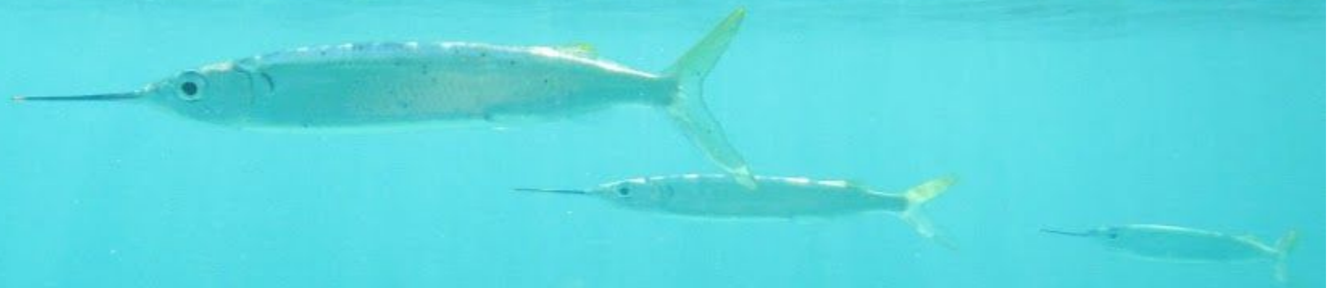
Spatial and temporal modelling



Robert Lennox
Ocean Tracking Network/
Dalhousie University

Disclaimer

- Not a statistician
- But… ecology requires good statistical practice
- Very little formal training in statistics and math
- Good collaboration with many statisticians

From the beginning


CARLOS OSORIO PH

Rob Lennox, a Carleton University student, handles a fish caught in the Toronto Harbour. Conse
using a high-tech method to get a picture of fish habitats in the city's harbour.

laughed "Only the government can

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From the beginning


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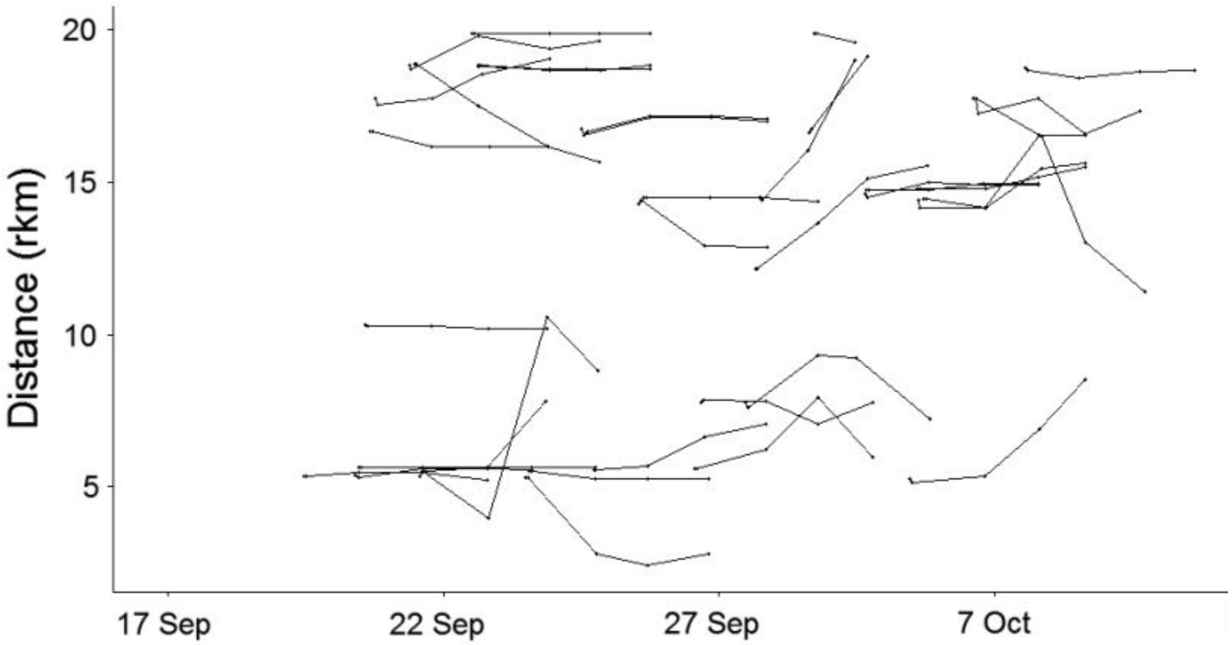
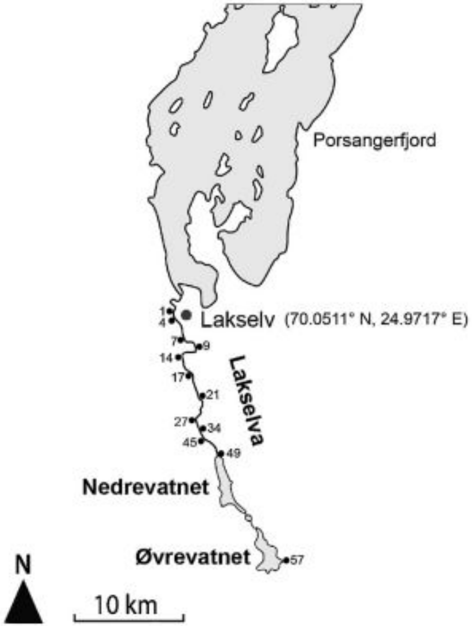
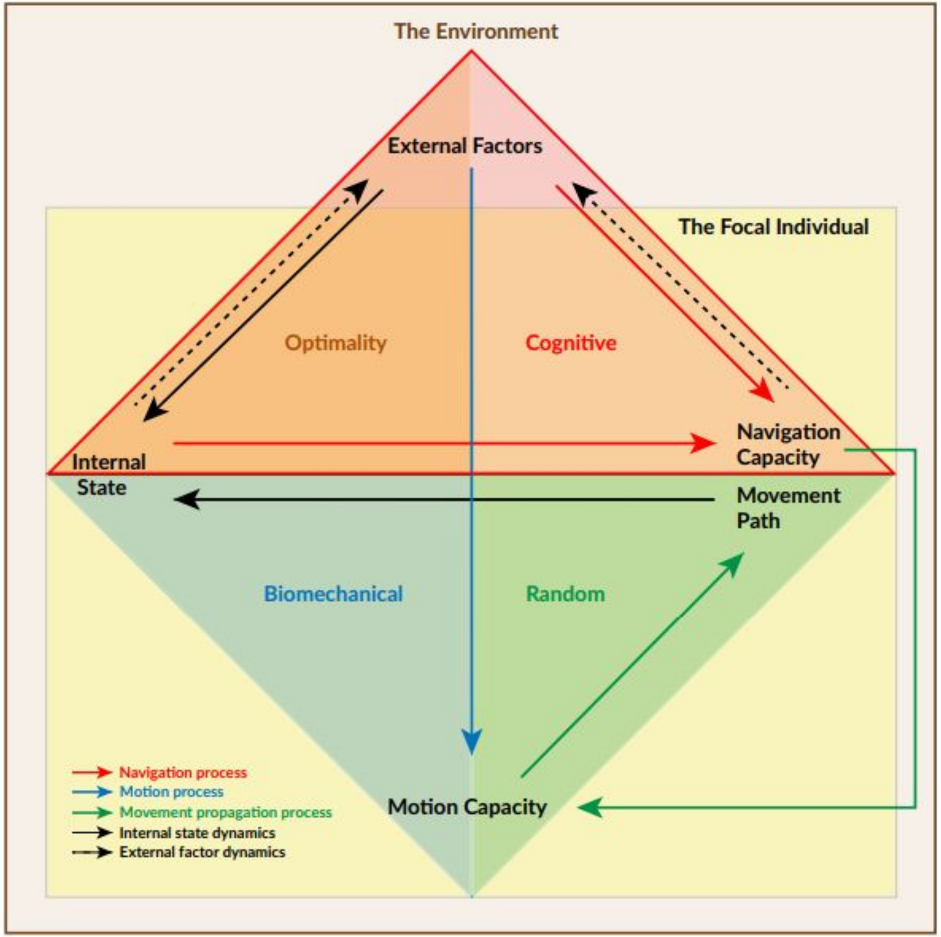
Movement in one dimension - relatively easy!

Movement in one dimension - relatively easy!





More to fish movement than a single dimension



Received: 15 February 2022 | Accepted: 29 June 2022
DOI: 10.1111/jfb.15153

REVIEW PAPER

The movement ecology of fishes

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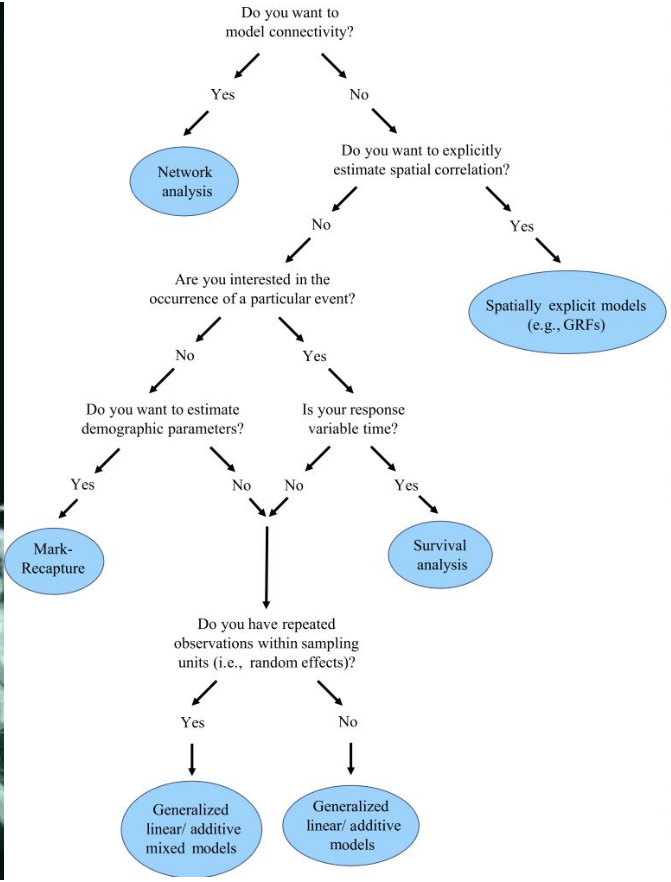
Funding information
Canada Foundation for Innovation, Grant/Award Number: OTN; Great Lakes Fishery Commission, Grant/Award Number: GLATOS; NSERC, Grant/Award Number: Cooke DG

Abstract

Movement of fishes in the aquatic realm is fundamental to their ecology and survival. Movement can be driven by a variety of biological, physiological and environmental factors occurring across all spatial and temporal scales. The intrinsic capacity of movement to impact fish individually (e.g., foraging) with potential knock-on effects throughout the ecosystem (e.g., food web dynamics) has garnered considerable interest in the field of movement ecology. The advancement of technology in recent decades, in combination with ever-growing threats to freshwater and marine systems, has further spurred empirical research and theoretical considerations. Given the rapid expansion within the field of movement ecology and its significant role in informing management and conservation efforts, a contemporary and multidisciplinary review about the various components influencing movement is outstanding. Using an

Need tools that can help us to work in at least two dimensions



REVIEW

Methods in Ecology and Evolution

Current and emerging statistical techniques for aquatic telemetry data: A guide to analysing spatially discrete animal detections

Kim Whoriskey[1] | Eduardo G. Martins[2] | Marie Auger-Méthé[3,4] | Lee F. G. Gutowsky[5,6] | Robert J. Lennox[5,7] | Steven J. Cooke[5] | Michael Power[8] | Joanna Mills Flemming[1]

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Funding information
Natural Sciences and Engineering Research Council of Canada; Canada Research Chairs; Ocean Tracking Network; BC Hydro; Killam Trusts; Canadian Statistical Sciences Institute (CANSSI)

Handling Editor: Luca Börger

Abstract

1. Telemetry, or the remote monitoring of animals with electronic transmitters and receivers, has vastly enhanced our ability to study aquatic animals. Radio telemetry, acoustic telemetry and passive integrated transponders are three common technologies that generate detection data — time-stamped, tag-specific records that are logged by receivers.
2. We review current statistical methods and comment on potential future directions for analysing detection data derived from fixed telemetry receiver arrays.
3. To illustrate how different methods may be used to achieve diverse study objectives, we provide a case study dataset collected by an array of 42 acoustic telemetry receivers on 187 bull trout in the Kinbasket Reservoir of British Columbia. To close, we present a decision tree for guiding the selection of a method based on study objectives and sampling design.
4. This paper provides both experienced and novice telemetry researchers with the knowledge and tools to facilitate more comprehensive analysis of detection data and, in so doing, ask a wide variety of ecological questions that will enhance our understanding of aquatic organisms.

