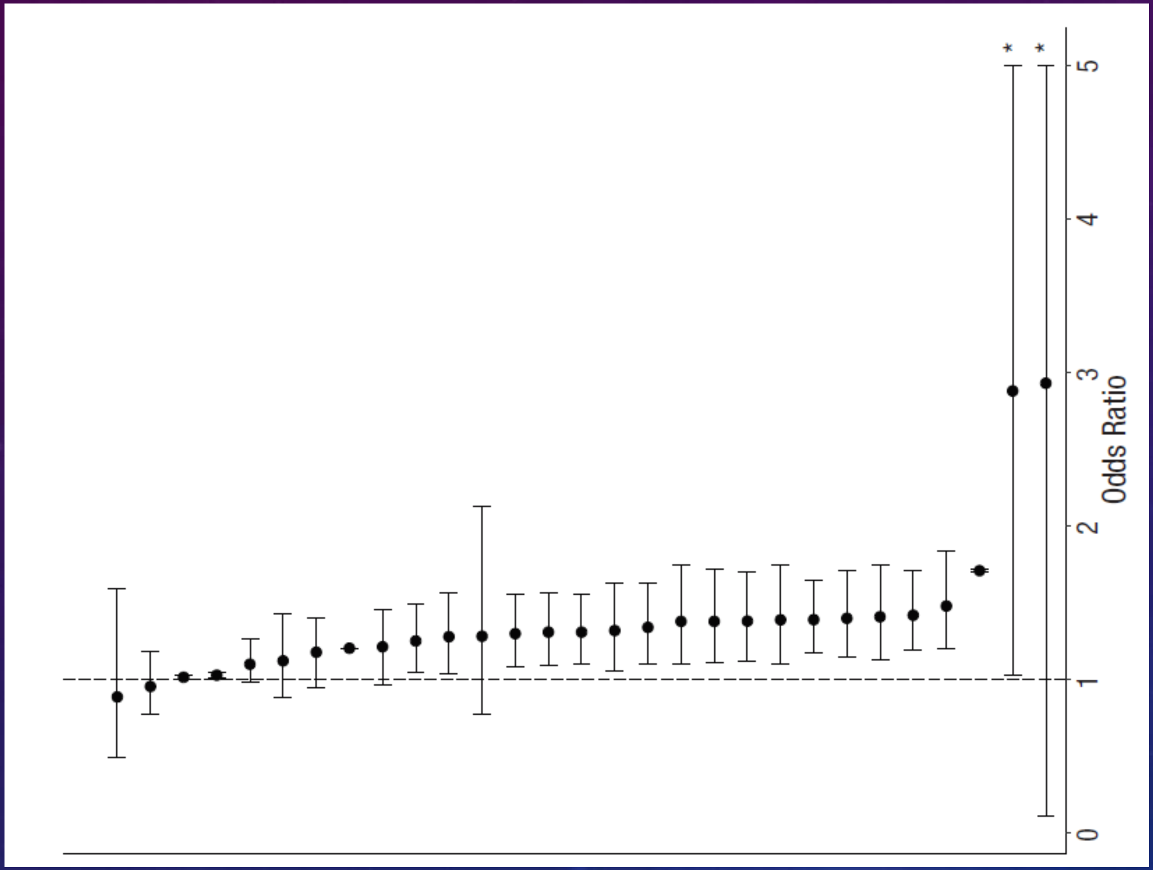


8 OCTOBER 2015 | VOL 526 | NATURE | 191

Mario Balotelli, playing for Manchester City, is shown a red card during a match against Arsenal.

- Analytic approaches varied widely across teams
- 20 teams (69%) found a statistically significant + effect and 9 teams (31%) did not observe a significant relationship.

Silberzahn *et al.* (2018). Many Analysts, One Data Set: Making Transparent How Variations in Analytic Choices Affect Results. Advances in Methods and Practices in Psychological Science. DOI: https://doi.org/10.1177/2515245917747646

WHAT IS (ECOLOGICAL) REALITY…?

- A response (acorn count), three designed effects (species, site, and year) and 7 environmental variables
- ‘‘explain variation in response variable (acorn count) using the predictors available’’
- responses from a skilled average self-reported statistical expertise of 6.7 on scale of 1 [low] to 10 [high]) diverse group of 24 ecologists
- no two final models included exactly the same set of predictors
- not a single predictor was included in every final model

So whatever reality is… filters are hard to undo!

