BEFORE WE START

ASSESSMENT ME 2019/2020

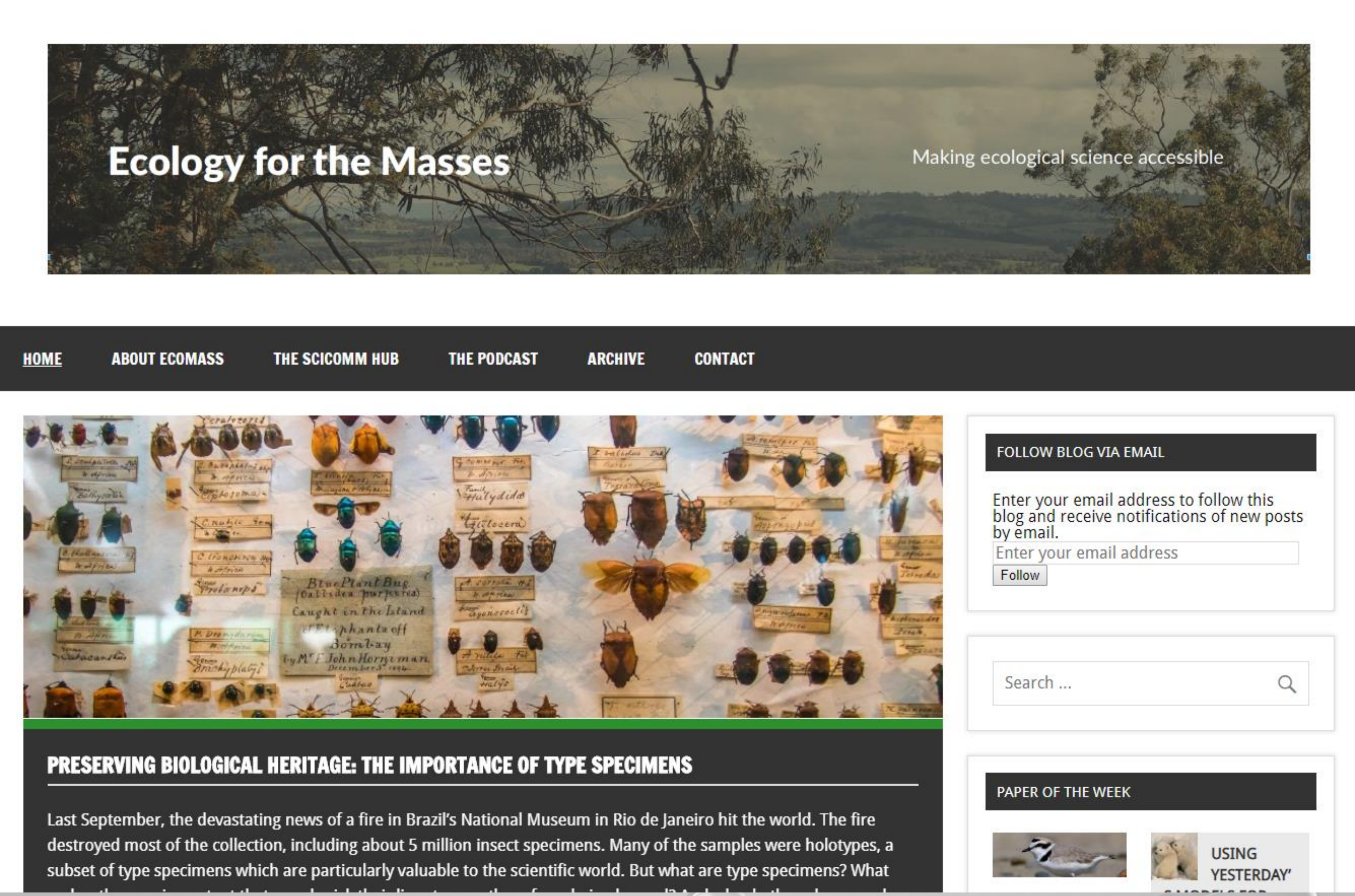
- MINI PRACTICAL WORK WITH OWN DATA – 15% (GROUPS OF 3)
- PRACTICAL WORK MECOCO – 20 % (GROUPS OF 1) (ASIDE: WITH THE POTENCIAL TO WRITE A JOINT PAPER, NOT FOR THE ASSESSMENT, BUT CERTAINLY A PLUS)
- PRACTICAL MODELLING WORK (OWN DATA OR DATA FROM OTHERS) – 45 % (GROUPS OF 4, 4 PAGES, ORAL PRESENTATION 10 MINS)
- WORK ON A MODEL OF YOUR CHOICE, THEORETICAL VEINED, USING AN EXAMPLE PAPER (OF STUDENTS CHOICE, BUT SUBJECT TO PREVIOUS AGREEMENT FROM TEACHER)) – 20 % (GROUPS OF 4, 4 PAGES + ORAL PRESENTATION 10 MINS)

EMMA 2019 – 15 Novembro 2019, FCUL

"…Espera-se também, ao divulgar este acontecimento junto aos estudantes de Biologia do país, aproximá-los dos centros de investigação e dos investigadores que trabalham nesta área.

O objetivo é proporcionar uma oportunidade de networking ímpar e identificar estratégias que permitam criar uma verdadeira comunidade de investigadores com interesse na temática dos mamíferos marinhos, potenciando assim esforços conjuntos à escala nacional…."

http://emma2019.campus.ciencias.ulisboa.pt/



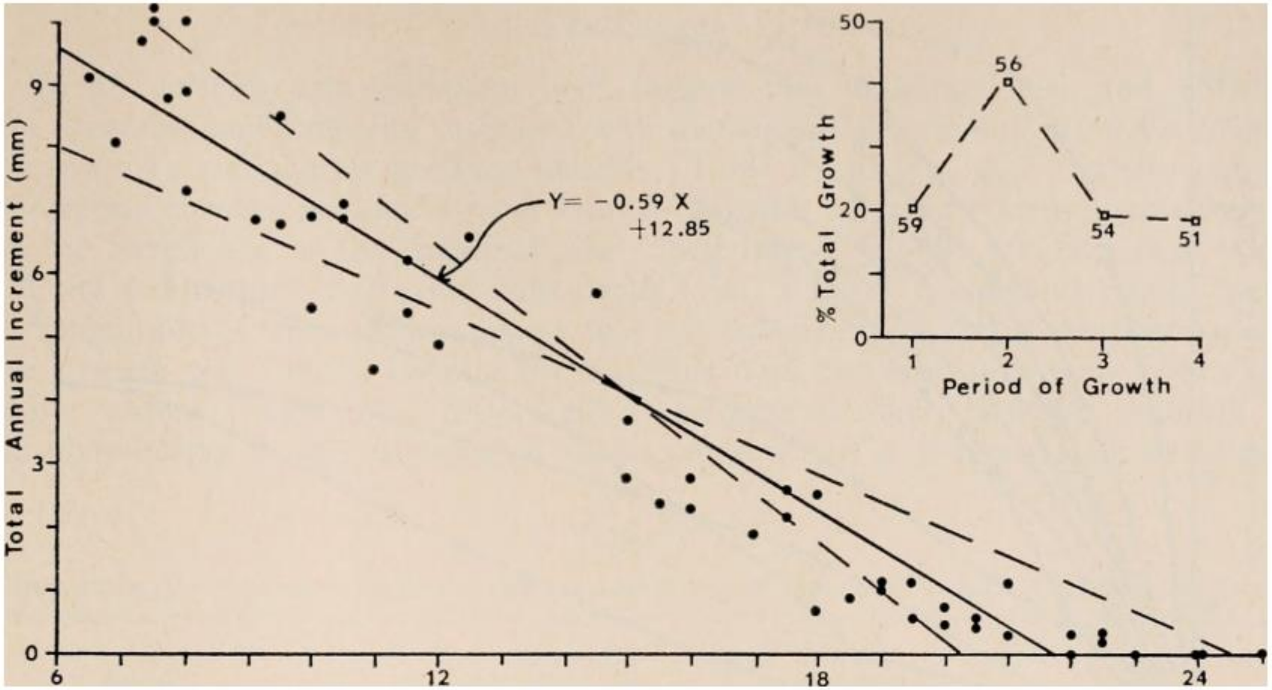
https://ecologyforthemasses.com/

Ecology for the Masses

Bob O'Hara: The Rise of the Ecological Modeller

Sam Perrin

3 days ago



Non-scientists still often think of ecologists as field workers in cargo shorts, running around a grassland with a notebook and a tape measure. Whilst I'd be remiss to say this wasn't a percentage of us, the last two decades has seen the rise of ecological modelling, which has resulted in a new breed of ecologist. One who is capable of working almost exclusively with data, producing species distribution maps and population fluctuation graphs without leaving the office.

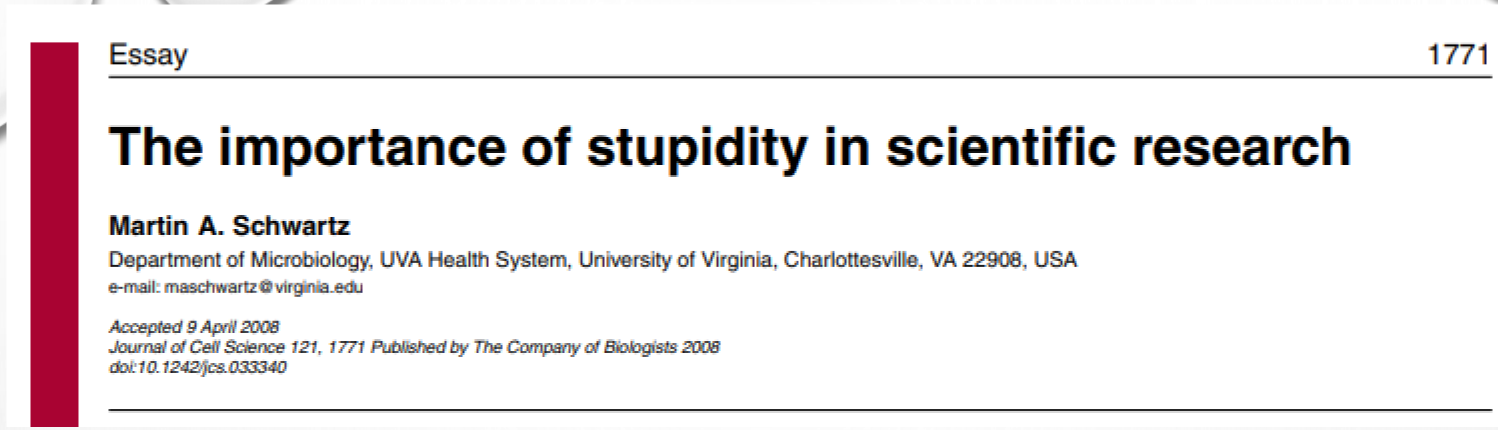
At the forefront of this group is Bob O'Hara, who has long claimed he plans to retire

https://ecologyforthemasses.com/2019/09/24/bob-ohara-the-rise-of-the-ecological-modeller/

SP: What are some of the main problems with ecological modelling today?