KEYWORDS
acoustic telemetry, detection data, movement ecology, Ocean Tracking Network, PIT tag, radio telemetry, statistical methods

1 | INTRODUCTION

Aquatic animals live in habitats that create inherent challenges for those attempting to study their ecology, behaviour and physiology.

Telemetry enables the remote monitoring of free-living animals, whereby a signal emanating from a device (i.e., transmitter or tag) carried by an animal transfers information to a receiver. The advent of telemetry tools has provided researchers with effective means of

We can even work in three dimensions, or four!

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Methods in Ecology and Evolution

REVIEW

Positioning aquatic animals with acoustic transmitters

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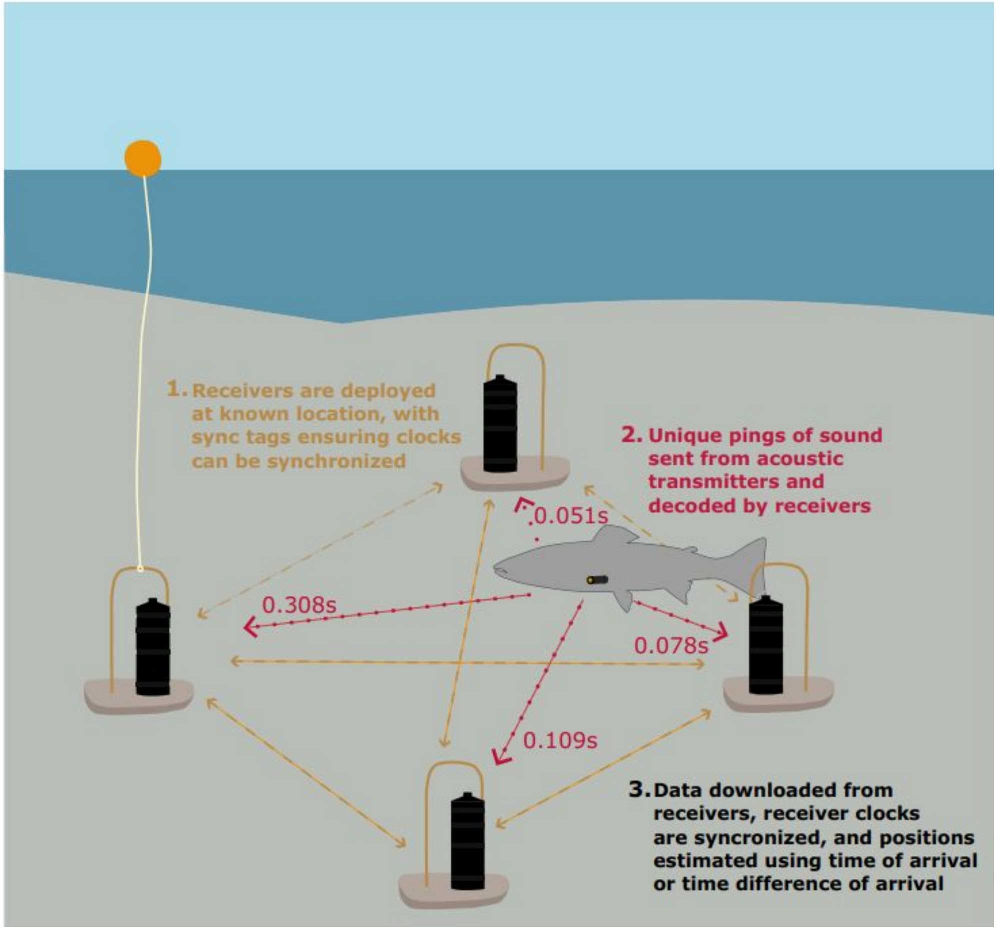
Handling Editor: Gavin Simpson

Abstract

1. Geolocating aquatic animals with acoustic tags has been ongoing for decades, relying on the detection of acoustic signals at multiple receivers with known positions to calculate a 2D or 3D position, and ultimately recreate the path of an aquatic animal from detections at fixed stations.
2. This method of underwater geolocation is evolving with new software and hardware options available to help investigators design studies and calculate positions using solvers based predominantly on time-difference-of-arrival and time-of-arrival.
3. We provide an overview of the considerations necessary to implement positioning in aquatic acoustic telemetry studies, including how to design arrays of receivers, test performance, synchronize receiver clocks and calculate positions from the detection data. We additionally present some common positioning algorithms,



Ecological modelling is overwhelming

- Linear models
- Mixed models
- Hierarchical models
- Additive models
- Multiple regression
- Survival analysis/ time-to-event
- Multivariable regression
- Machine learning
- Non-linear effects
- Correlation
- Causative modelling
- Species distribution models
- Step selection models
- Resource selection models
- Regression tree analysis
- Predictive modelling
- Bayesian zero inflated hierarchical probabilistic inference

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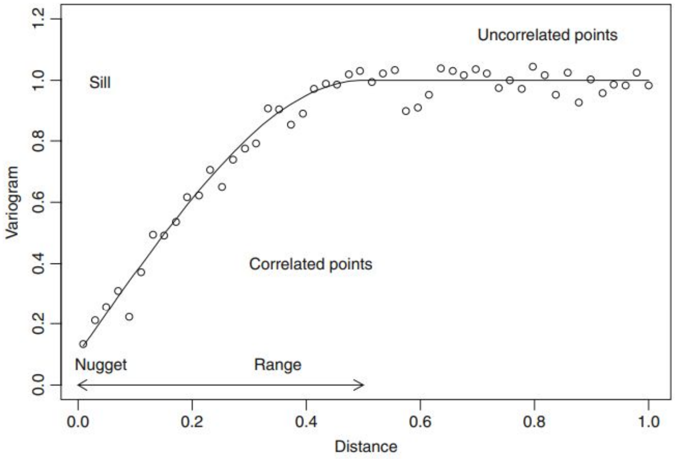
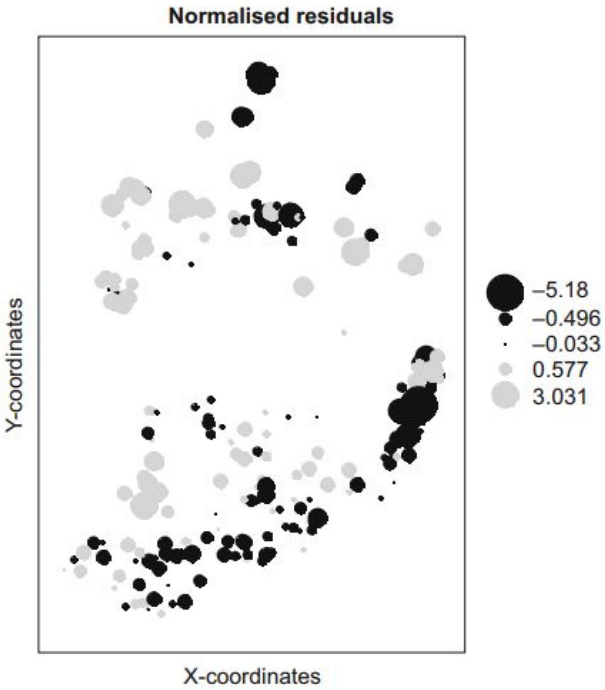
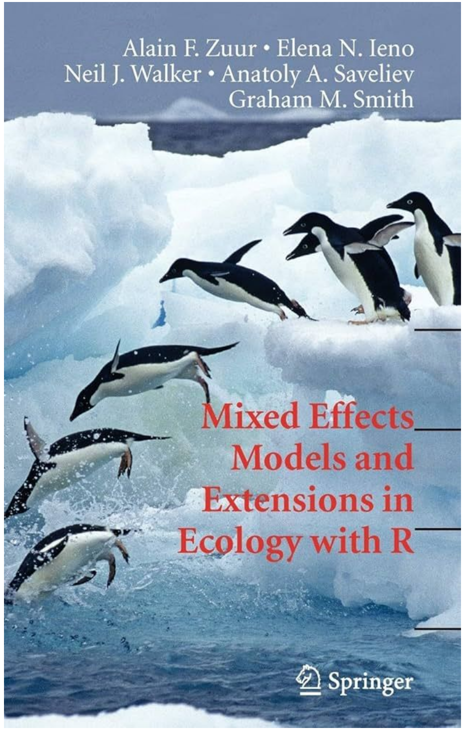
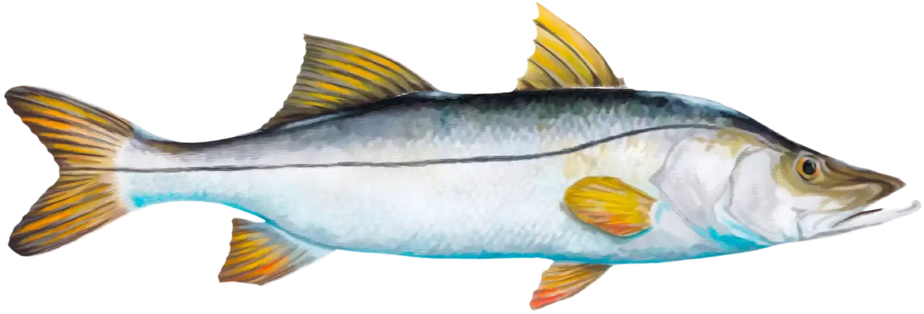
Ecological modelling is spatial