Stanton-Geddes et al. 2014. In defense of P values: comment on the statistical methods actually used by ecologists. Ecology 95: 637--642

esa

ECOSPHERE

Applied statistics in ecology: common pitfalls and simple solutions

E. Ashley Steel,[1,†] Maureen C. Kennedy,[2] Patrick G. Cunningham,[3] and John S. Stanovick[4]

[1]Statistics, Pacific Northwest Research Station, USDA Forest Service, 400 N34th Street, Suite 201, Seattle, Washington 98103 USA
[2]Environmental and Forest Sciences, University of Washington, 400 N34th Street, Suite 201, Seattle, Washington 98103 USA
[3]Statistics, Pacific Northwest Research Station, USDA Forest Service, 3200 SW Jefferson Way, Corvallis, Oregon 97331 USA
[4]Statistics, Northern Research Station, USDA Forest Service, 11 Campus Boulevard, Suite 200, Newtown Square, Pennsylvania 19073 USA

Citation: Steel, E. A., M. C. Kennedy, P. G. Cunningham, and J. S. Stanovick. 2013. Applied statistics in ecology: common pitfalls and simple solutions. Ecosphere 4(9):115. http://dx.doi.org/10.1890/ES13-00160.1

SETTING UP AN ANALYSIS

EXPERIMENTAL DESIGN

APPLICATION OF STATISTICS

INTERPRETATION OF STATISTICAL TESTS AND MODELS

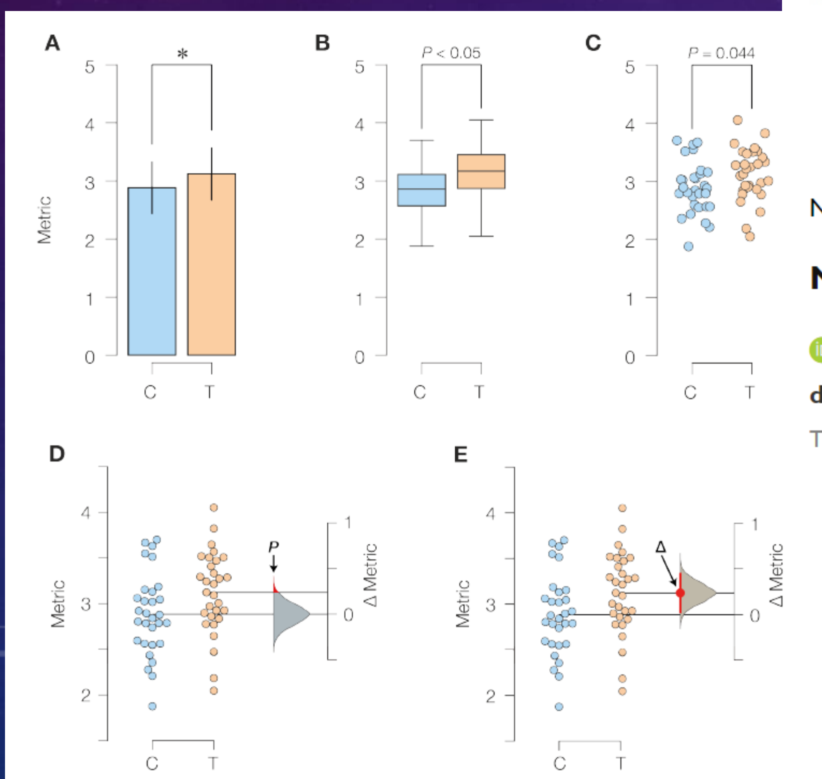
COMMON STATISTICAL PITFALLS IN SETTING UP AN ANALYSIS

Failure to explore the data

Arbitrary thresholds, metrics, and indicators

Assuming that observations are independent

Mismatched sampling frame and population



Cold Spring Harbor Laboratory
bioRxiv