BO: My rather rude response is that it's done by people who aren't competent mathematically. I really feel that you should have some understanding of the mathematics. You don't need to be professors in mathematics, but people should be able to get a reasonable grasp of the mathematics behind the models. A lot of it is the use of computers. They make it very easy to do very complicated things. And you get to the point where you don't really understand how your model works. And what's the point of having a model if you don't understand what's going on in it.

That's the problem. It's just become too easy for people to do things badly. Take species distribution models for example. The problem is that you just grab the data from GBIF, you put it into a modelling package like MaxEnt, you get some pretty graphs. But there's lots of problems with GBIF data. You need to do some careful thinking through about what the data is, which of it to use, how to use it. And MaxEnt itself requires an understanding of the ecological processes behind your data. These aren't just black boxes.



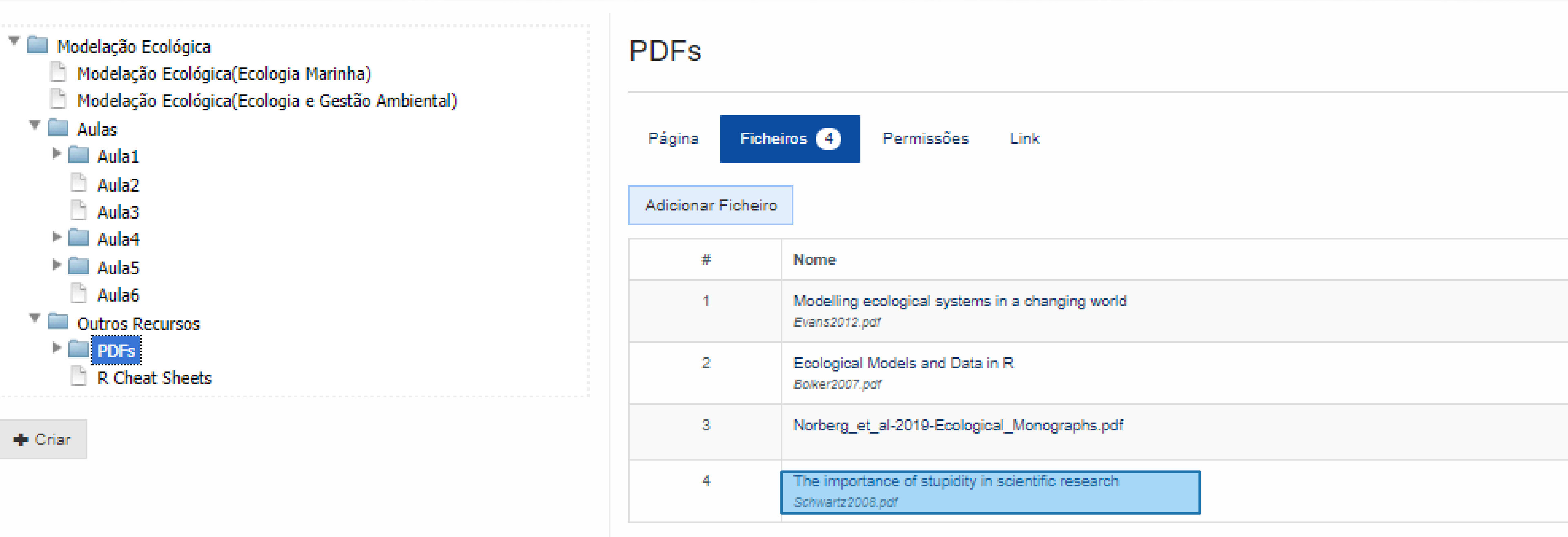
Essay 1771

The importance of stupidity in scientific research

Martin A. Schwartz
Department of Microbiology, UVA Health System, University of Virginia, Charlottesville, VA 22908, USA
e-mail: maschwartz@virginia.edu

Accepted 9 April 2008
Journal of Cell Science 121, 1771 Published by The Company of Biologists 2008
doi:10.1242/jcs.033340

"The more comfortable we become with being stupid, the deeper we will wade into the unknown and the more likely we are to make big discoveries."



Ecological Monographs, 89(3), 2019, e01370

A comprehensive evaluation of predictive performance of 33 species distribution models at species and community levels

Anna Norberg,[1,34] Nerea Abrego,[2,3] F. Guillaume Blanchet,[4] Frederick R. Adler,[5,6] Barbara J. Anderson,[7] Jani Anttila,[1] Miguel B. Araújo,[8,9,10] Tad Dallas,[1] David Dunson,[11] Jane Elith,[12] Scott D. Foster,[13] Richard Fox,[14] Janet Franklin,[15] William Godsoe,[16] Antoine Guisan,[17,18] Bob O'Hara,[19] Nicole A. Hill,[20] Robert D. Holt,[21] Francis K. C. Hui,[22] Magne Husby,[23,24] John Atle Kålås,[25] Aleksi Lehikoinen,[26] Miska Luoto,[27] Heidi K. Mod,[18] Graeme Newell,[28] Ian Renner,[29] Tomas Roslin,[3,30] Janne Soininen,[27] Wilfried Thuiller,[31] Jarno Vanhatalo,[1] David Warton,[32] Matt White,[28] Niklaus E. Zimmermann,[33] Dominique Gravel,[4] and Otso Ovaskainen[1,2]

- Modelação Ecológica
  - Modelação Ecológica(Ecologia Marinha)
  - Modelação Ecológica(Ecologia e Gestão Ambiental)
  - Aulas
    - Aula1
    - Aula2
    - Aula3
    - Aula4
    - Aula5
    - Aula6
  - Outros Recursos
    - PDFs
    - R Cheat Sheets

Criar

PDFs

Página | Ficheiros 4 | Permissões | Link

Adicionar Ficheiro

#	Nome
1	Modelling ecological systems in a changing world *Evans2012.pdf*
2	Ecological Models and Data in R *Bolker2007.pdf*
3	Norberg_et_al-2019-Ecological_Monographs.pdf
4	The importance of stupidity in scientific research *Schwartz2008.pdf*

MODELAÇÃO ECOLÓGICA

Class 5 / Aula 5

01 11 2019

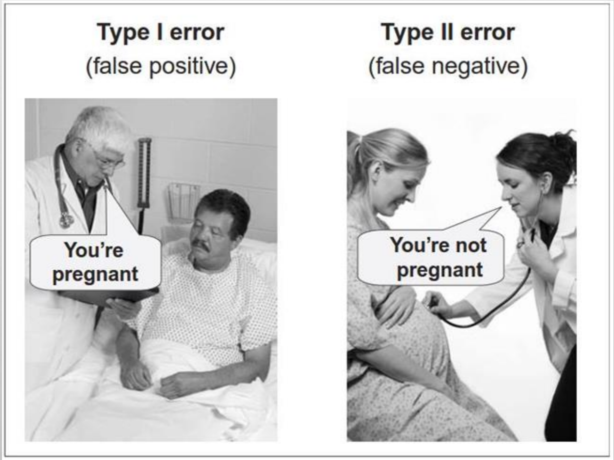
TESTS, DECISIONS AND ERRORS

		Decision	
		normal coin	biased coin
Reality	normal coin	**correct decision**	**type I error**
	biased coin	**type II error**	**correct decision**

In reality, the question about which is worse, a type I or a type II error, is a discussion on the realms of philosophy

Opinions might diverge, and it will be decided on a case by case basis.

In Statistics, type I errors are believed to be worth, and so when we build a test, is against those we guard ourselves (we set a significance level)