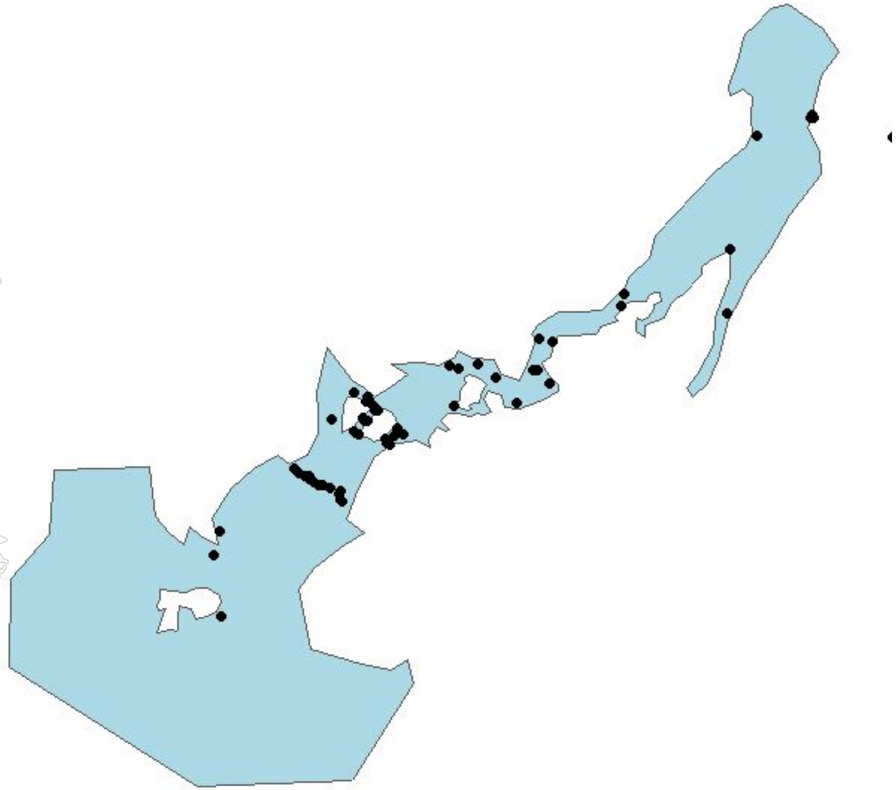


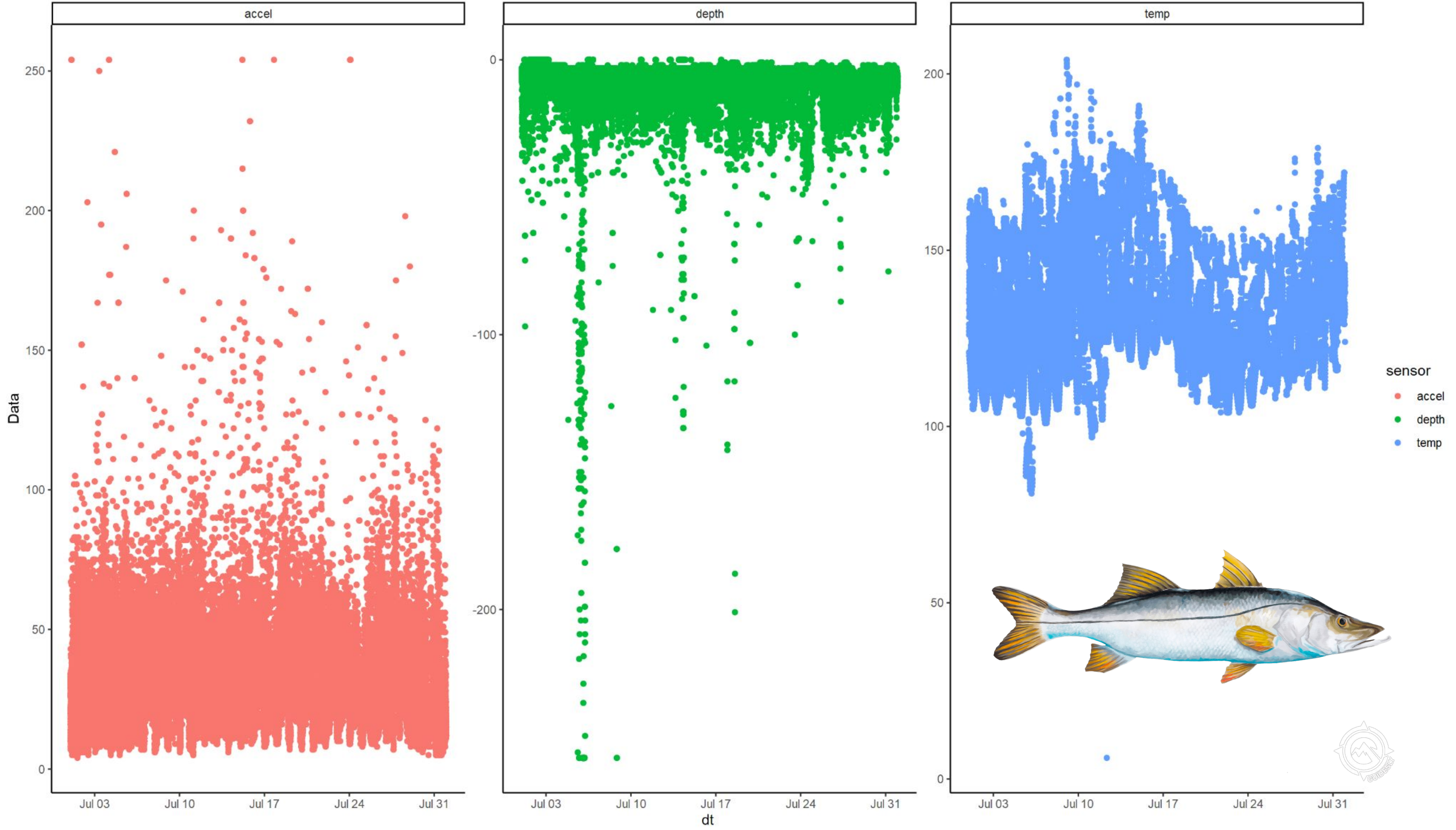




Snook movements in Clam Bayou on Sanibel Island*







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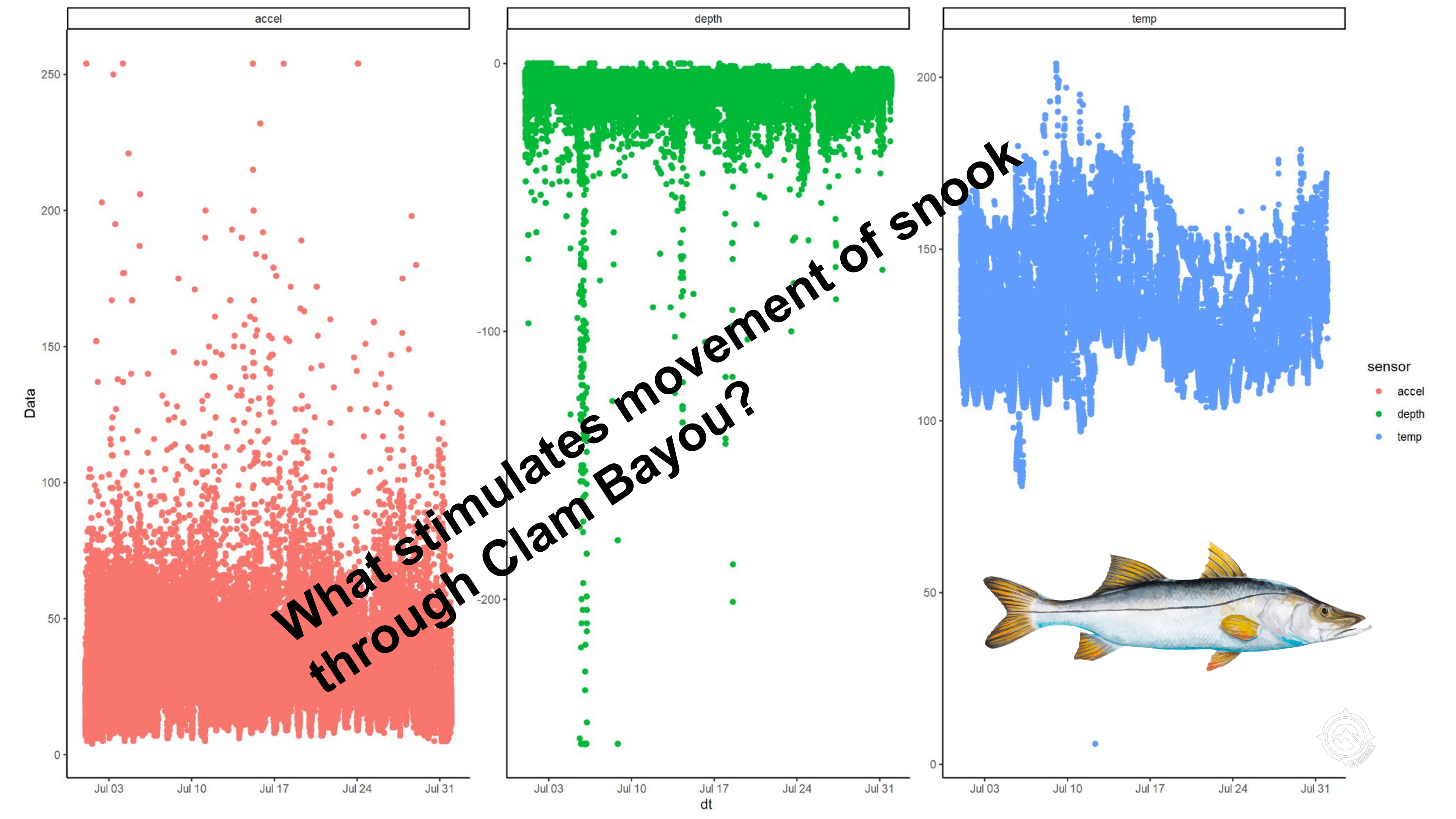
What stimulates movement of snook through Clam Bayou?
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How I think about ecological modelling

- Partitioning variance
- What affects a response?
- Lots of individual variation in movement

Y ~ treatment + 1|ID + time + space

Treatment   Individual   Space and Time

How I think about ecological modelling

- Partitioning variance
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Treatment Individual Space and Time

How I think about ecological modelling

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Y ~ treatment + 1|ID + time + space

Treatment Individual Space and Time

Spatiotemporal Modelling

Tobler's First Law of Geography

Everything is related to everything else, but closer things are more related to each other

- This implies that animal responses must depend on location
- Important to include space as a covariate in models with acoustic telemetry

How can we incorporate space and time in hypothesis testing?

PeerJ

Hierarchical generalized additive models in ecology: an introduction with mgcv

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ABSTRACT

In this paper, we discuss an extension to two popular approaches to modeling complex structures in ecological data: the generalized additive model (GAM) and the hierarchical model (HGLM). The hierarchical GAM (HGAM), allows modeling of nonlinear functional relationships between covariates and outcomes where the shape of the function itself varies between different grouping levels. We describe the theoretical connection between HGAMs, HGLMs, and GAMs, explain how to model different assumptions about the degree of intergroup variability in functional response, and show how HGAMs can be readily fitted using existing GAM software, the **mgcv** package in R. We also discuss computational and statistical issues with fitting these models, and demonstrate how to fit HGAMs on example data. All code and data used to generate this paper are available at: github.com/eric-pedersen/mixed-effect-gams.

Subjects Ecology, Statistics, Data Science, Spatial and Geographic Information Science
Keywords Generalized additive models, Hierarchical models, Time series, Functional regression, Smoothing, Regression, Community ecology, Tutorial, Nonlinear estimation

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Additional Information and Declarations can be found on page 39

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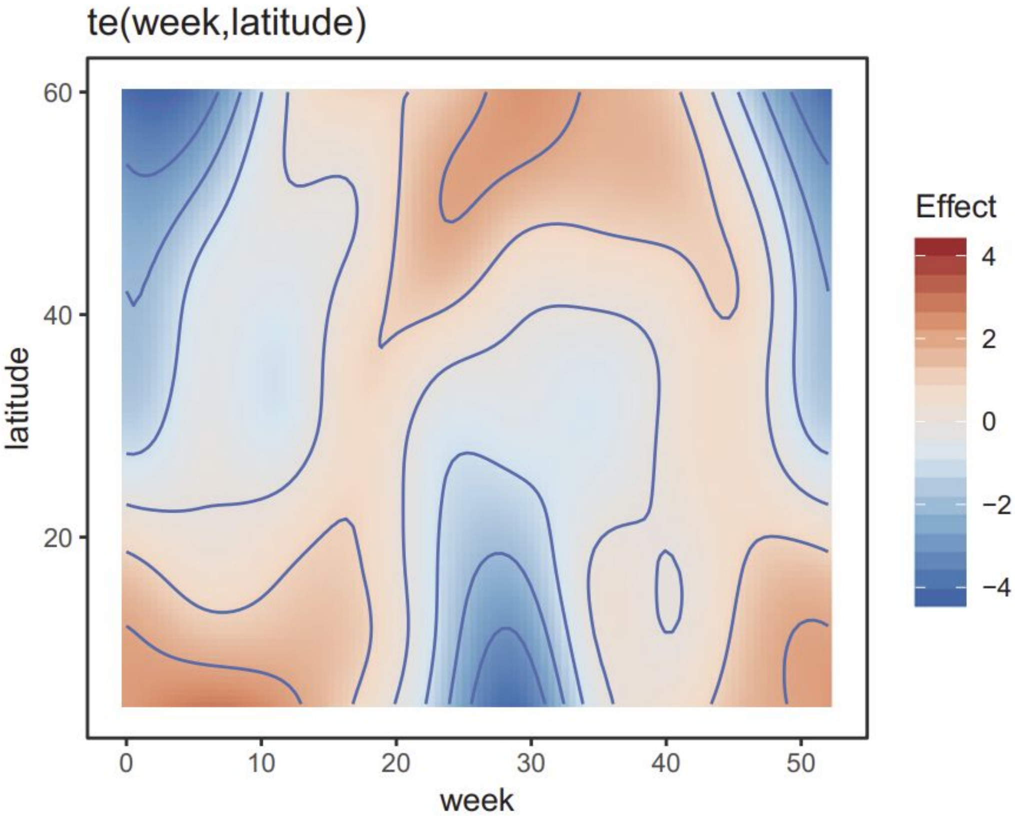
INTRODUCTION