THE PREPRINT SERVER FOR BIOLOGY

New Results

Moving beyond *P* values: Everyday data analysis with estimation plots

Joses Ho, Tayfun Tumkaya, Sameer Aryal, Hyungwon Choi, Adam Claridge-Chang

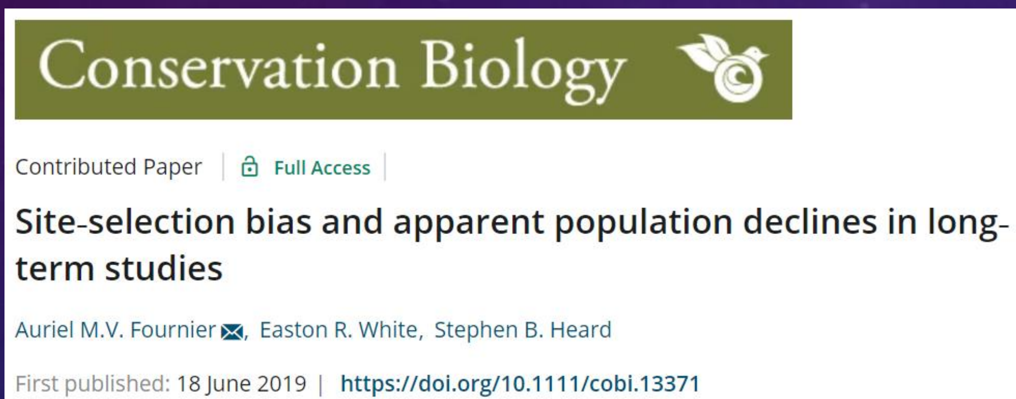
doi: https://doi.org/10.1101/377978

COMMON PITFALLS IN EXPERIMENTAL DESIGN

Control sites (or reference sites) differ from treatment sites before the treatment occurs

Measurement strategies that confound experimental designs

Failure to model covariates at the correct level



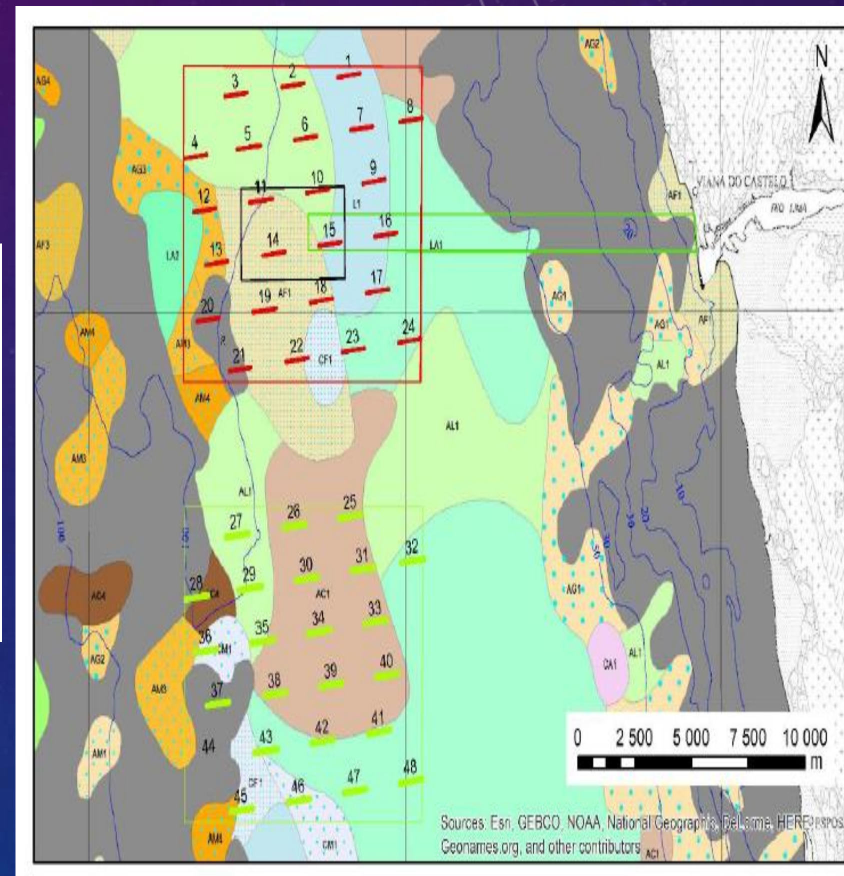
Conservation Biology

Contributed Paper | Full Access

Site-selection bias and apparent population declines in long-term studies

Auriel M.V. Fournier, Easton R. White, Stephen B. Heard

First published: 18 June 2019 | https://doi.org/10.1111/cobi.13371



PITFALLS IN THE APPLICATION OF STATISTICS

Unnecessary data transformations

Not dealing appropriately with zeros

Ignoring underlying correlation structure

Failure to plot the residuals

Conducting too many tests

Blind use of a new fancy tool

ECOLOGY
ECOLOGICAL SOCIETY OF AMERICA

Report | Free Access

The arcsine is asinine: the analysis of proportions in ecology

David I. Warton, Francis K. C. Hui

First published: 01 January 2011 | https://doi.org/10.1890/10-0340.1 | Cited by: 937

Methods in Ecology and Evolution
British Ecological Society

Methods in Ecology and Evolution 2010, **1**, 118–122 doi: 10.1111/j.2041-210X.2010.00021.x