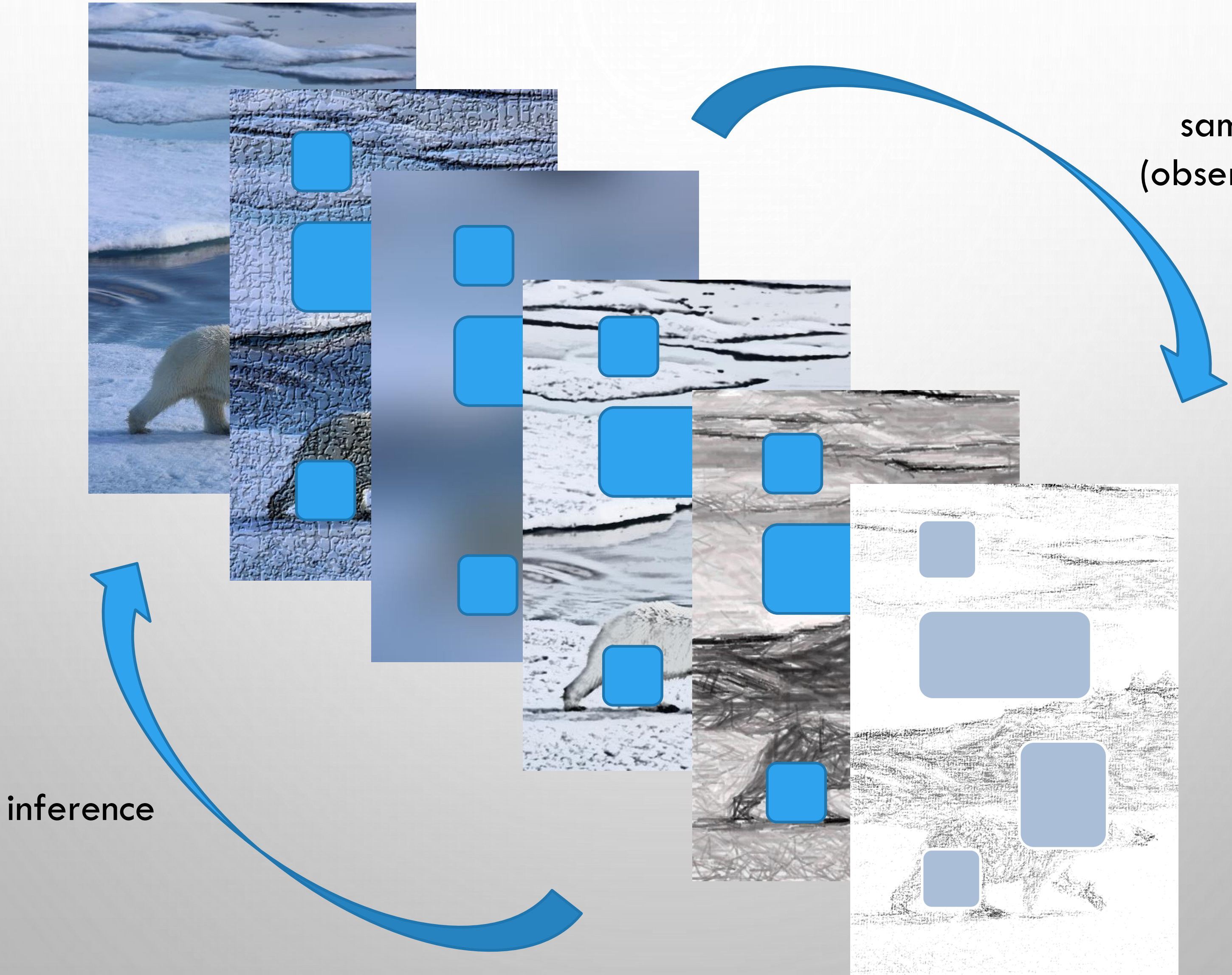


Type I error: there was no wolf, but they though there was

Type II error: there was a wolf, but they though there wasn't

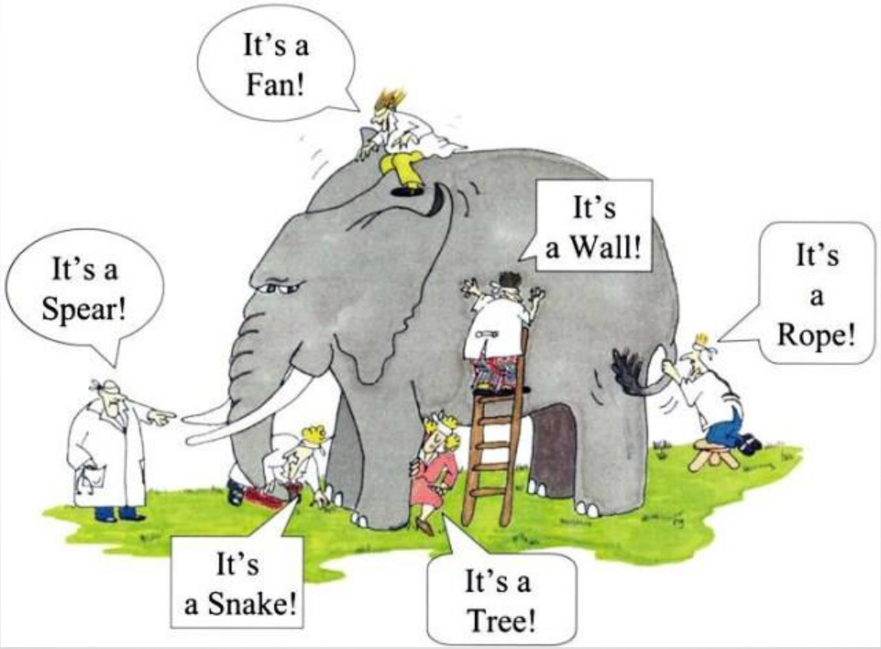
NATURE AND FILTERS

NATURE AND FILTERS



Filters are not necessarily unbiased!

A model is a useful simplification of reality.



A model should be as simple as possible, but, not simpler!

UMA MOTIVAÇÃO PARA MODELAR

Estimar tamanhos de populações naturais

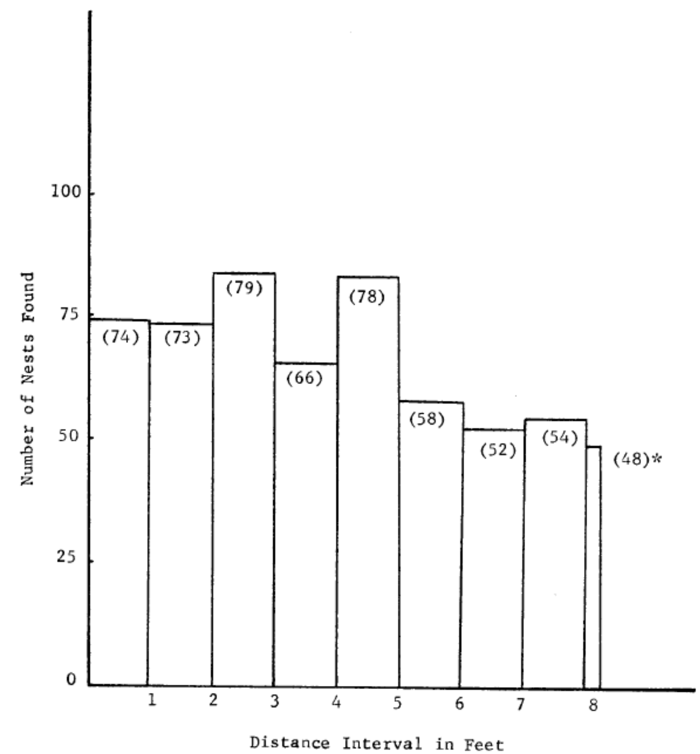


Fig. 2. Histogram of waterfowl nests located on belt transects, Monte Vista National Wildlife Refuge, Colorado, 1967 and 1968. *One-quarter-foot interval expanded by a factor of four (not used in calculations).

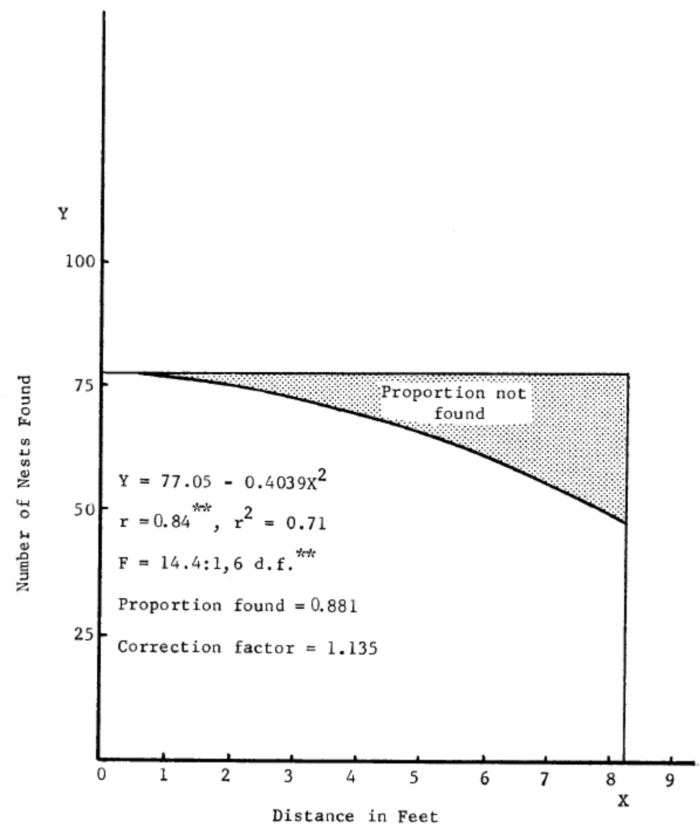


Fig. 3. Quadratic equation used to represent the relationship between distance from the center line of the transect

Anderson, D. R. & Pospahala, R. S. 1970 Correction of bias in belt transect studies of immotile objects *Journal of Wildlife Management* 34: 141-146