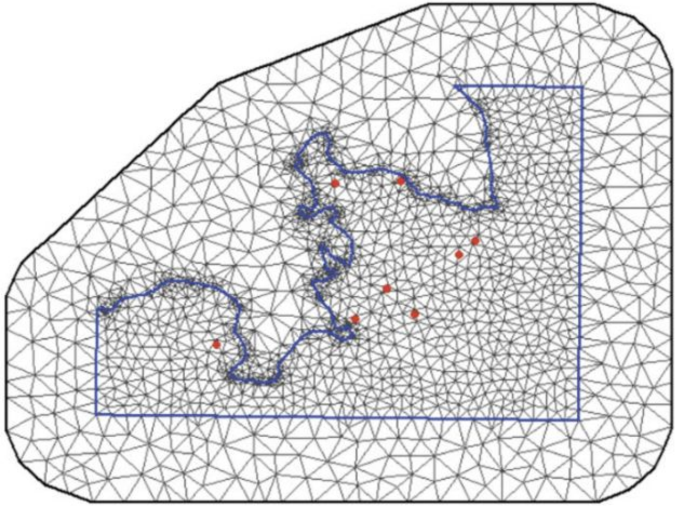
Two of the most popular and powerful modeling techniques currently in use by ecologists are generalized additive models (GAMs; Wood, 2017a) for modeling flexible regression functions, and generalized linear mixed models ("hierarchical generalized linear models" (HGLMs) or simply "hierarchical models"; Bolker et al., 2009; Gelman et al., 2013) for modeling between-group variability in regression relationships.

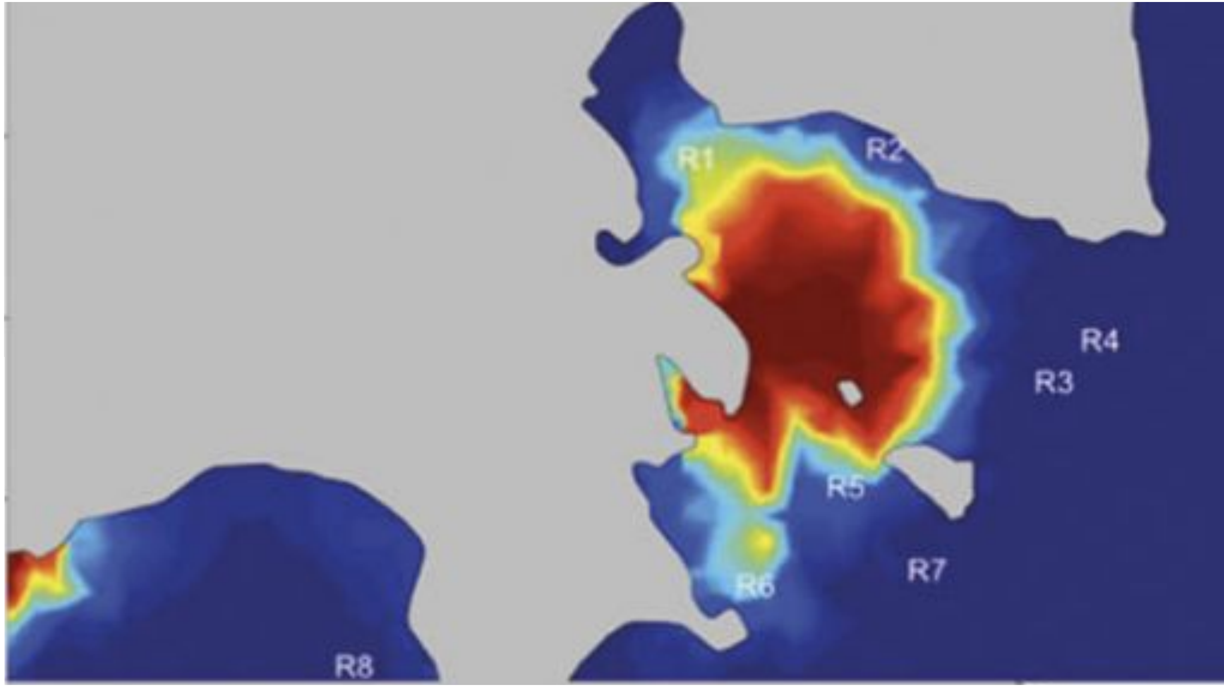
At first glance, GAMs and HGLMs are very different tools used to solve different problems. GAMs are used to estimate smooth functional relationships between predictor variables and the response. HGLMs, on the other hand, are used to estimate linear relationships between predictor variables and response (although nonlinear relationships can also be modeled through quadratic terms or other transformations of the predictor variables), but impose a structure where predictors are organized into groups (often

How to cite this article Pedersen EJ, Miller DL, Simpson GL, Ross N. 2019. Hierarchical generalized additive models in ecology: an introduction with mgcv. PeerJ 7:e6876 DOI 10.7717/peerj.6876



Tessellation-based spatial smoothing with SPDE (INLA)