Do not log-transform count data

Robert B. O'Hara[1]* and D. Johan Kotze[2]

[1]*Biodiversity and Climate Research Centre, Senckenberganlage 25, D-60325 Frankfurt am Main, Germany and*
[2]*Department of Environmental Sciences, PO Box 65, University of Helsinki, Helsinki FI-00014, Finland*

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Ecology Letters, (2005) **8**: 1235–1246 doi: 10.1111/j.1461-0248.2005.00826.x

REVIEWS AND SYNTHESES

Zero tolerance ecology: improving ecological inference by modelling the source of zero observations

Tara G. Martin,[1]* Brendan A. Wintle,[2] Jonathan R. Rhodes,[3] Petra M. Kuhnert,[4] Scott A. Field,[5] Samantha J. Low-Choy,[6] Andrew J. Tyre[7]† and Hugh P. Possingham[1]

Abstract

A common feature of ecological data sets is their tendency to contain many zero values. Statistical inference based on such data are likely to be inefficient or wrong unless careful thought is given to how these zeros arose and how best to model them. In this paper, we propose a framework for understanding how zero-inflated data sets originate and deciding how best to model them. We define and classify the different kinds of zeros that occur in ecological data and describe how they arise: either from 'true zero' or 'false zero' observations. After reviewing recent developments in modelling zero-inflated data

Received: 6 November 2018 | Revised: 12 February 2019 | Accepted: 27 March 2019

DOI: 10.1111/2041-210X.13185

Check for updates

RESEARCH ARTICLE

Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

What does a zero mean? Understanding false, random and structural zeros in ecology

Anabel Blasco-Moreno[1,3] | Marta Pérez-Casany[2] | Pedro Puig[3] | Maria Morante[4] | Eva Castells[4,5]

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Trends in Ecology & Evolution

Log in Register

REVIEW | VOLUME 24, ISSUE 3, P127-135, MARCH 01, 2009

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Generalized linear mixed models: a practical guide for ecology and evolution

Benjamin M. Bolker • Mollie E. Brooks • Connie J. Clark • ... John R. Poulsen • M. Henry H. Stevens • Jada-Simone S. White • Show all authors

Published: January 29, 2009 • DOI: https://doi.org/10.1016/j.tree.2008.10.008

Submitted 29 October 2018
Accepted 31 March 2019
Published 27 May 2019

PeerJ

Hierarchical generalized additive models in ecology: an introduction with mgcv

Eric J. Pedersen[1,2], David L. Miller[3,4], Gavin L. Simpson[5,6] and Noam Ross[7]

PITFALLS IN THE APPLICATION OF STATISTICS

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Not dealing appropriately with zeros

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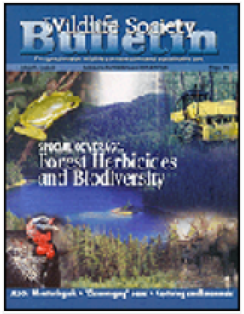
Blind use of a new fancy tool

[Wildlife Societ...](#) / [Vol. 26, No. 4,...](#) / Statistical Tes...



JOURNAL ARTICLE

Statistical Tests in Publications of The Wildlife Society

Steve Cherry

Wildlife Society Bulletin (1973-2006)

Vol. 26, No. 4, Commemorative Issue Celebrating the 50th Anniversary of "A Sand County Almanac" and the Legacy of Aldo Leopold (Winter, 1998), pp. 947-953

The 1995 issue of *The Journal of Wildlife Management* (the *Journal*) has >2,400 *P*-values. I believe that is too many. In this article I argue that authors who publish in the *Journal* and in the *Wildlife Society Bulletin* (the *Bulletin*) are overusing and misusing hypothesis tests. They are conducting too many unnecessary tests, and they are making common mistakes in carrying out and interpreting the results of the tests they conduct. A major cause of the overuse of testing in the *Journal* and the *Bulletin* seems to be the mistaken belief that testing is necessary in order for a study to be valid or scientific.