UM EXEMPLO: AMOSTRAGEM POR DISTÂNCIAS

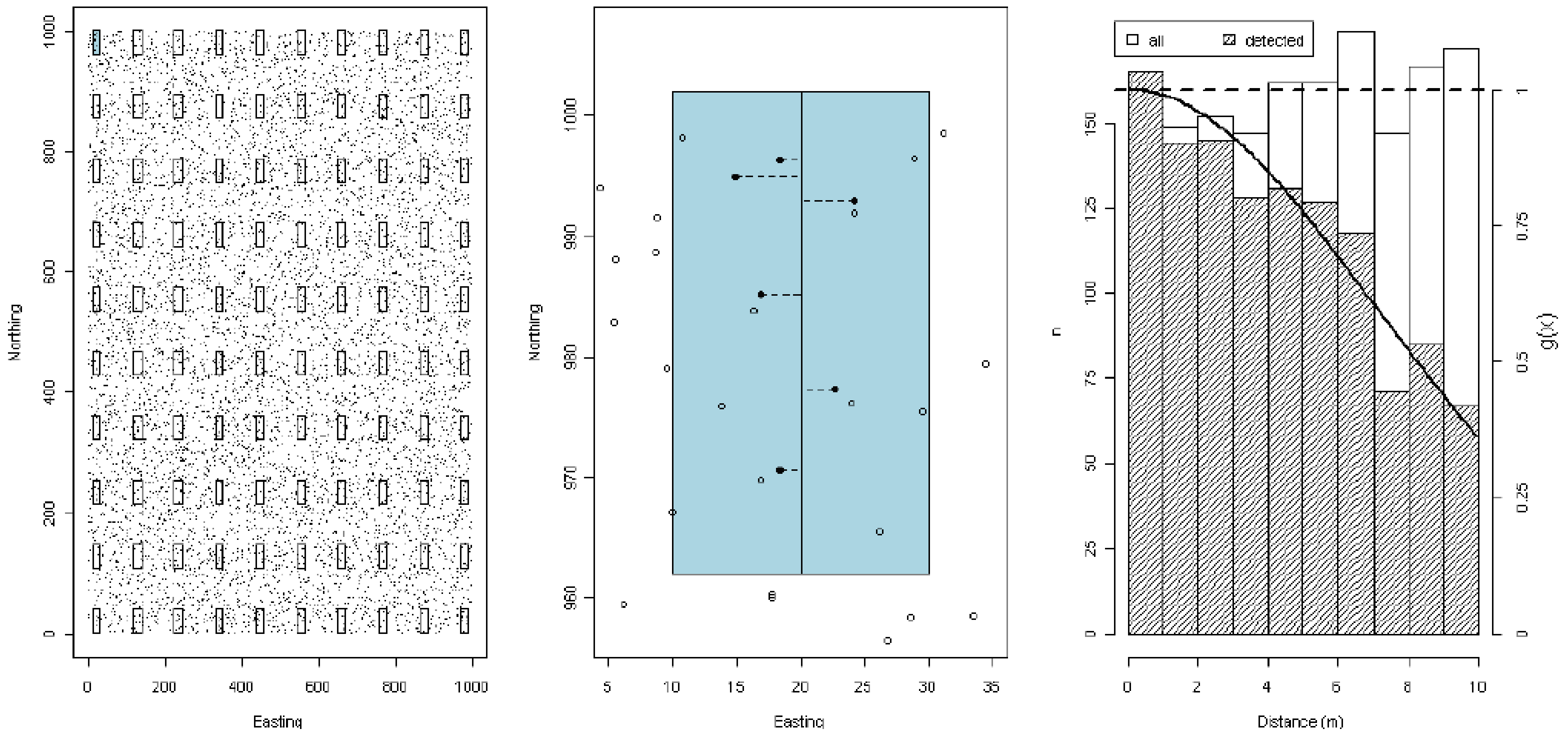


Figure 1. Distance sampling details. Left: survey area, with simulated tortoises shown as dots and areas covered as transects as rectangles. Middle: the top left transect from the left panels is magnified, with the distances to the detected tortoises shown as dashed lines. Right: histogram of the distances to all animals in the covered areas, as well as the distances to the detected animals. The detection function used to simulate the detections is shown as a solid line and the dashed line represents the average number of detections per bin if detection was certain at all distances (i.e. the total number of animals per bin)

Marques, T. A. 2009 Distance sampling: estimating animal density *Significance* **6**: 136-137

THE PROBLEM AND THE SOULTION

parameter

- NOT ALL ANIMALS ARE DETECTED WITH EQUAL PROBABILITY
- IF WE CAN OBTAIN (I.E. ESTIMATE!) THE PROBABILITY OF DETECTING AN ANIMAL (P), WE CAN OBTAIN AN ESTIMATE OF THE NUMBER OF EXISTING ANIMALS (N), BASED ON THE NUMBER OF DETECTED ANIMALS (n),
- $\hat{N} = N / \hat{P}$

^ a parameter estimate

- THEREFORE WE NEED A MODEL FOR DETECTABILITY
- THE CONCEPT OF A DETECTION FUNCTION, g(X), REPRESENTING THE PROBABILITY OF DETECTING AN ANIMAL AT DISTANCE X FROM THE TRANSECT

TABLE 1. Commonly used key functions and series expansions for the detection function (see fig. 2.6 in Buckland et al. [2001] for the shape of the key functions).

Key		Series expansion	
Uniform [a]	$1/w$	Cosine	$\sum_{j=2}^{m} a_j \cos(j\pi y_s)$
Half-normal	$\exp(-y^2/(2\sigma^2))$	Simple polynomial	$\sum_{j=2}^{m} a_j (y_s)^{2j}$
Hazard-rate	$1 - \exp[-(y/\sigma)^{-b}]$	Hermite [b]	$\sum_{j=2}^{m} a_j H_{2j}(y_s)$

[a] If a series expansion is included with the uniform, then $j = 1, \ldots, m$ instead of $2, \ldots, m$.
[b] $H(x)$ denotes a Hermite function (see Kotz and Johnson [1982] for details).

parameters

Marques, T. A. et al. 2007 Improving estimates of bird density using multiple covariate distance sampling *The Auk* **124**:1229-1243

DETECTION FUNCTIONS

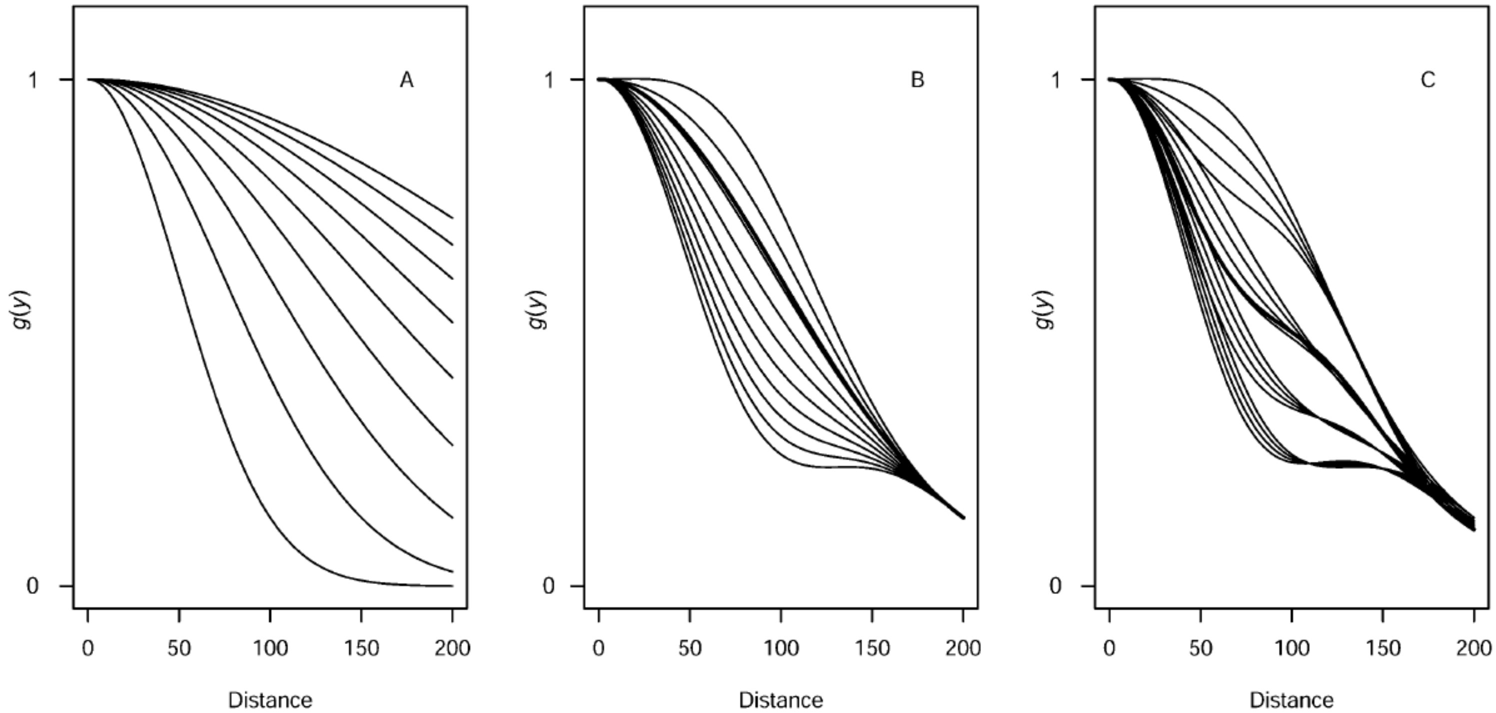


FIG. 1. Illustration of detection-function model formulation and the added flexibility provided by adjustment terms. (A) Half-normal detection function, with different scale parameters (σ = 50, 75, …, 225, 250). (B) Half-normal with σ = 100 and several different values of a single cosine adjustment term (j = 2 in Table 1). (C) Half-normal with σ = 100 and several different values of two cosine adjustment terms (j = 2, 3 in Table 1).

THIS IS A SIMPLE MODEL… IS IT TOO SIMPLE?

Make the scale parameter of the detection function become a function of additional covariates

$$\sigma = \exp\left(\beta_0 + \sum_{j=1}^{J} \beta_j z_j\right)$$

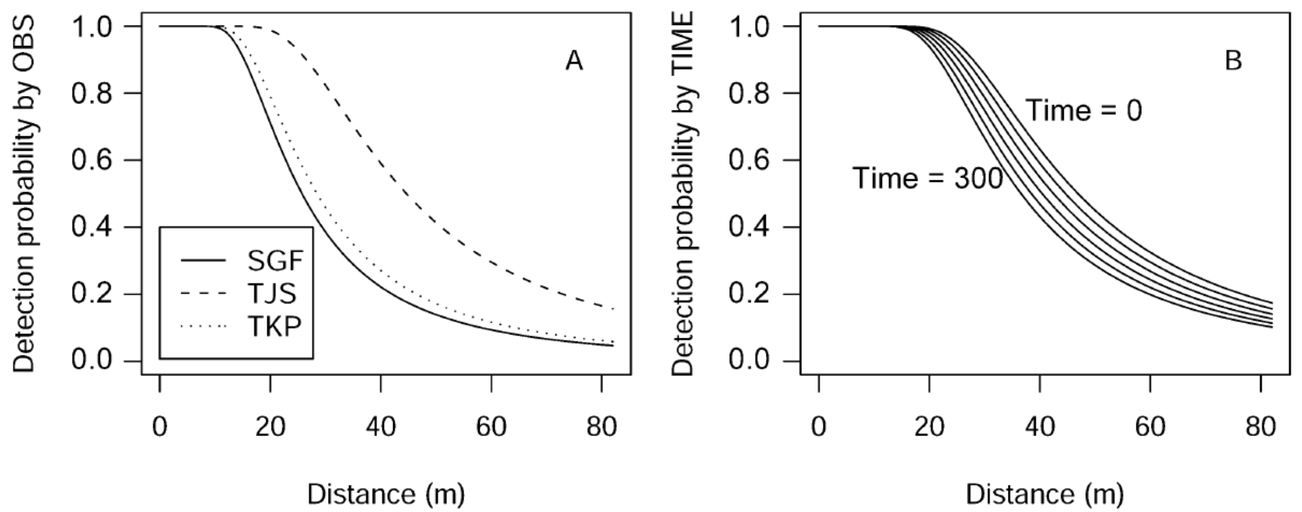


Fig. 7. Marginal detection functions for Hawaii Amakihi plotted for different values of (A) observer and (B) time of day (minutes after sunrise). (A) Time is fixed at 0900 HST. (B) Detection probabilities are shown for observer TJS at hourly intervals between 0 and 300 min after sunrise.