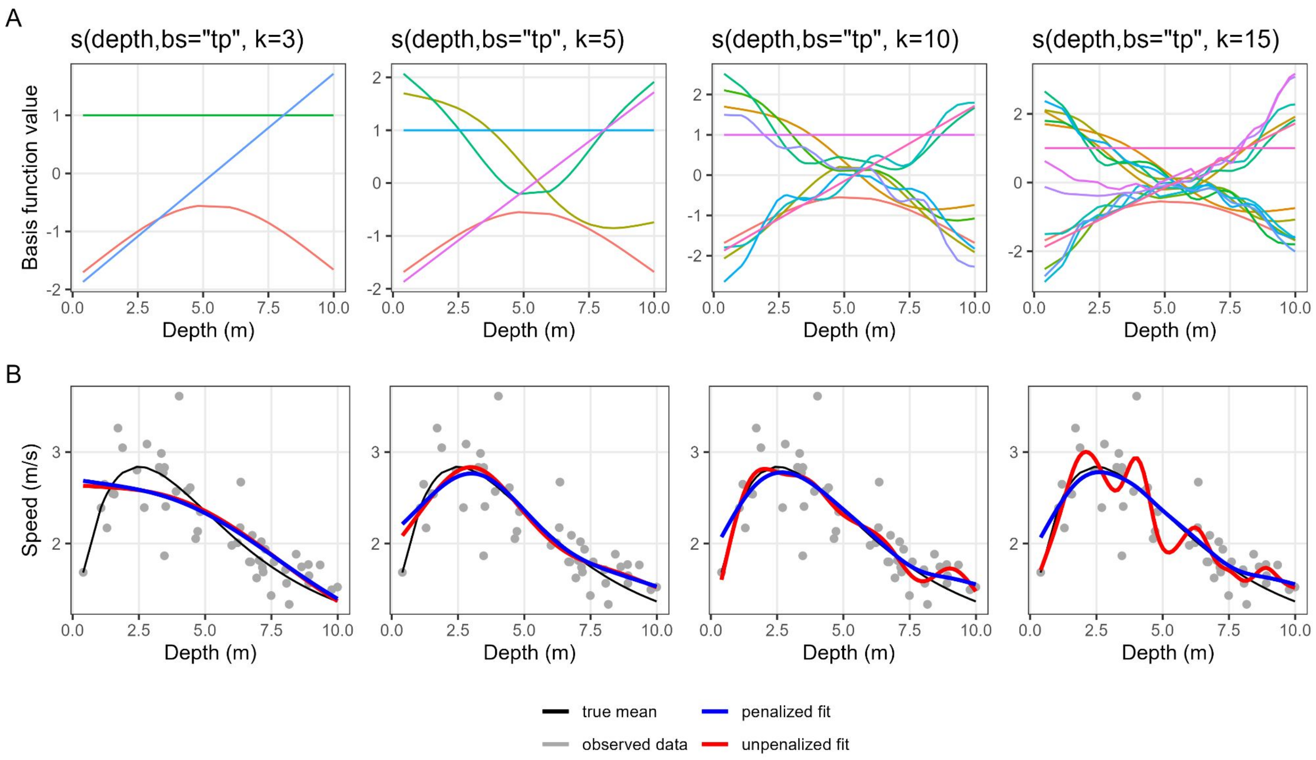




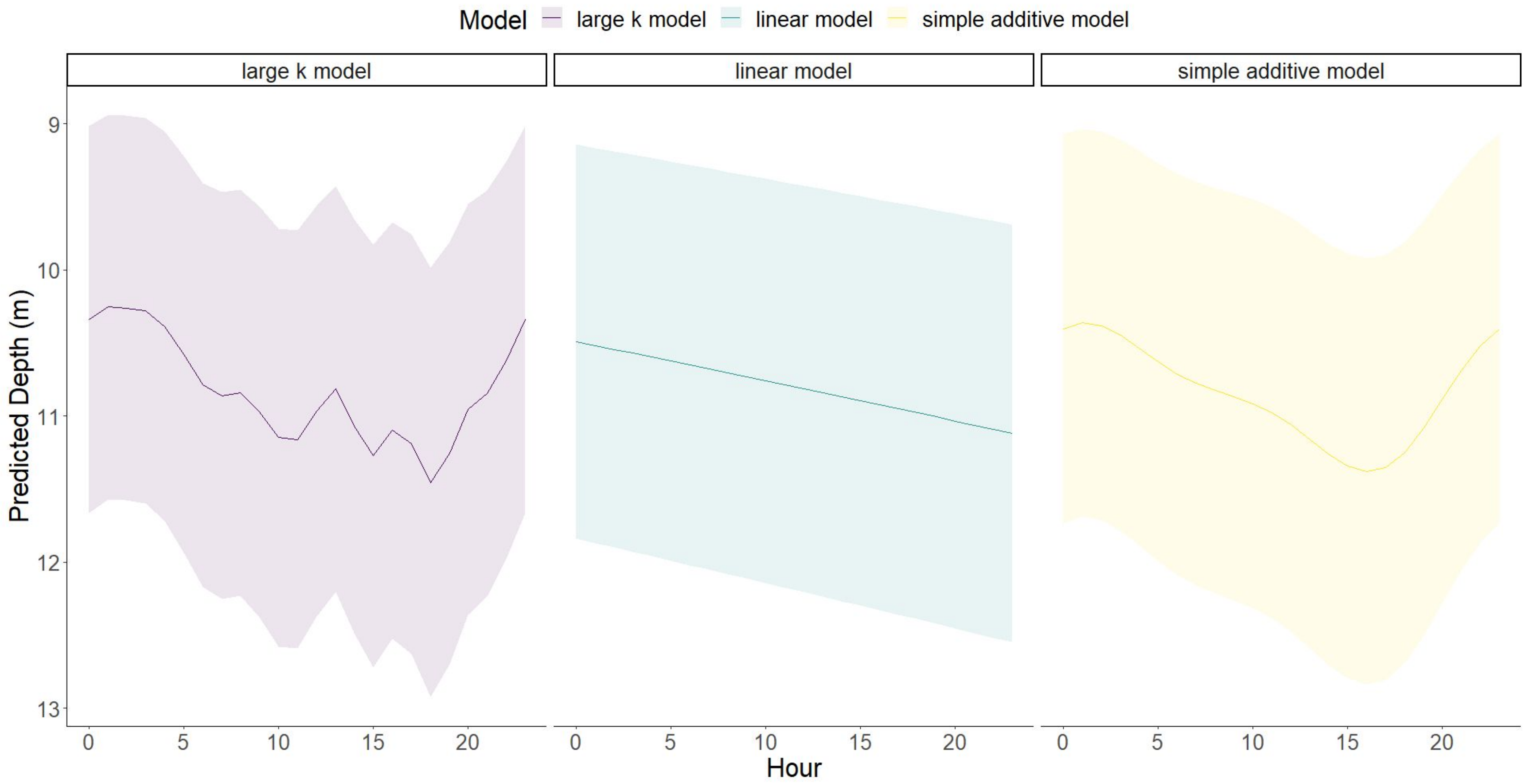
Lucas Griffin and Friends 2019

The basis function - the math behind the magic

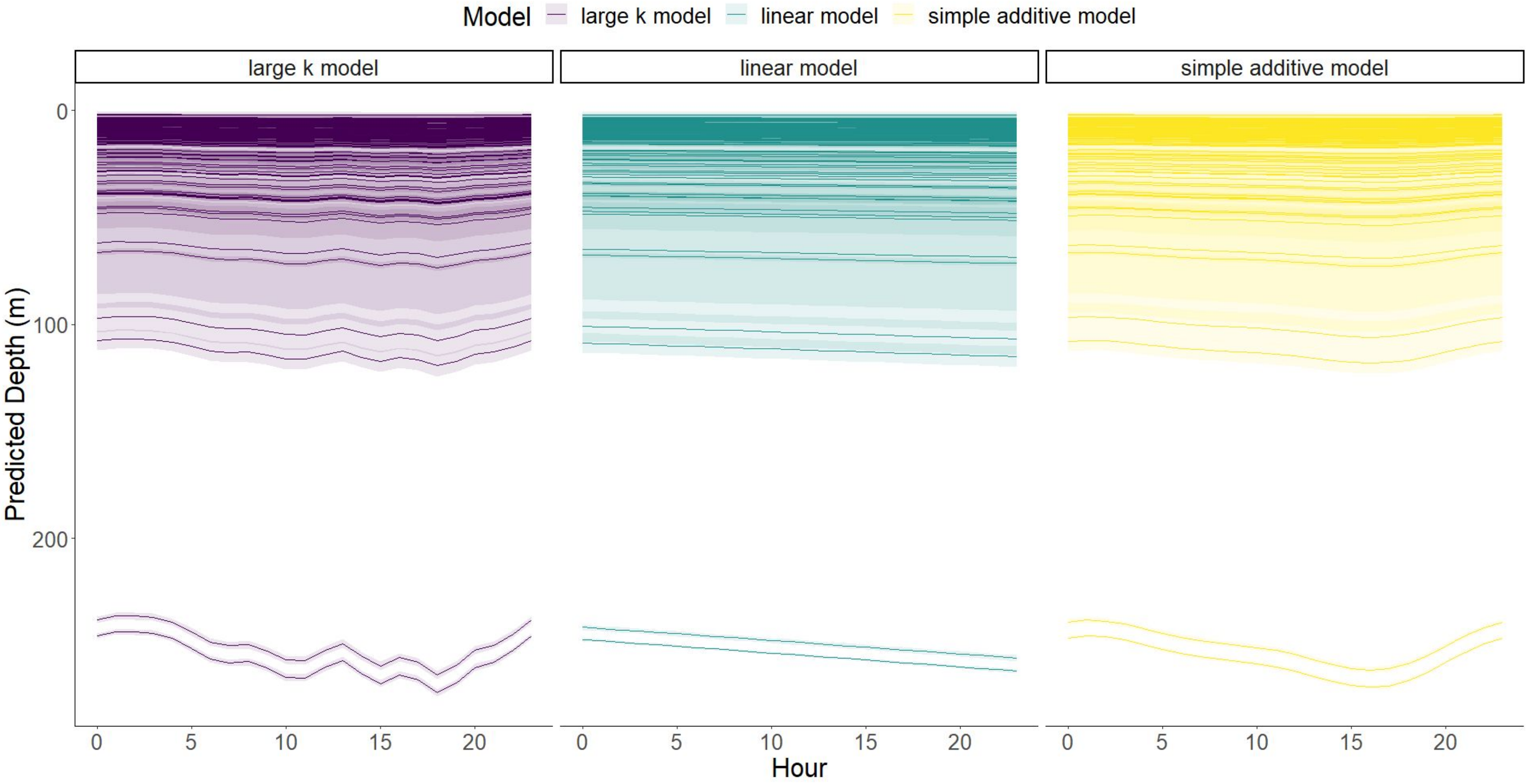
- GAMs use a linear combination of basis functions
- Basis functions are penalised to reduce overfitting



Making some choices

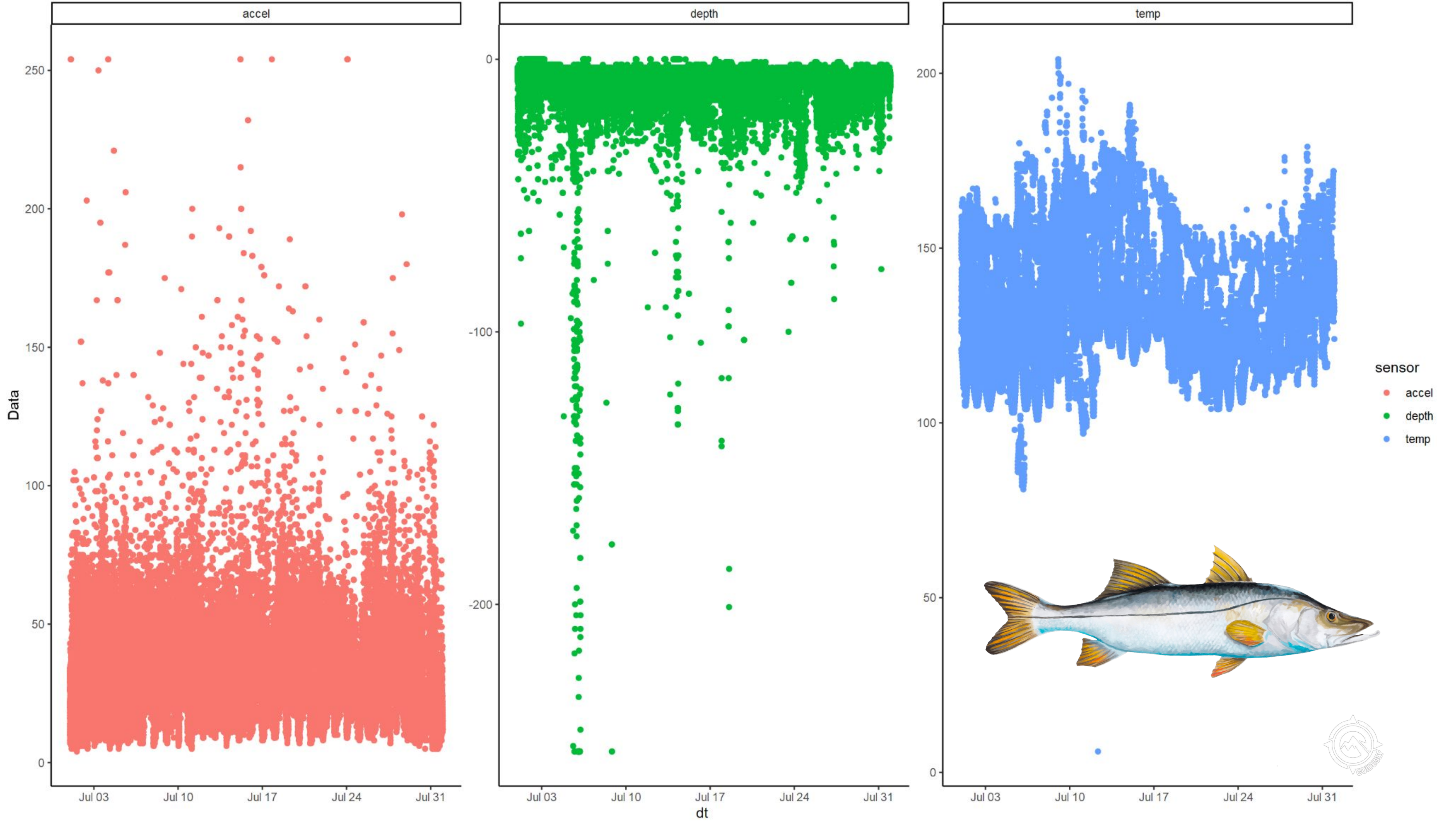


Making some choices



5. Pick the right regression family

Gaussian	Change in depth, temperature, or acceleration, location along a one-dimensional gradient (e.g. latitude, longitude) where the zero point on the gradient is arbitrary	Pillans et al. (2022)
Binomial	Presence or absence, inside or outside area of interest, at risk or not at risk of exposure based on time and location of a detected animal, probability of being at rest at a given time	Lennox et al. (2022)
Conditional logistic	Modelling true presence and pseudo-absence data from tracking data on environmental covariates to calculate selection strength	McCabe et al. (2021) bird data
Cox.ph	Modelling time-to-event for individually tagged animals to reach an outcome such as departure from an area, recapture by fishers, or natural mortality (e.g. Whoriskey et al. 2019) with smoothed covariates.	Storms et al. (2022) tracked moths
Negative binomial	Count of individuals at a location	Bino et al. (2018)
Poisson	Count of individuals at a location	Hessler et al. (2023)
Gamma	Depth, temperature, acceleration	Nash et al. 2022
Tweedie	Potentially can be used for modelling continuous zero-inflated variables, such as movement speed for individuals that alternate between moving and resting	Westrelin et al. (2018); Rodrigues et al. (2022)
Beta	Fraction of the day spent active, Depth as a fraction of the water column	Secor et al. (2021)