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Methods in Ecology and Evolution British Ecological Society

Methods in Ecology and Evolution 2014, **5**, 1192–1197 doi: 10.1111/2041-210X.12252

FORUM

Maxent is not a presence–absence method: a comment on Thibaud *et al.*

Gurutzeta Guillera-Arroita*, José J. Lahoz-Monfort and Jane Elith

On the Reliability of N-Mixture Models for Count Data

Richard J. Barker[1,*] Matthew R. Schofield,[1] William A. Link,[2] and John R. Sauer[2]

[1]Department of Mathematics and Statistics, University of Otago, P. O. Box 56 Dunedin 9016, New Zealand
[2]U.S. Geological Survey, Patuxent Wildlife Research Center, Maryland 20708, U. S. A.
*email: rbarker@maths.otago.ac.nz

SUMMARY. N-mixture models describe count data replicated in time and across sites in terms of abundance N and detectability p. They are popular because they allow inference about N while controlling for factors that influence p without the need for marking animals. Using a capture–recapture perspective, we show that the loss of information that results from not marking animals is critical, making reliable statistical modeling of N and p problematic using just count data. One cannot reliably fit a model in which the detection probabilities are distinct among repeat visits as this model is over-specified. This makes uncontrolled variation in p problematic. By counter example, we show that even if p is constant after adjusting for covariate effects (the "constant p" assumption) scientifically plausible alternative models in which N (or its expectation) is non-identifiable or does not even exist as a parameter, lead to data that are practically indistinguishable from data generated under an N-mixture model. This is particularly the case for sparse data as is commonly seen in applications. We conclude that under the constant p assumption reliable inference is only possible for relative abundance in the absence of questionable and/or untestable assumptions or with better quality data than seen in typical applications. Relative abundance models for counts can be readily fitted using Poisson regression in standard software such as R and are sufficiently flexible to allow controlling for p through the use covariates while simultaneously modeling variation in relative abundance. If users require estimates of absolute abundance, they should collect auxiliary data that help with estimation of p.

Solution:

Choose a statistical tool based on the research question at hand and the design under which the data were collected rather than statistical-fashion. Understand that tool, its paradigm, limitations,
potential biases, and assumptions.

PITFALLS IN THE INTERPRETATION OF STATISTICAL TESTS AND MODELS

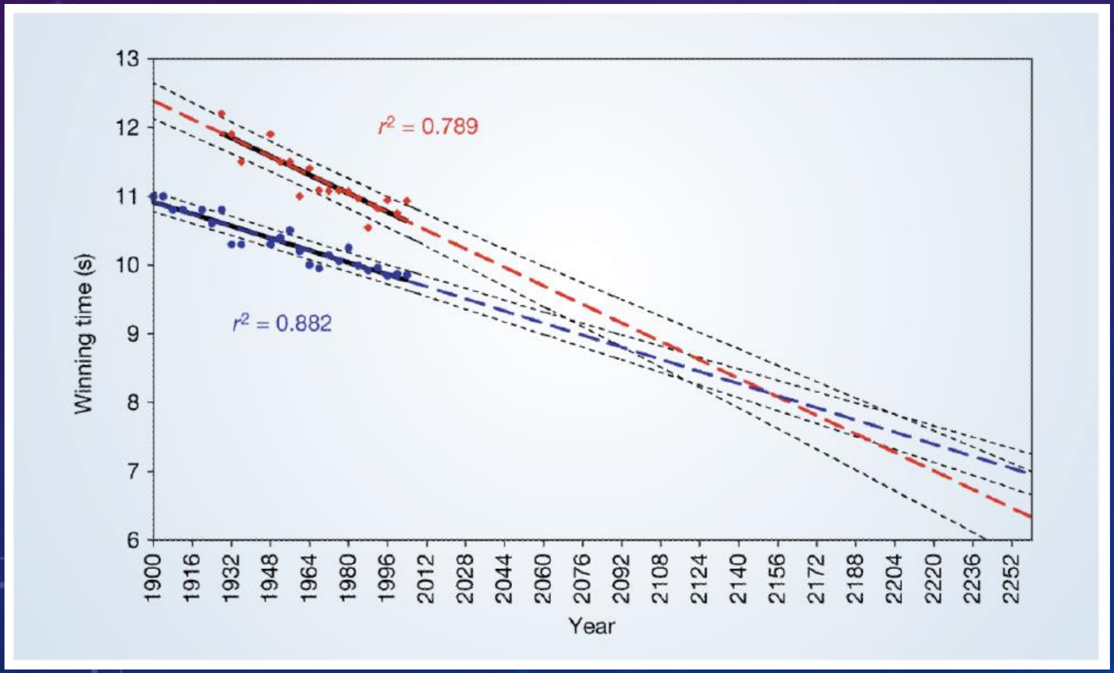
Extrapolation

Misinterpretation of a non-significant p-value

Inappropriate comparisons of p values

Implying ecological significance from statistical significance where there are very large sample sizes

Misinterpretation of coefficients in multiple regression models



nature
International journal of science

Brief Communication | Published: 29 September 2004

Athletics

Momentous sprint at the 2156 Olympics?