A model is a simplification, a **useful** one, of reality

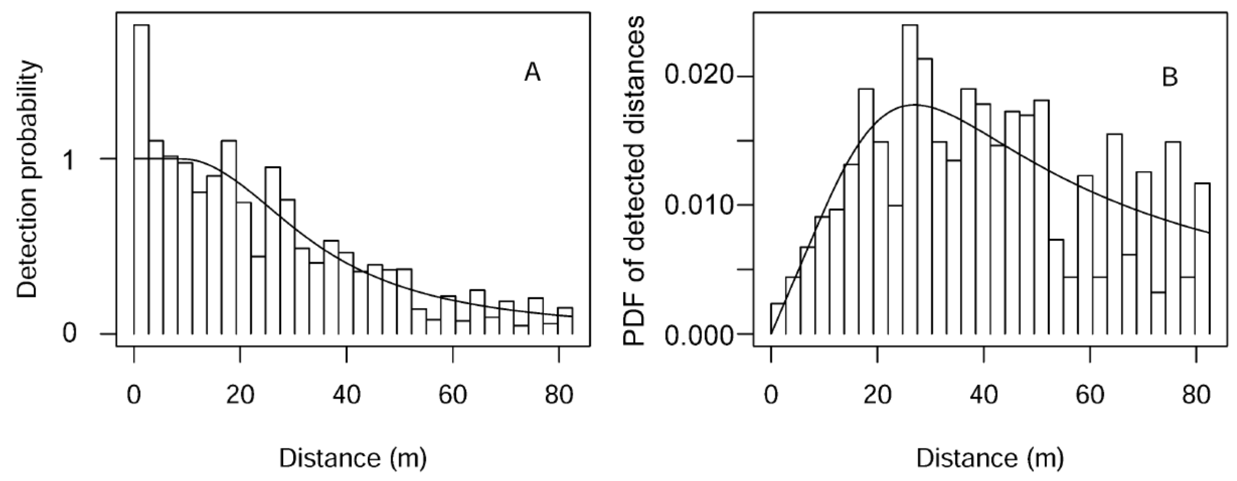


FIG. 6. (A) The estimated MCDS detection function for Hawaii Amakihi, based on the best model (lowest AIC value) and averaged over the observed covariate values for observer (OBS) and time of day (TIME). The detection function is superimposed over the histogram of observed distances, which have been scaled to adjust for increasing area surveyed at increasing distances from the survey point. (B) The corresponding estimated probability density function (PDF) of detected distances, superimposed over the histogram of actual distance data.

Such a simple model (and some more complicated extensions!) became the basis of the most widely used method for estimating wild animal density.

A MODEL ALWAYS HAS ASSUMPTIONS, IMPLICIT OR EXPLICIT (HOPEFULLY, THE LATER)

In distance sampling…

1. Large number of Transects allocated at random with respect to the animal distribution
2. Animals on the line or point are detected g(0)=1
3. Animal movement slow compared to observer movement
4. Distances measured without errors

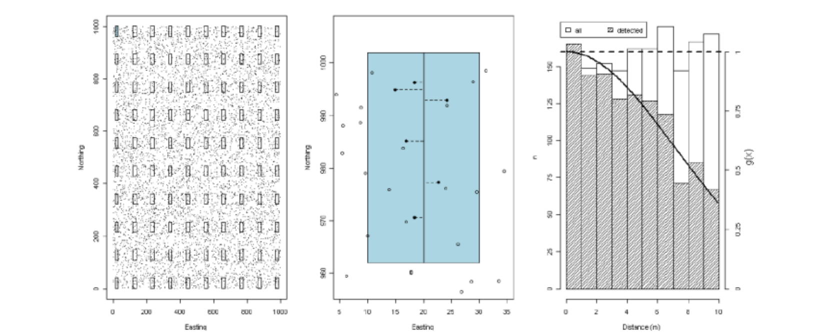


Figure 1. Distance sampling details. Left: survey area, with simulated tortoises shown as dots and areas covered as transects as rectangles. Middle: the top left transect from the left panels is magnified, with the distances to the detected tortoises shown as dashed lines. Right: histogram of the distances to all animals in the covered areas, as well as the distances to the detected animals. The detection function used to simulate the detections is shown as a solid line and the dashed line represents the average number of detections per bin if detection was certain at all distances (i.e. the total number of animals per bin)

IF ASSUMPTIONS ARE VIOLATED

bias

SOME MODEL EXAMPLES…

THE POLAR BEAR IS A PET SPECIES OF MINE

AN EXAMPLE OF A MODEL TO PROJECT INTO THE FUTURE

BIOLOGY LETTERS

rsbl.royalsocietypublishing.org

Research

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click for updates

Cite this article: Regehr EV *et al.* 2016 Conservation status of polar bears (*Ursus maritimus*) in relation to projected sea-ice declines. *Biol. Lett.* **12**: 20160556.
http://dx.doi.org/10.1098/rsbl.2016.0556

Received: 30 June 2016
Accepted: 21 October 2016

Conservation biology

Conservation status of polar bears (*Ursus maritimus*) in relation to projected sea-ice declines

Eric V. Regehr[1], Kristin L. Laidre[2], H. Resit Akçakaya[3], Steven C. Amstrup[4], Todd C. Atwood[5], Nicholas J. Lunn[6], Martyn Obbard[7], Harry Stern[2], Gregory W. Thiemann[8] and Øystein Wiig[9]

[1]Marine Mammals Management, US Fish and Wildlife Service, Anchorage, AK 99503, USA
[2]Polar Science Center, Applied Physics Laboratory, University of Washington, Seattle, WA 98105, USA
[3]Department of Ecology and Evolution, Stony Brook University, Stony Brook, NY 11794, USA
[4]Polar Bears International, Bozeman, MT 59772, USA
[5]Alaska Science Center, US Geological Survey, Anchorage, AK 99508, USA
[6]Environment and Climate Change Canada, Edmonton, Alberta, Canada T6G 2E9
[7]Ontario Ministry of Natural Resources and Forestry, Peterborough, Ontario, Canada K9J 7B8
[8]Faculty of Environmental Studies, York University, Toronto, Ontario, Canada M3J 1P3
[9]Natural History Museum, University of Oslo, Oslo 0318, Norway

rsbl.royalsocietypublishing.org *Biol. Lett.* **12**: 20160556

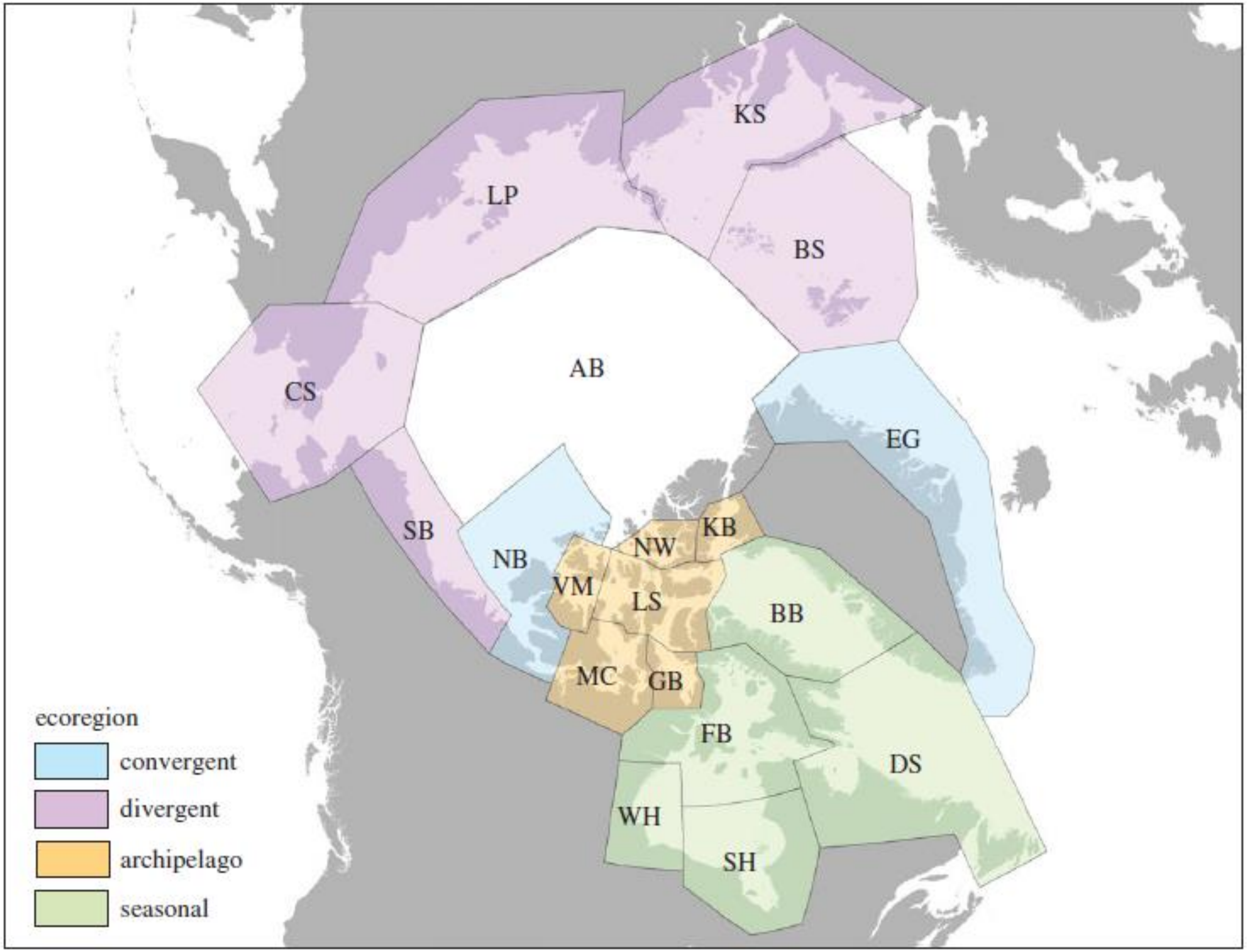


Figure 1. The four polar bear ecoregions and 19 subpopulations. Convergent ecoregion: East Greenland (EG) and Northern Beaufort Sea (NB). Divergent ecoregion: Southern Beaufort Sea (SB), Chukchi Sea (CS), Laptev Sea (LP), Kara Sea (KS) and Barents Sea (BS). Archipelago ecoregion: M'Clintock Channel (MC), Viscount Melville Sound (VM), Norwegian Bay (NW), Kane Basin (KB), Lancaster Sound (LS) and Gulf of Boothia (GB). Seasonal ecoregion: Western Hudson Bay (WH), Foxe Basin (FB), Baffin Bay (BB), Davis Strait (DS) and Southern Hudson Bay (SH). The Arctic Basin (AB) subpopulation likely has few year-round resident polar bears and was excluded from analyses (see electronic supplementary material).