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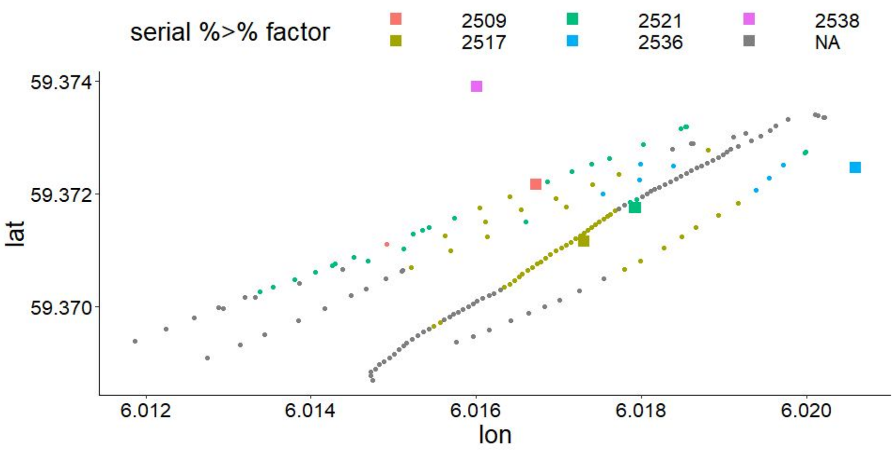
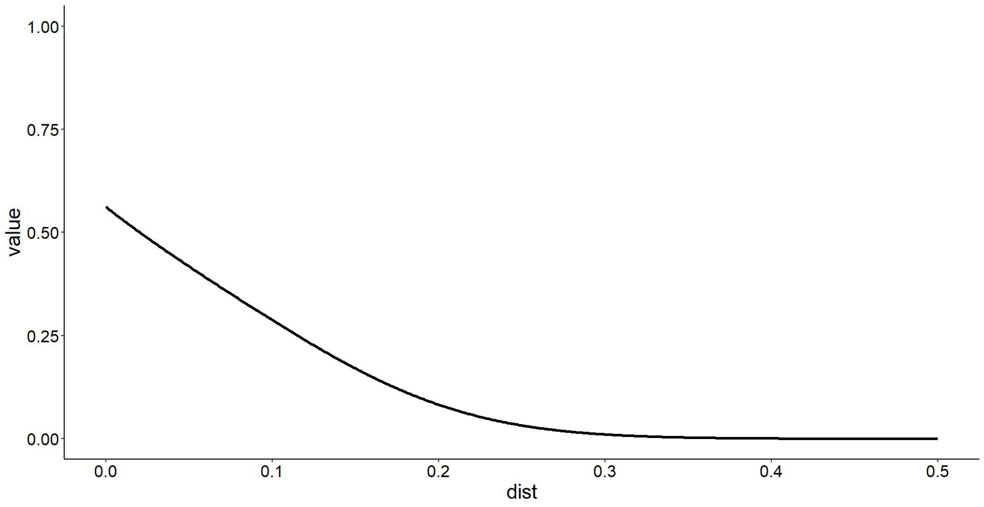
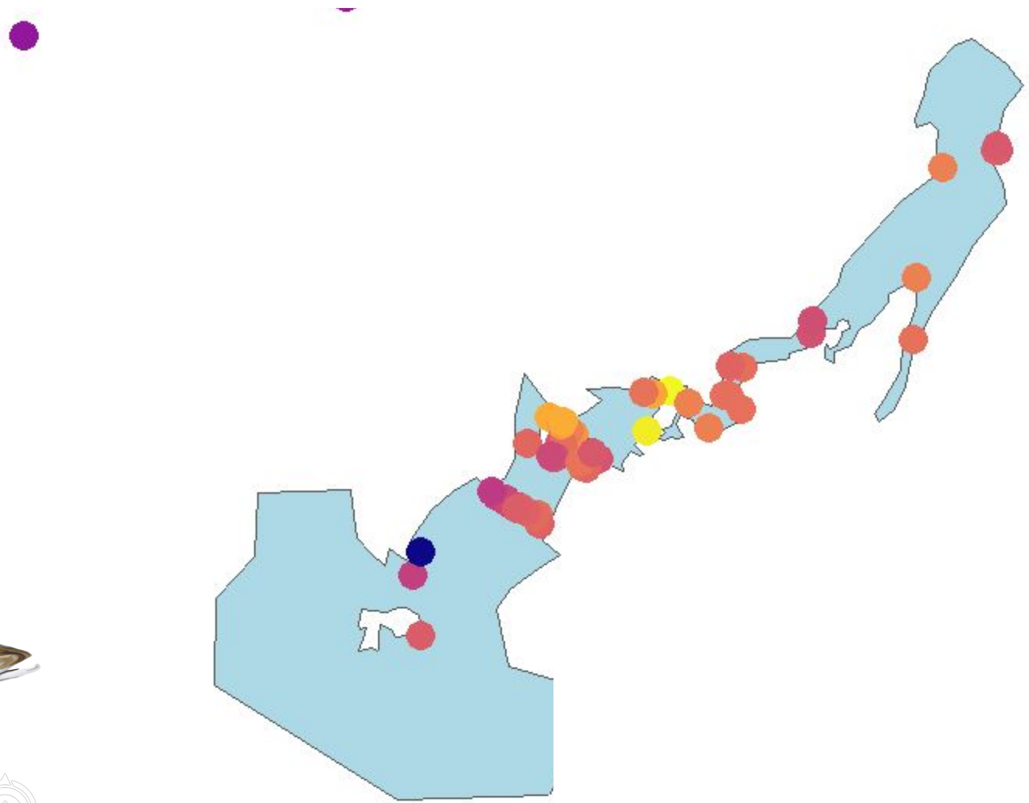
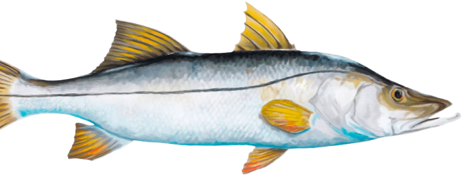
Range testing with GAMs