Andrew J. Tatem, Carlos A. Guerra, Peter M. Atkinson & Simon I. Hay

Nature **431**, 525 (2004) | Download Citation

Women sprinters are closing the gap on men and may one day overtake them.

PITFALLS IN THE INTERPRETATION OF STATISTICAL TESTS AND MODELS

Extrapolation

Misinterpretation of a non-significant p-value

Inappropriate comparisons of p values

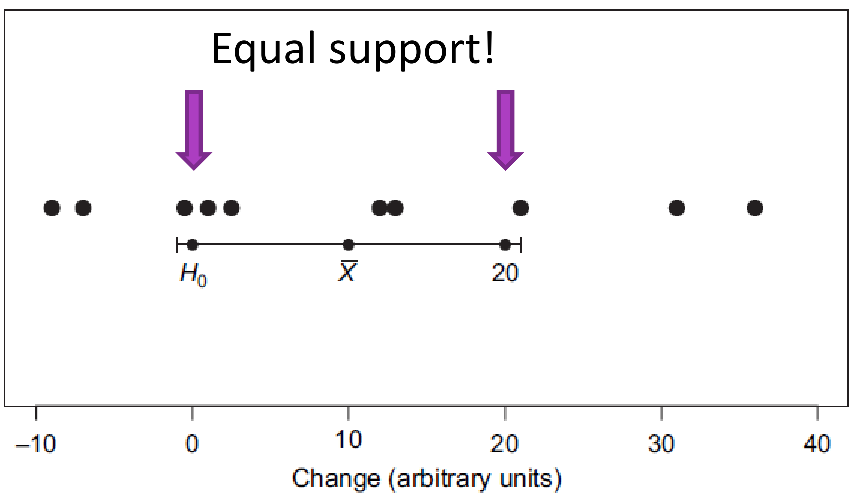
Implying ecological significance from statistical significance

Misinterpretation of coefficients in multiple regression models

Biol. Rev. (2007), 82, pp. 591–605. 591
doi:10.1111/j.1469-185X.2007.00027.x

Effect size, confidence interval and statistical significance: a practical guide for biologists

Shinichi Nakagawa[1,*] and Innes C. Cuthill[2]



“THE *P* VALUE WAS NEVER MEANT TO BE USED THE WAY IT’S USED TODAY.”

STATISTICAL ERRORS

P values, the ‘gold standard’ of statistical validity, are not as reliable as many scientists assume.

BY REGINA NUZZO

Lack of effect vs. lack of power !

A statistical significant result is, mostly, a sample size statement

- Non significant result → small sample size
- Significant result → large sample size

And so what… you know sample size to begin with, no need for a test to tell you that!

The Journal of ... / Vol. 64, No. 4,... / Null Hypothesis...

JOURNAL ARTICLE

Null Hypothesis Testing: Problems, Prevalence, and an Alternative

David R. Anderson, Kenneth P. Burnham and William L. Thompson

The Journal of Wildlife Management
Vol. 64, No. 4 (Oct., 2000), pp. 912-923

"The most curious problem with null hypothesis testing, as the primary method for data analysis and inference, is that nearly all null hypothesis are false on a priori grounds..."

statistical significance does not imply biological significance

ACTA OECOLOGICA 34 (2008) 9–11

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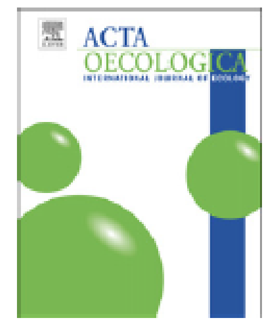

Original article

Statistical significance and biological relevance: A call for a more cautious interpretation of results in ecology

*Alejandro Martínez-Abraín**

THE AMERICAN STATISTICIAN
2019, VOL. 73, NO. S1, 1–19: Editorial
https://doi.org/10.1080/00031305.2019.1583913

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EDITORIAL

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Moving to a World Beyond "$p < 0.05$"

Special issue: 43 papers on statistical significance

"We conclude, based on our review of the articles in this special issue and the broader literature, that
it is time to stop using the term "statistically significant" entirely. Nor should variants such as "significantly different," "$p < 0.05$," and "nonsignificant" survive, whether expressed in words, by asterisks in a table, or in some other way."