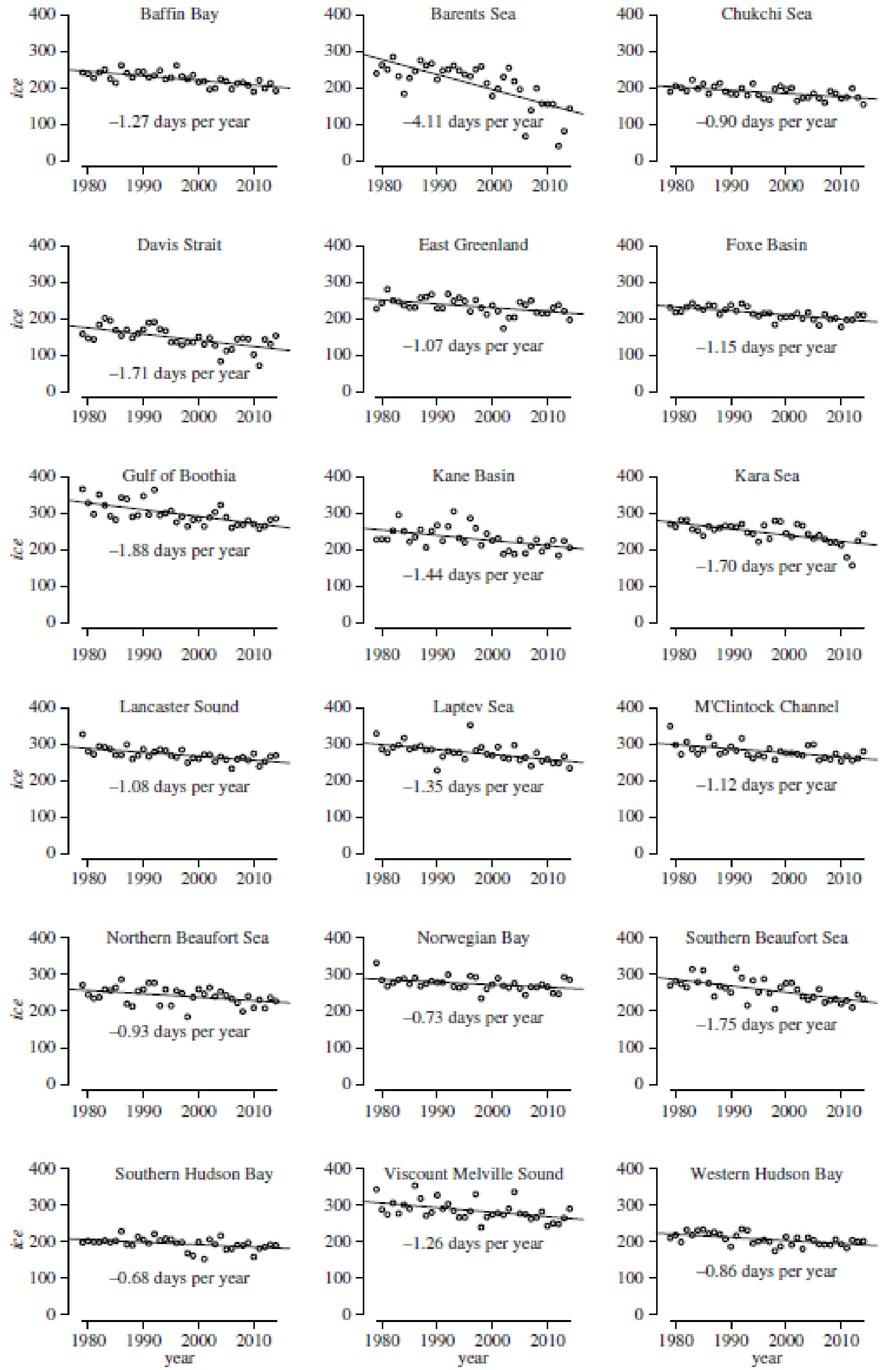


Figure 2. Trends in the standardized sea-ice metric (*ice*), representing important habitat for polar bears, within each subpopulation area during 1979 – 2014.

…and a bunch of (hopefully plausible) assumptions later!

Table 1. Simulation results for per cent change in the mean global population size of polar bears.

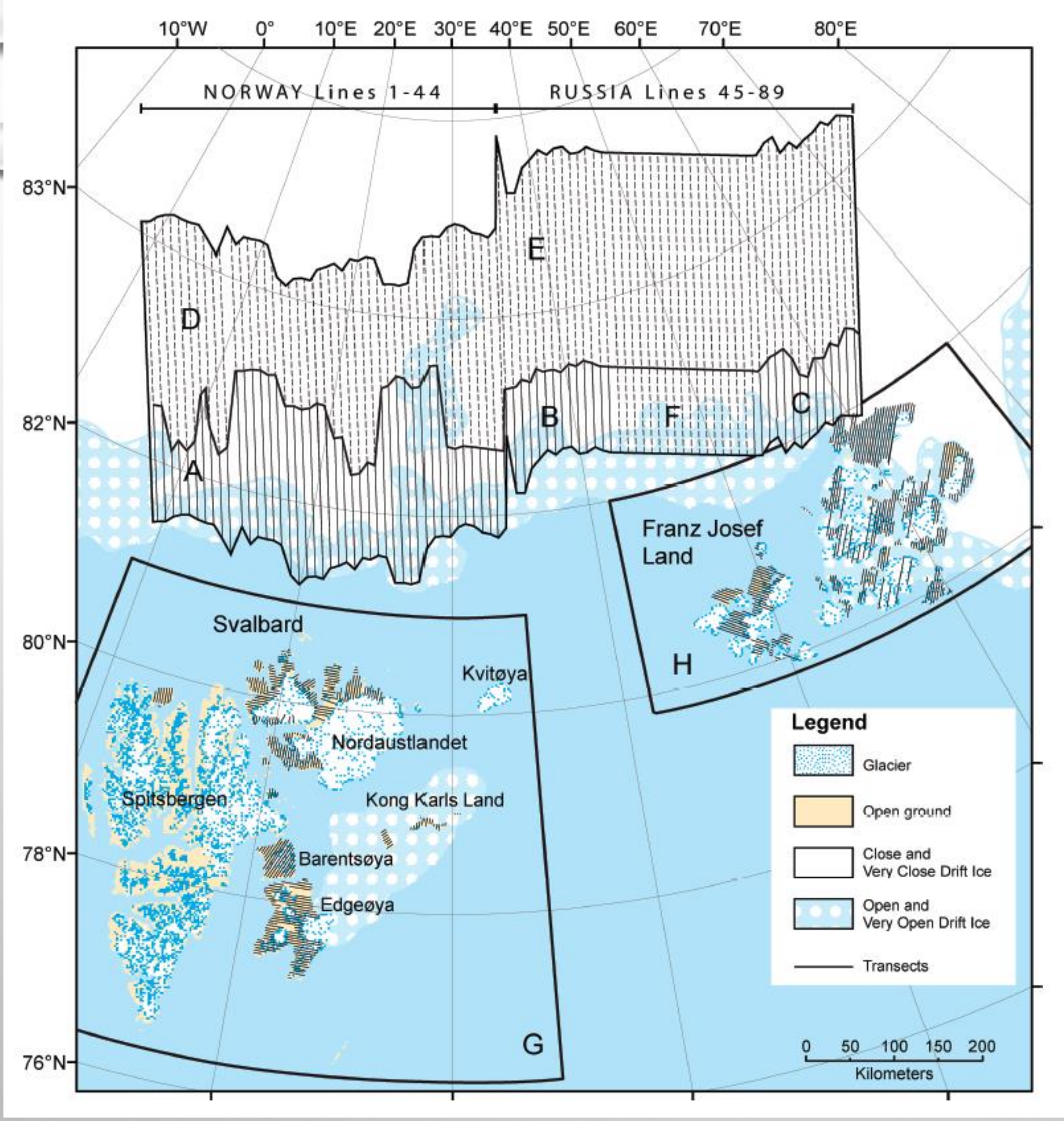
approach for projections[a]	duration of three polar bear generations (years)	per cent change in mean global population size: median	lower 95%CI	upper 95%CI	probability of decline: ≥0%	≥30%	≥50%	≥80%
1	35	−30	−35	−25	1.00	0.56	0.00	0.00
1	41	−34	−40	−29	1.00	0.95	0.00	0.00
2	35	−4	−62	50	0.55	0.20	0.06	0.00
2	41	−4	−68	56	0.55	0.24	0.08	0.00
3	35	−43	−76	−20	1.00	0.86	0.30	0.01
3	41	−45	−79	−21	1.00	0.88	0.35	0.02

[a]Approach 1 assumed a one-to-one proportional relationship between sea ice and abundance. Approaches 2 and 3 estimated global and ecoregion-specific relationships between sea ice and empirical estimates of abundance, respectively. Results from each approach are shown for the mean and 95th percentile of estimated GL.

rsbl.royalsocietypublishing.org *Biol. Lett.* **12**: 20160556

https://www.azquotes.com/quote/520553

Sometimes assumptions are just prejudice in disguise…



2004 Survey

The myth: there are no polar bears in glaciers

Aars, J.; Marques, T. A.; Buckland, S. T.; Andersen, M.; Belikov, S.; Boltunov, A. & Wiig, Ø. 2009 Estimating the Barents Sea polar bear subpopulation size *Marine Mammal Science* **25**: 35-52

2015 Survey photos

Table 1. Estimates of polar bear density and abundance within areas of seven different strata covered by line transect surveys, based on analyses in the program Distance. Nor = Norwegian area, Rus = Russian area, G = Glacier, L = Land, SI = Sea Ice around FJL, PI = Pack Ice, obs = number of distance observations used to fit the curves after 5% truncation of observations, $\hat{D}$ = estimated bear density (per 100 km^2), $\hat{N}$ = estimated number of bears in surveyed areas.