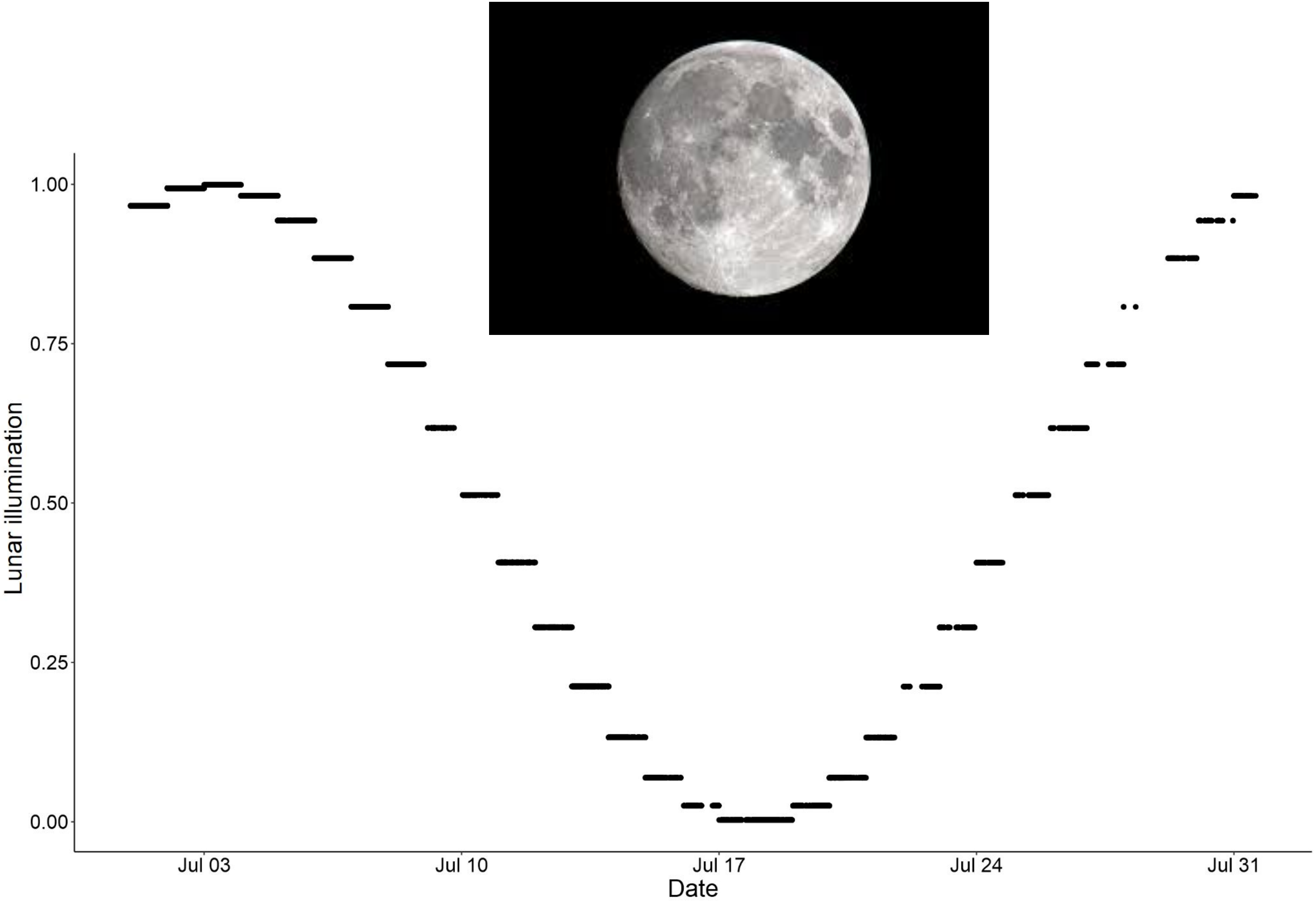
Mean acceleration by sampling point



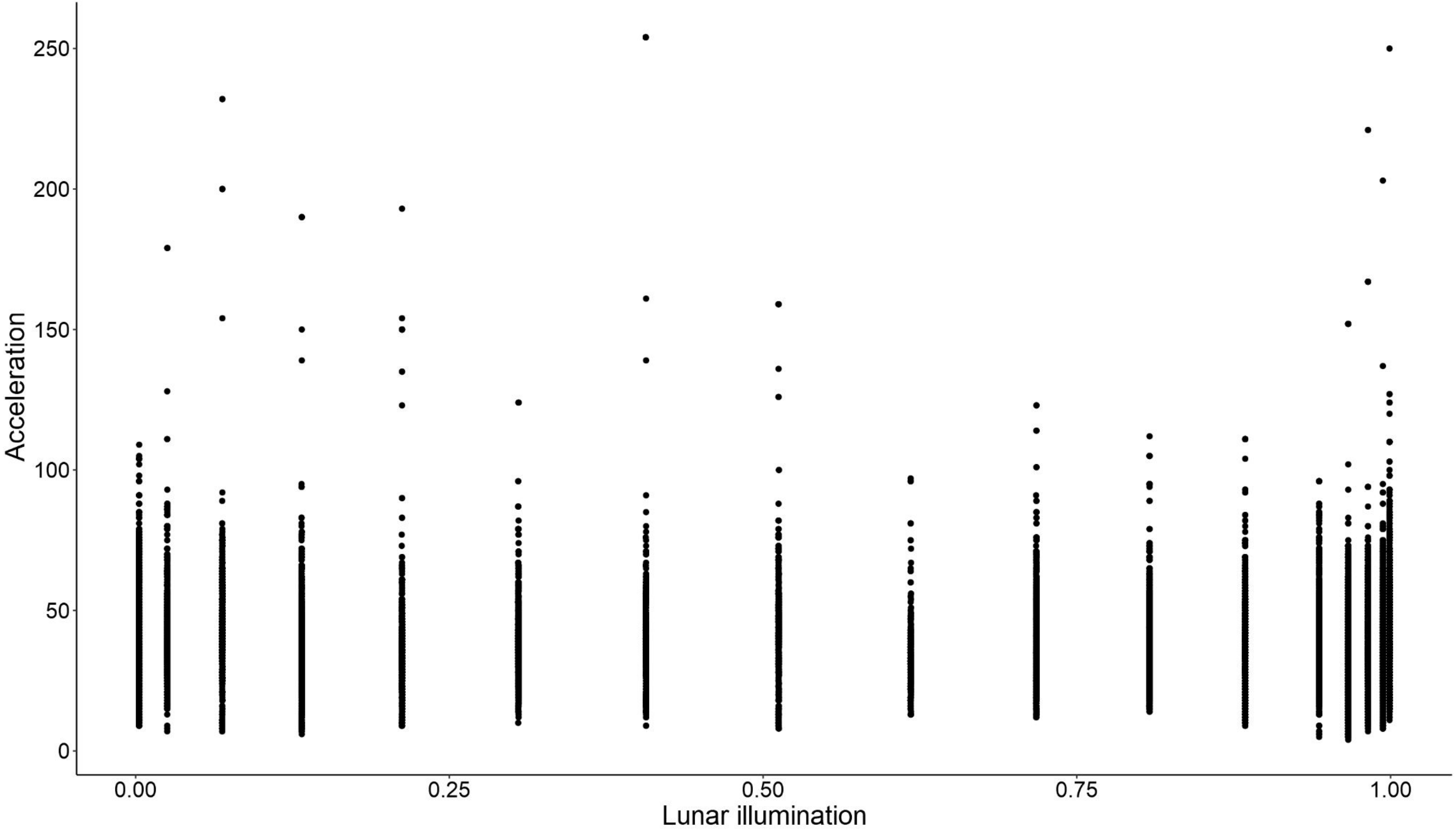


Lunar effects

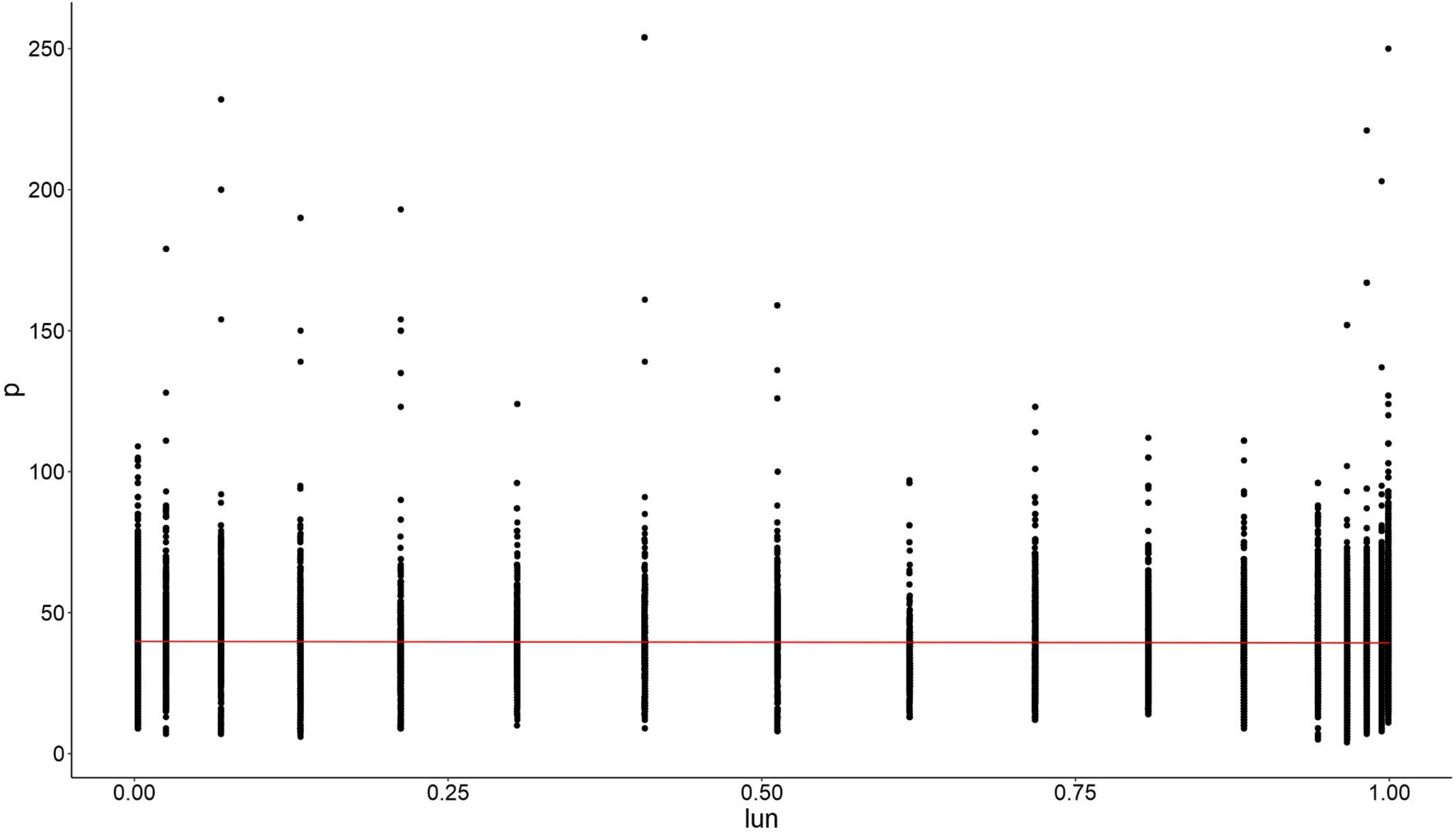
- MOON
- Important correlation to date



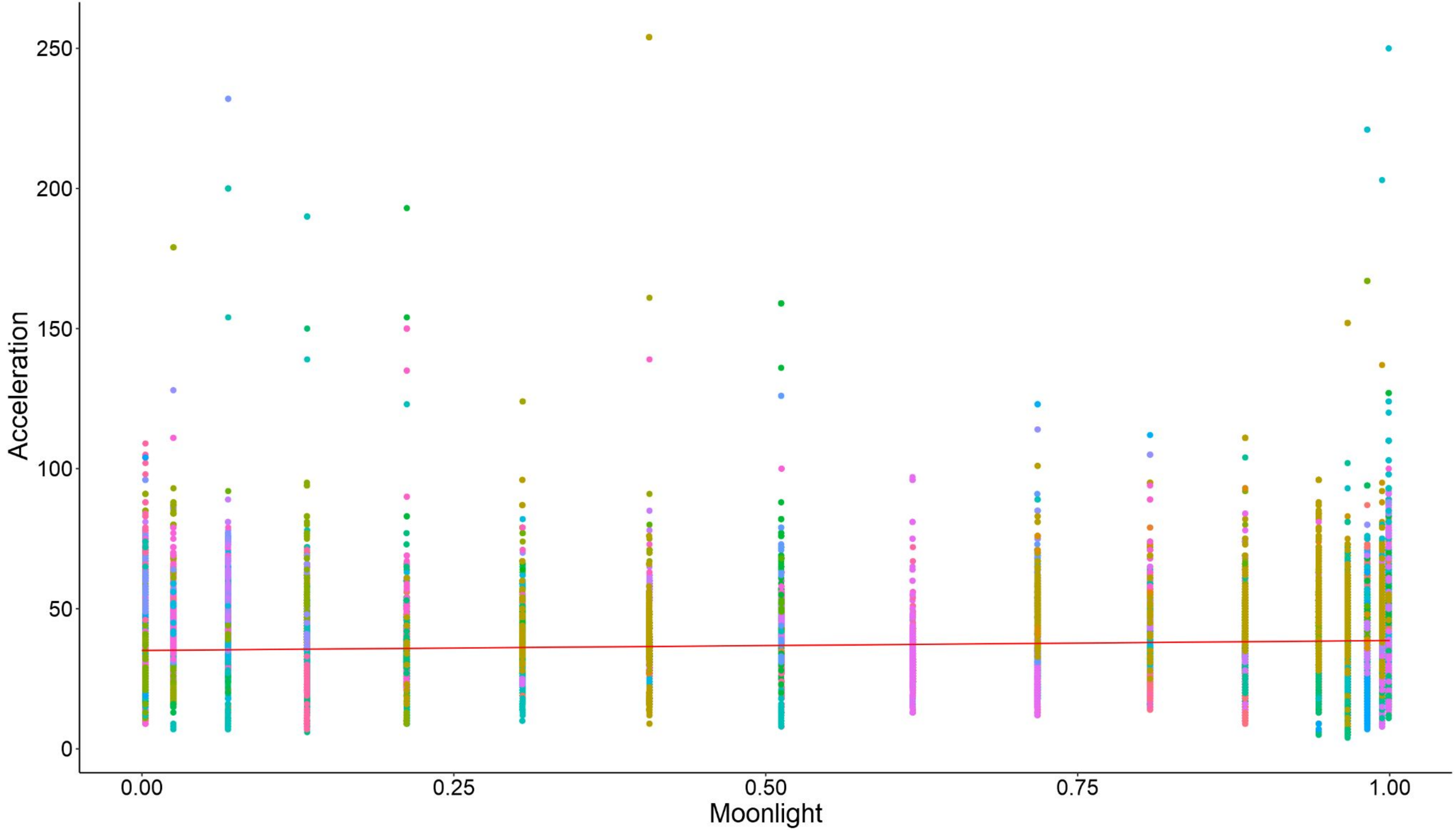
Is activity affected by lunar illumination?



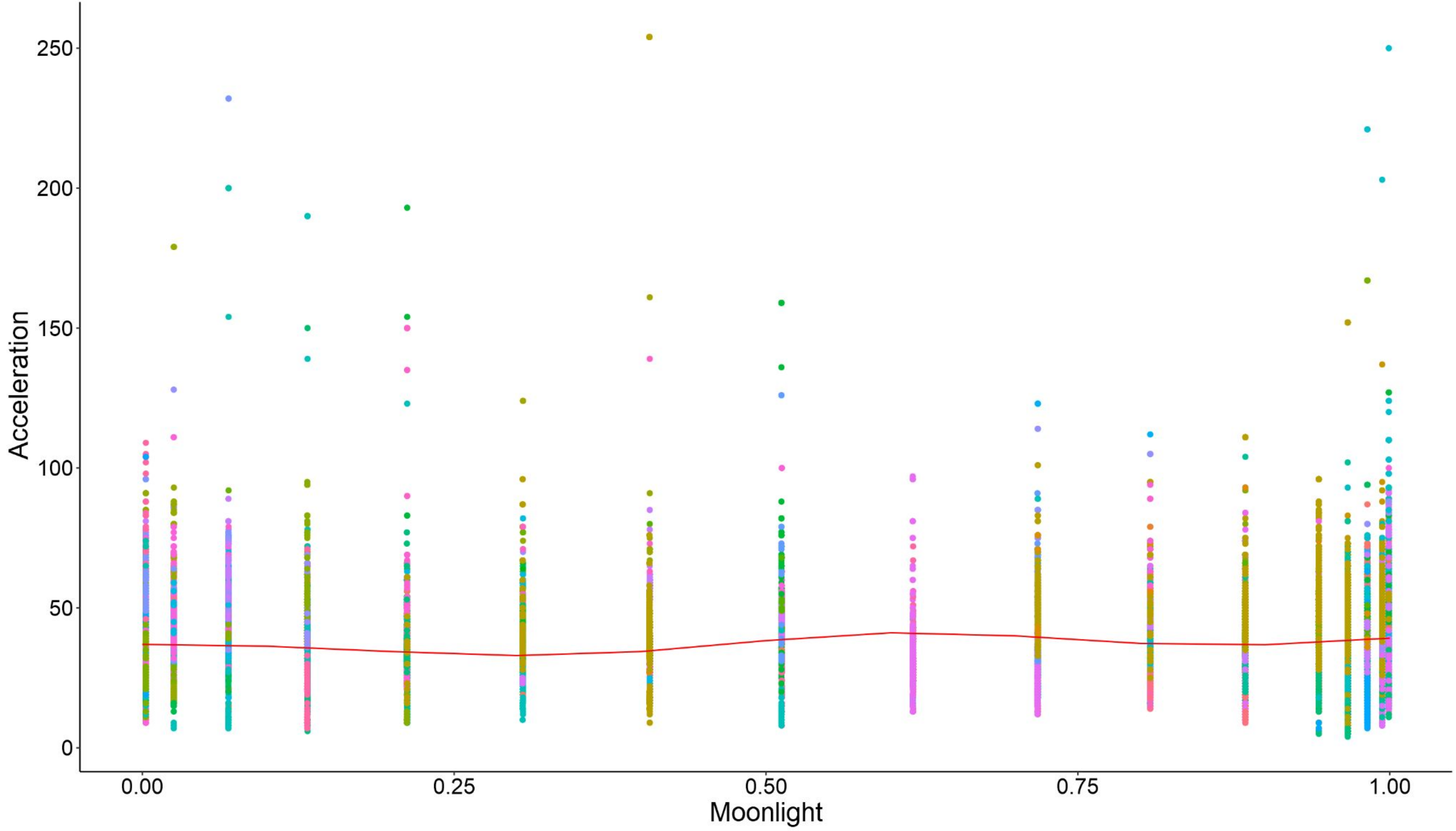
Linear regression acceleration ~ moonlight