The statement is not that you can't use P-values, but that you should consider carefully each time what it means in practice rather than making a blind black and white decision

- Statistical significance is dead?
- It does not matter if you agree with progress, the only thing you can do about it is to adapt!

PeerJ

Lack of quantitative training among early-career ecologists: a survey of the problem and potential solutions

Submitted 31 December 2013
Accepted 31 January 2014
Published 4 March 2014

Frédéric Barraquand[1,11], Thomas H.G. Ezard[2,11], Peter S. Jørgensen[3,11], Naupaka Zimmerman[4,11], Scott Chamberlain[5], Roberto Salguero-Gómez[6,7,11], Timothy J. Curran[8,11] and Timothée Poisot[9,10,11]

"…Ecology is moving into an **increasingly quantitative** era… which demands a general review of **mathematical, statistical and programming training** …"

"…**Collaborative research** projects and data sets are both expanding in size and complexity, for which we need **ecologists trained in state-of-the-art modeling**"

"…our results indicate that **quantitative training in ecology is often insufficient**…"

"…**mathematics, statistics and programming are transferable skills** that boost employment prospects inside and outside of academia…"

PeerJ

Lack of quantitative training among early-career ecologists: a survey of the problem and potential solutions

Submitted 31 December 2013
Accepted 31 January 2014
Published 4 March 2014

Frédéric Barraquand[1,11], Thomas H.G. Ezard[2,11], Peter S. Jørgensen[3,11], Naupaka Zimmerman[4,11], Scott Chamberlain[5], Roberto Salguero-Gómez[6,7,11], Timothy J. Curran[8,11] and Timothée Poisot[9,10,11]

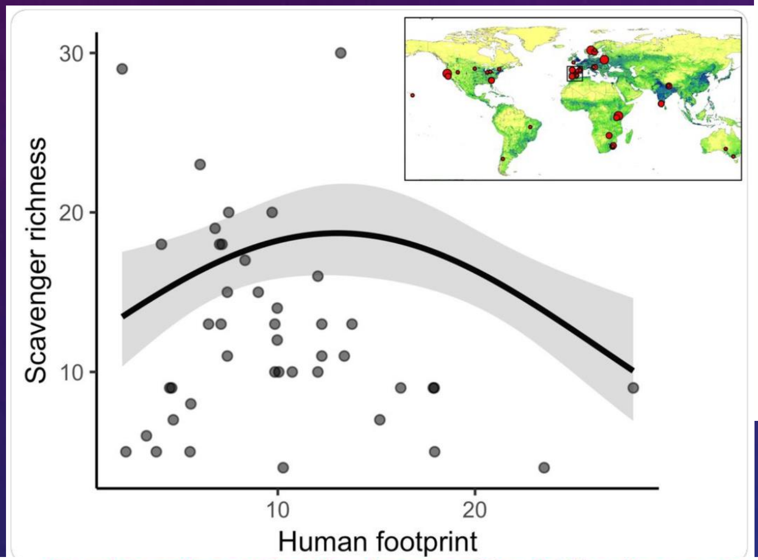
"This survey points to the widespread recognition of the **need for better quantitative training in ecology among early-career ecologists**, and highlights two useful means to do so:

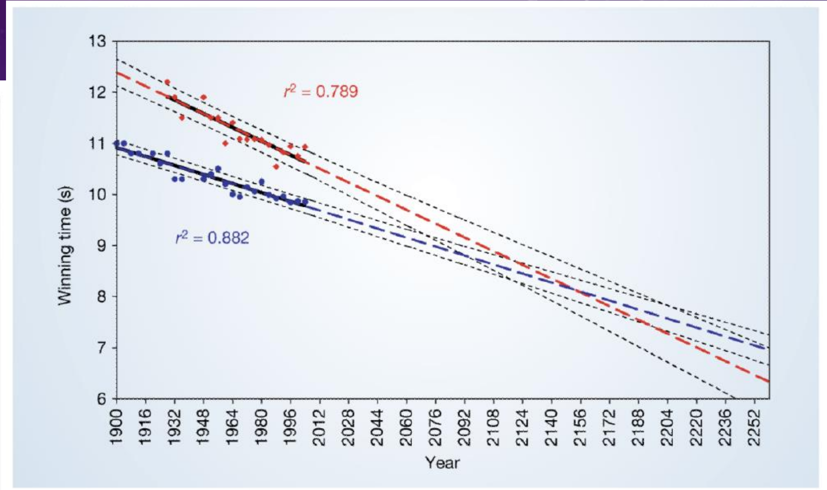
1. **additional mathematics/statistics** classes (especially calculus and algebra for undergraduates, when these are absent)
2. **making already existing ecology classes more quantitative**, combining mathematical, statistical, and programming concepts with ecological knowledge"