Strata	Km lines	Obs	$\hat{D}$	$\hat{D}$ 95% CI	$\hat{N}$	$\hat{N}$ 95% CI	Km^2
Nor G	1,055	3	0.5	(0.0; 1.2)	67	(0, 160)	13,271
Nor L	2,771	25	1.0	(0.6; 1.5)	84	(49, 121)	8,082
Nor PI	6,903	16	0.4	(0.2; 0.6)	212	(106, 318)	57,877
Rus G	1,757	16	1.6	(0.8; 3.1)	226	(106, 424)	13,714
Rus L	888	38	5.7	(3.3; 8.8)	137	(79, 212)	2,421
Rus PI	4,706	39	2.1	(1.3; 3.0)	483	(305, 678)	22,962
Rus SI	2,895	43	2.3	(1.4; 3.4)	185	(113, 271)	8,009
Total	20,975	180	1.1	(0.8; 1.4)	1,394	(1,060, 1,743)	126,336

In fact, we estimate that about 100*(67+226)/1394=21% of polar bears were in glaciers.

YET ANOTHER POLAR BEAR EXAMPLE – NOW ABOUT DEMOGRAPHICS!

Journal of Applied Ecology

Journal of Applied Ecology 2017, **54**, 1534–1543 doi: 10.1111/1365-2664.12864

Harvesting wildlife affected by climate change: a modelling and management approach for polar bears

Eric V. Regehr*,†,1, Ryan R. Wilson[1], Karyn D. Rode[2], Michael C. Runge[3] and Harry L. Stern[4]

[1]U.S. Fish and Wildlife Service, Anchorage, AK, USA; [2]U.S. Geological Survey, Anchorage, AK, USA; [3]U.S. Geological Survey, Laurel, MD, USA; and [4]University of Washington, Seattle, WA, USA

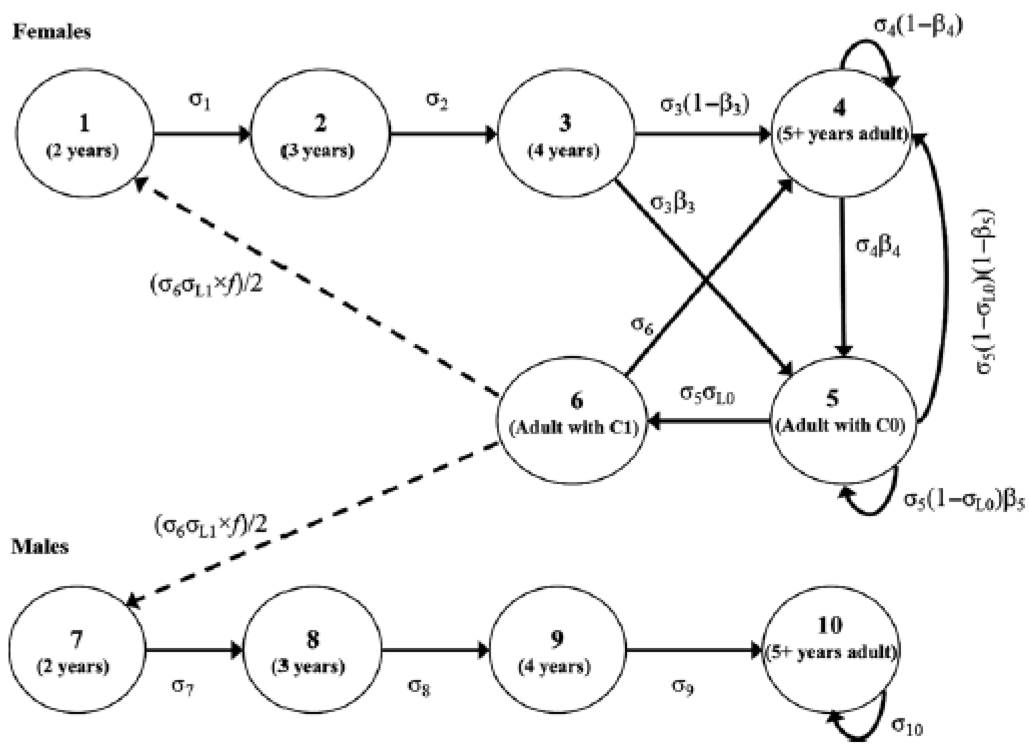
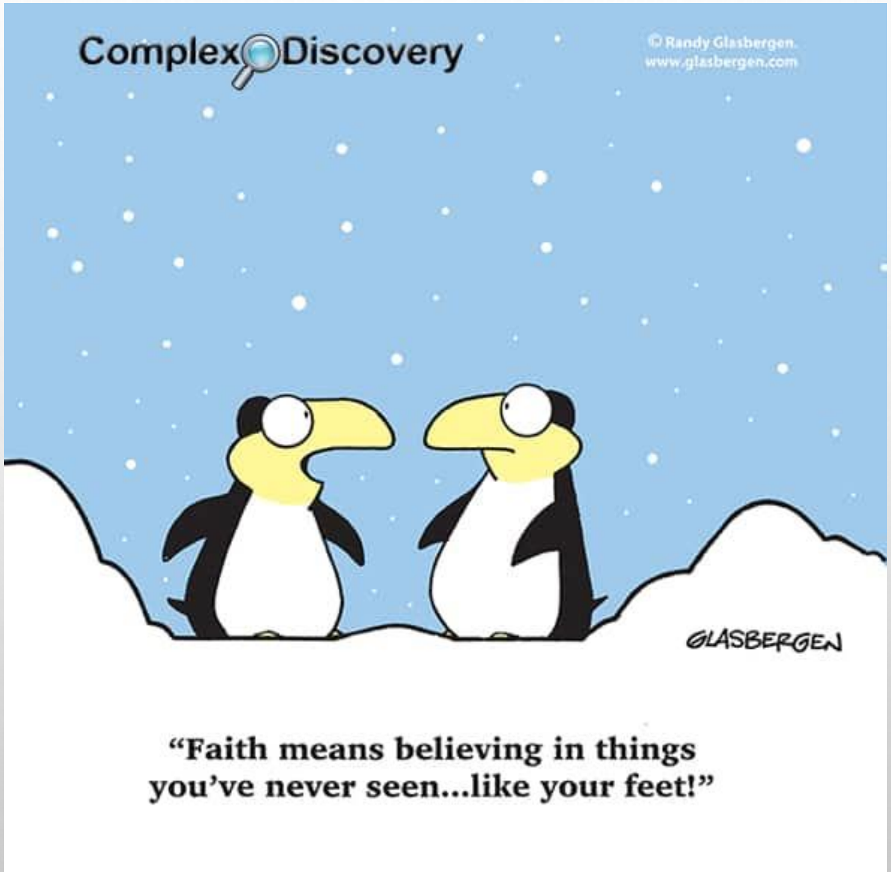


Fig. 1. The polar bear life cycle graph underlying the matrix-based projection model. Stages 1–6 are females and stages 7–10 are males; σ_i is the annual probability of survival of an individual in stage *i*, σ_{L0} and σ_{L1} are the probabilities of at least one member of a cub-of-the-year (C0) or yearling (C1) litter surviving, *f* is the expected size of C1 litters that survive to 2 years, and β_i is the probability, conditional on survival, of an individual in stage *i* breeding, thereby producing a C0 litter with at least one member surviving. Solid lines are stage transitions and dashed lines are reproductive contributions.

WARNING REMINDER: IN ANY GIVEN WEEK… I ASSUME THAT EVERYTHING I TOLD YOU IN PREVIOUS WEEKS THAT YOU SHOULD DO, YOU ACTUALLY DID…!

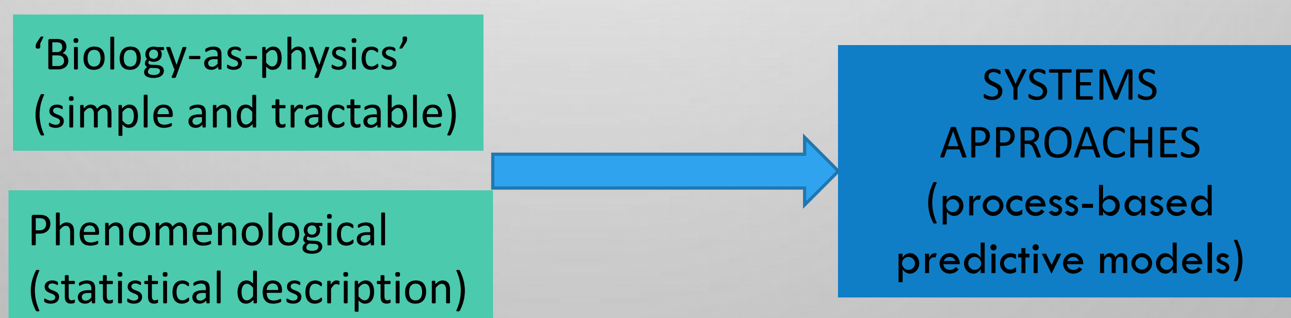


SOME WORK YOU HAD TO DO

Have you read the paper I suggested ?

Evans, M. R. 2011 Modelling ecological systems in a changing world *Philosophical Transactions of the Royal Society B: Biological Sciences 367*: 181-190 – to discuss later

Main conclusions?



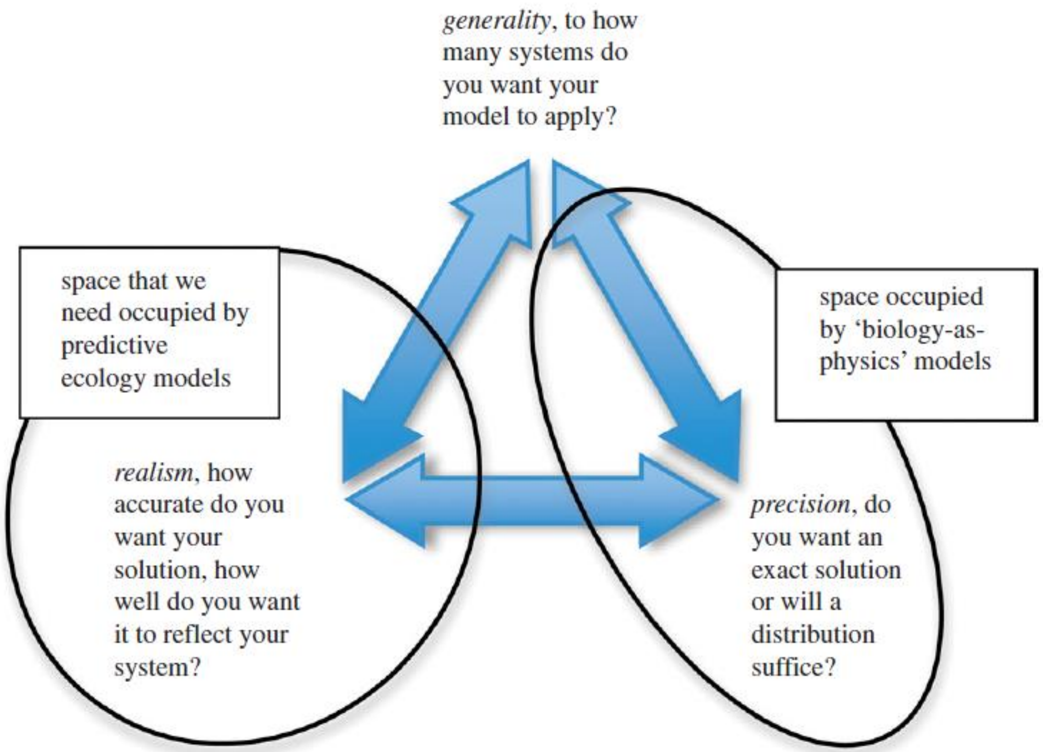


Figure 1. Schematic of modelling trade-offs. A modeller has to decide what characteristics their model will emphasize. Philosophical considerations suggest that they cannot have a model that maxmizes all these desirable characteristics.

'Biology-as-physics' (simple and tractable)

Phenomenological (statistical description)

→ SYSTEMS APPROACHES (process-based predictive models)

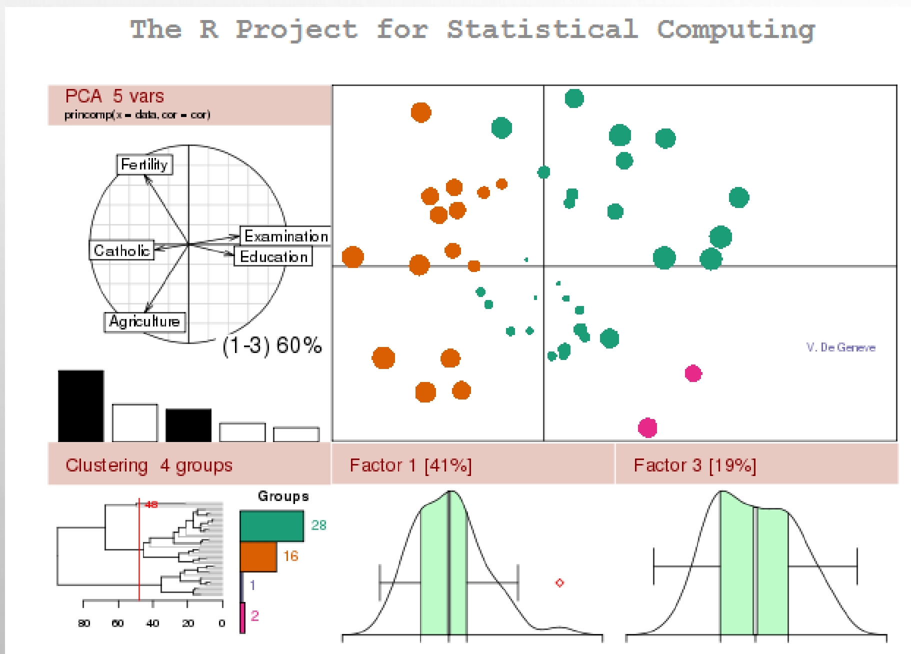
Evans, M. R. 2011 Modelling ecological systems in a changing world *Philosophical Transactions of the Royal Society B: Biological Sciences* 367: 181-190

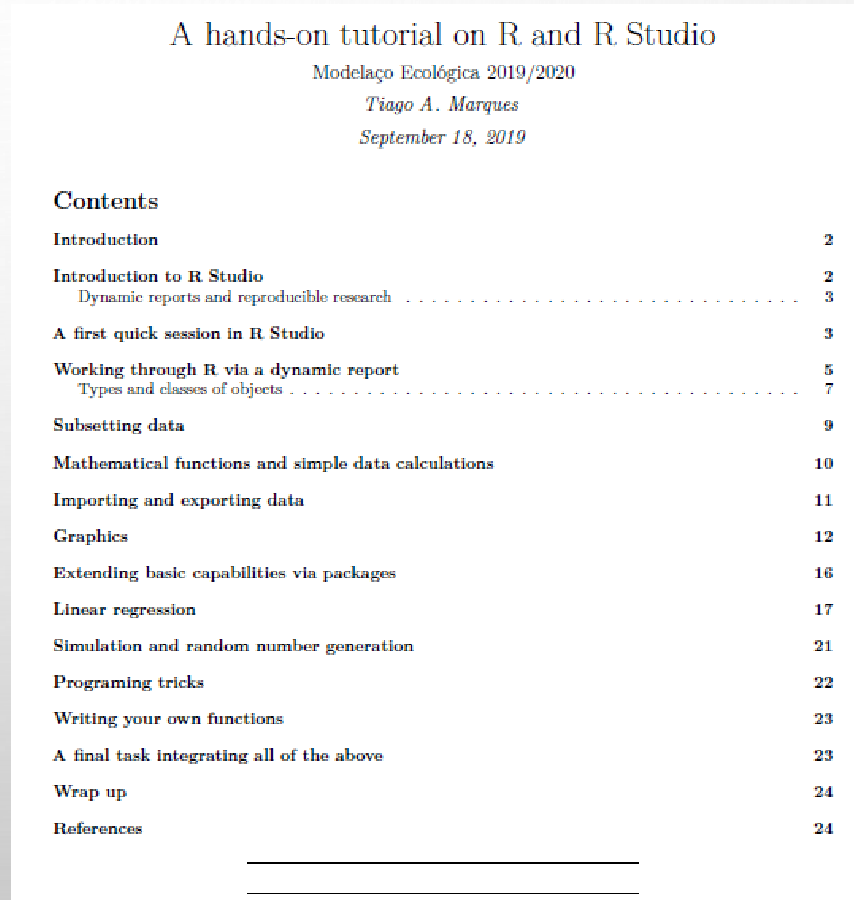
SOME WORK YOU HAD TO DO

What about the data ?

Collect the TPC data set as described in the 3rd class, and do a small dynamic report describing your initial question and your conclusions, and what would you do different if you were to start the data collection again – send me **by the end of the week** your group members, then the data (first, so I can comment if it looks adequate – **deadline 10 October**) and the report (**deadline by 20th October**) by e-mail.

ANY FINAL QUESTIONS ON THE HANDS-ON TUTORIAL?





A hands-on tutorial on R and R Studio

Modelaço Ecológica 2019/2020

Tiago A. Marques

September 18, 2019

Contents

From now on, I assume you master R and handling data in R

Practice R for modelling!

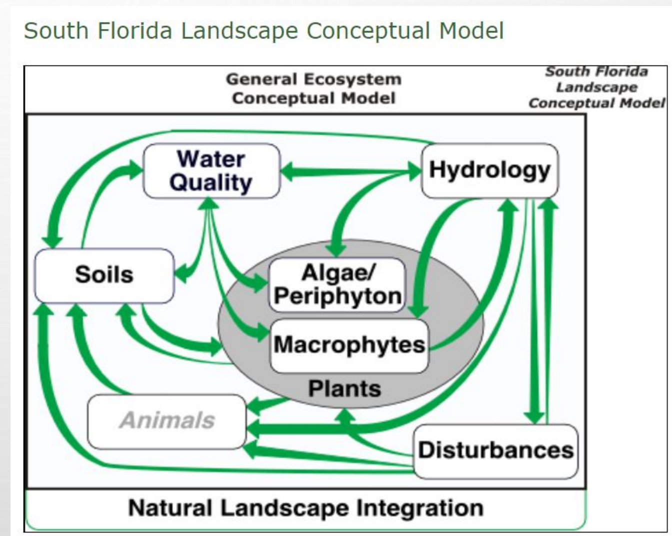
- Work over and master all that is in the R and Rstudio tutorial
- Work over and master the “Extra” material in TP1 - FT1.pdf
- Work over and master “merge” – see today extra material in Fenix
- Do online tutorials, play with datasets you know, etc.
- ME_FT2.pdf – more on R and data analysis (Aula5)

Practice, practice, practice!

Don’t complain ☺ : When you have questions or doubts, send me an e-mail. If your code breaks, send me an email. If you need background material about some topic, send me an e-mail.

To think, conceptually, about models

- Do ficha de trabalho ME_FT1.pdf (under aula TP5)



http://www.ecolandmod.com/background/sfcm/GECM.html