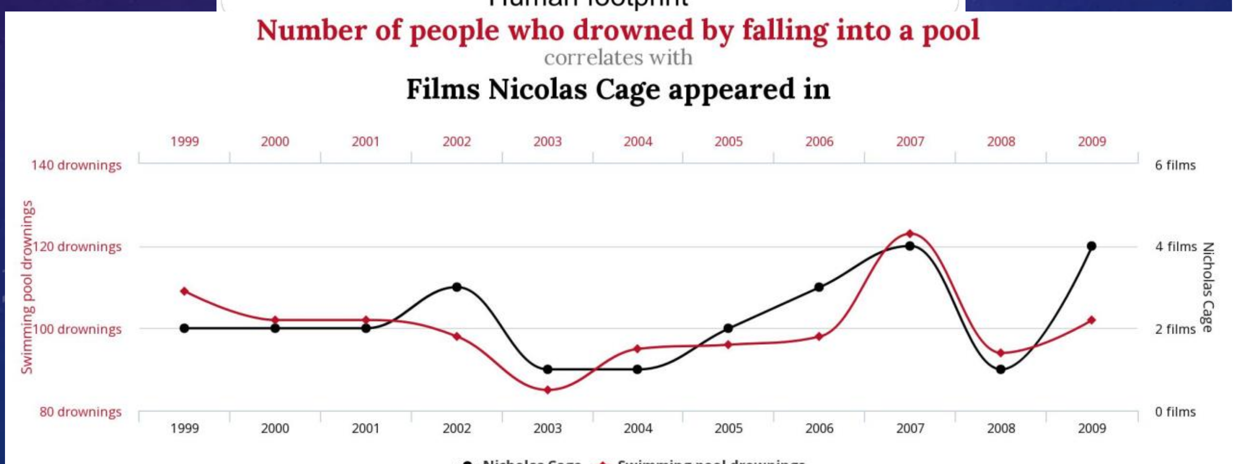
SO WHAT SHOULD WE AIM TO TEACH BIOLOGY STUDENTS? (SOME RANDOM THOUGHTS)

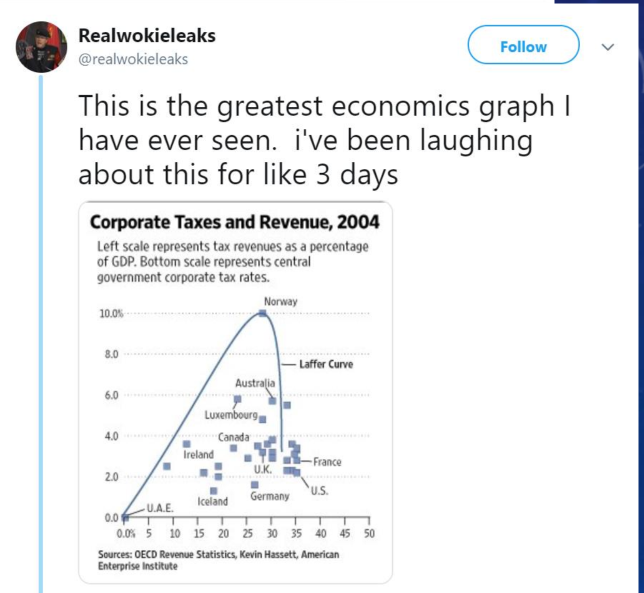
- Data: collection, processing, management
- **Think before acting**
- Randomness, variability, confounding
- **Uncertainty is a good thing**
- Models are not truth
- Decisions under uncertainty lead to errors
- R programing, dynamic reports and reproducible research
- Data visualization (if you can't plot it… is it real?)
- Regression models: GLMs, GAMs, GLMMs, GAMMs
- Bayesian paradigm
- The limitations of statistics

- An ecologist should know enough statistics to avoid major pitfalls, implement a set of standard methods and know when to ask for help
- Key: turn your brain on before turning on your computer!









NEXT STEPS FOR THIS THOUGHT PROCESS

http://www.isec2020.org/

1. (is happening) Getting feedback from this audience

2. (will happen) Hosting a round table discussion at Sydney’s ISEC

3. (could happen) Habilitation: propose course on Ecological Statistics

THANK YOU

- Any questions?

An inconvenient truth

Anonymous student:

"Was my decision correct? How do I know I did the right thing?"

Anonymous teacher:

"No one knows what reality is, so you don't."