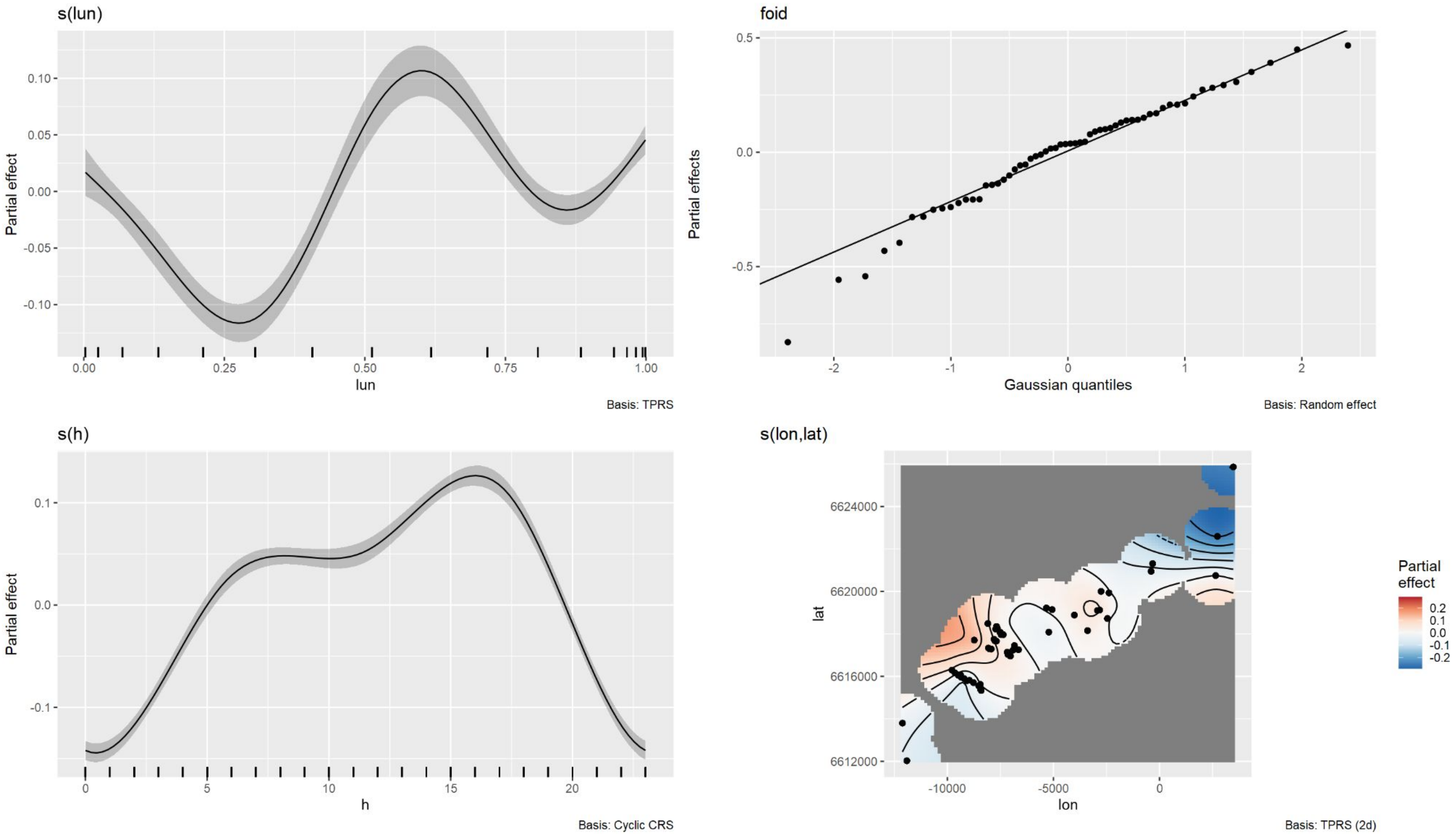
Linear mixed regression acceleration ~ moonlight + (1|ID)



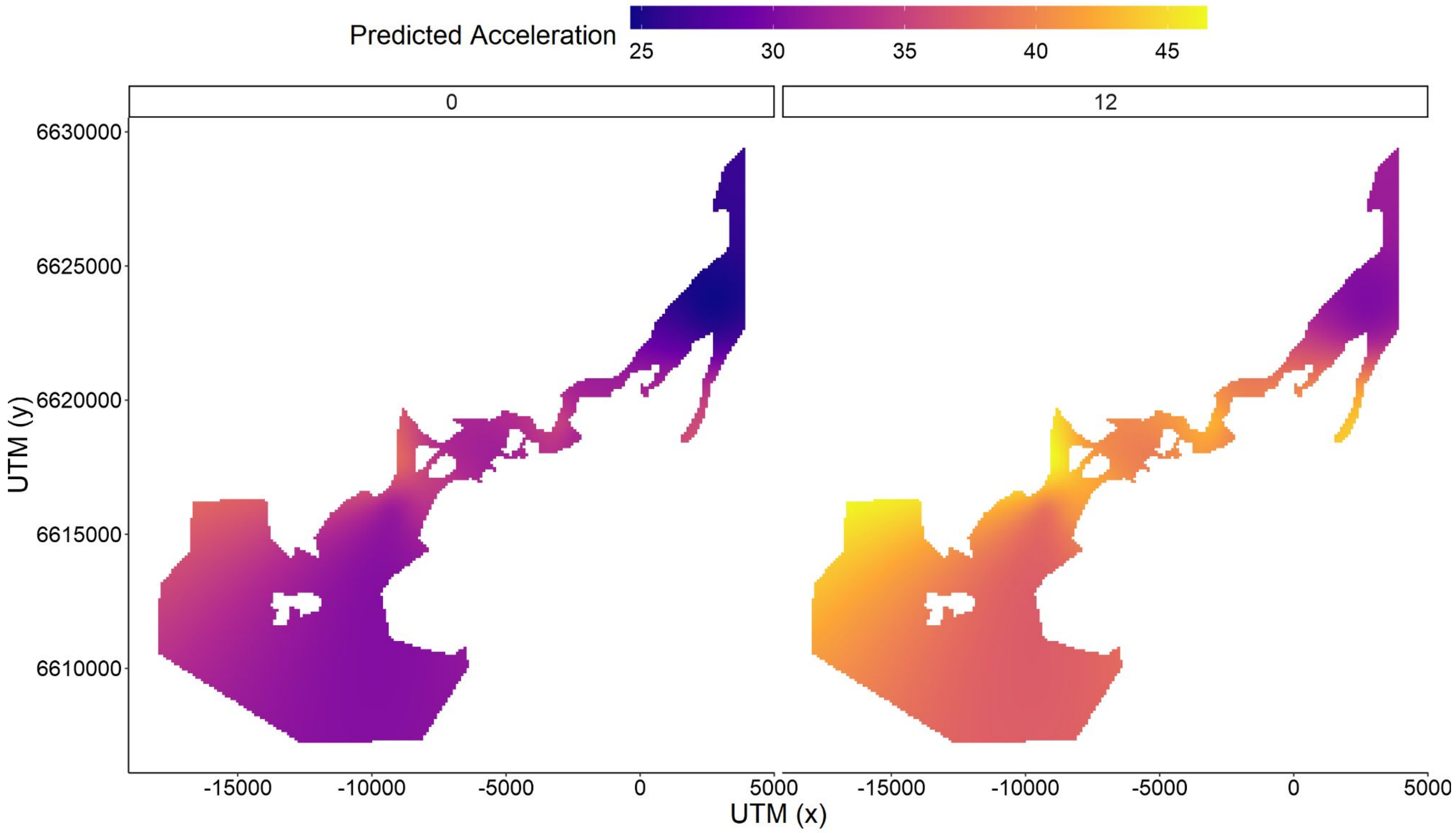
Additive mixed regression moonlight ~ s(moonlight) + (1|ID)



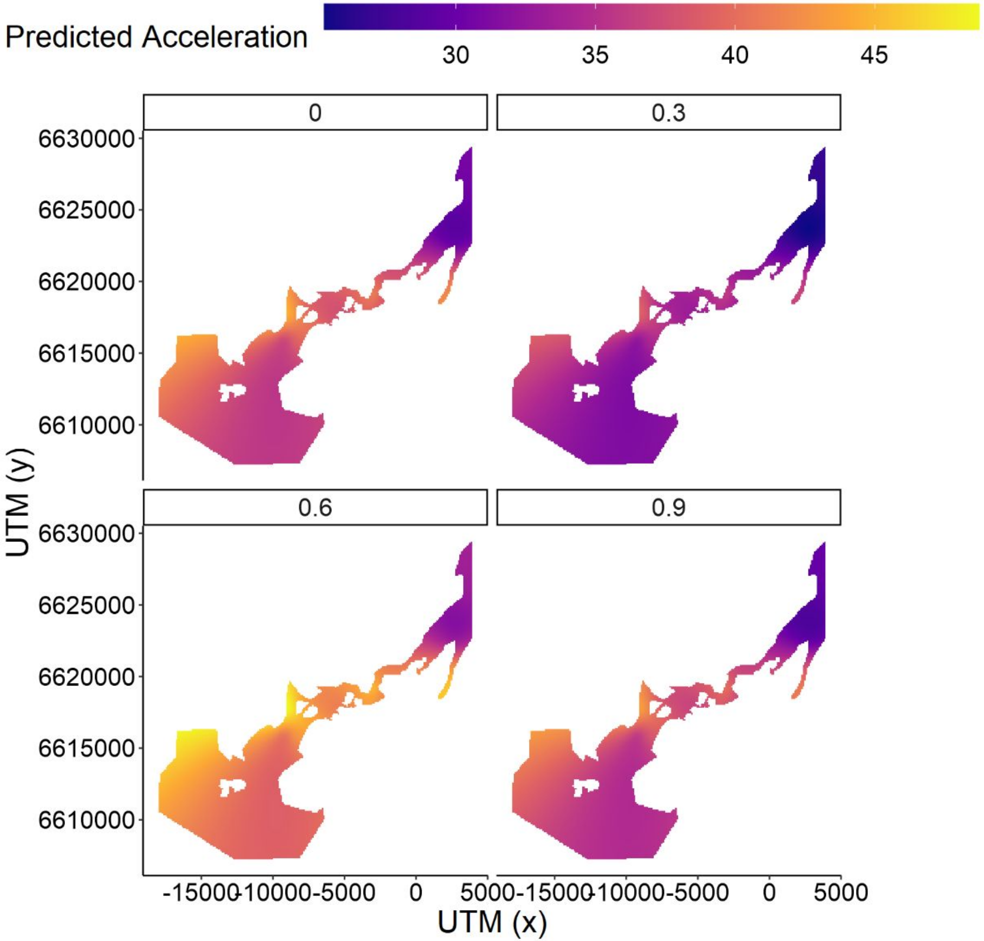
Full model summary with gratia::draw



Complex spatiotemporal model



Lunar effects across space



FAQ: Why smooths and not SPDE?

Understanding the Stochastic Partial Differential Equation Approach to Smoothing

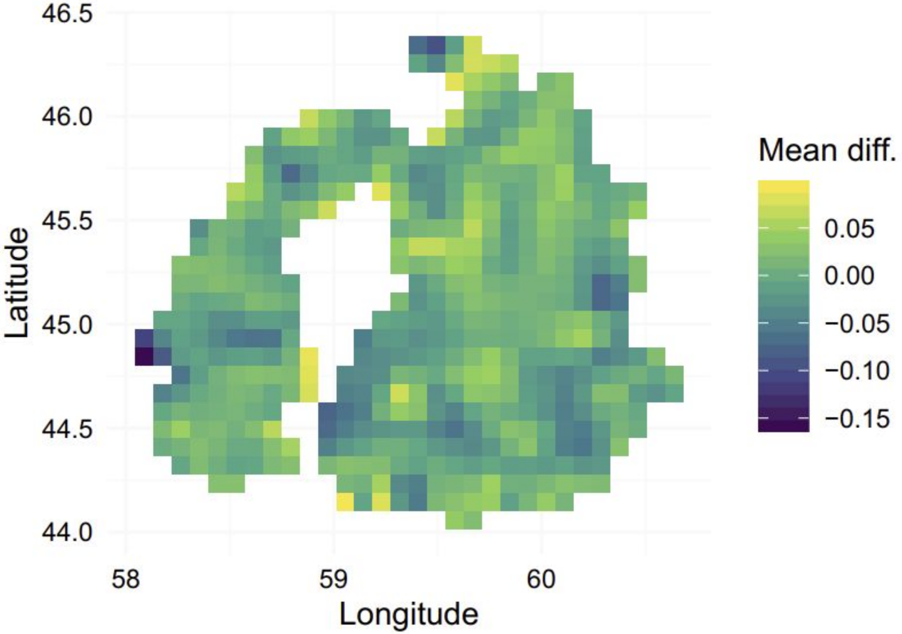
David L. MILLER, Richard GLENNIE, and Andrew E. SEATON

Correlation and smoothness are terms used to describe a wide variety of random quantities. In time, space, and many other domains, they both imply the same idea: quantities that occur closer together are more similar than those further apart. Two popular statistical models that represent this idea are basis-penalty smoothers (Wood in Texts in statistical science, CRC Press, Boca Raton, 2017) and stochastic partial differential equations (SPDEs) (Lindgren et al. in J R Stat Soc Series B (Stat Methodol) 73(4):423–498, 2011). In this paper, we discuss how the SPDE can be interpreted as a smoothing penalty and can be fitted using the R package `mgcv`, allowing practitioners with existing knowledge of smoothing penalties to better understand the implementation and theory behind the SPDE approach.

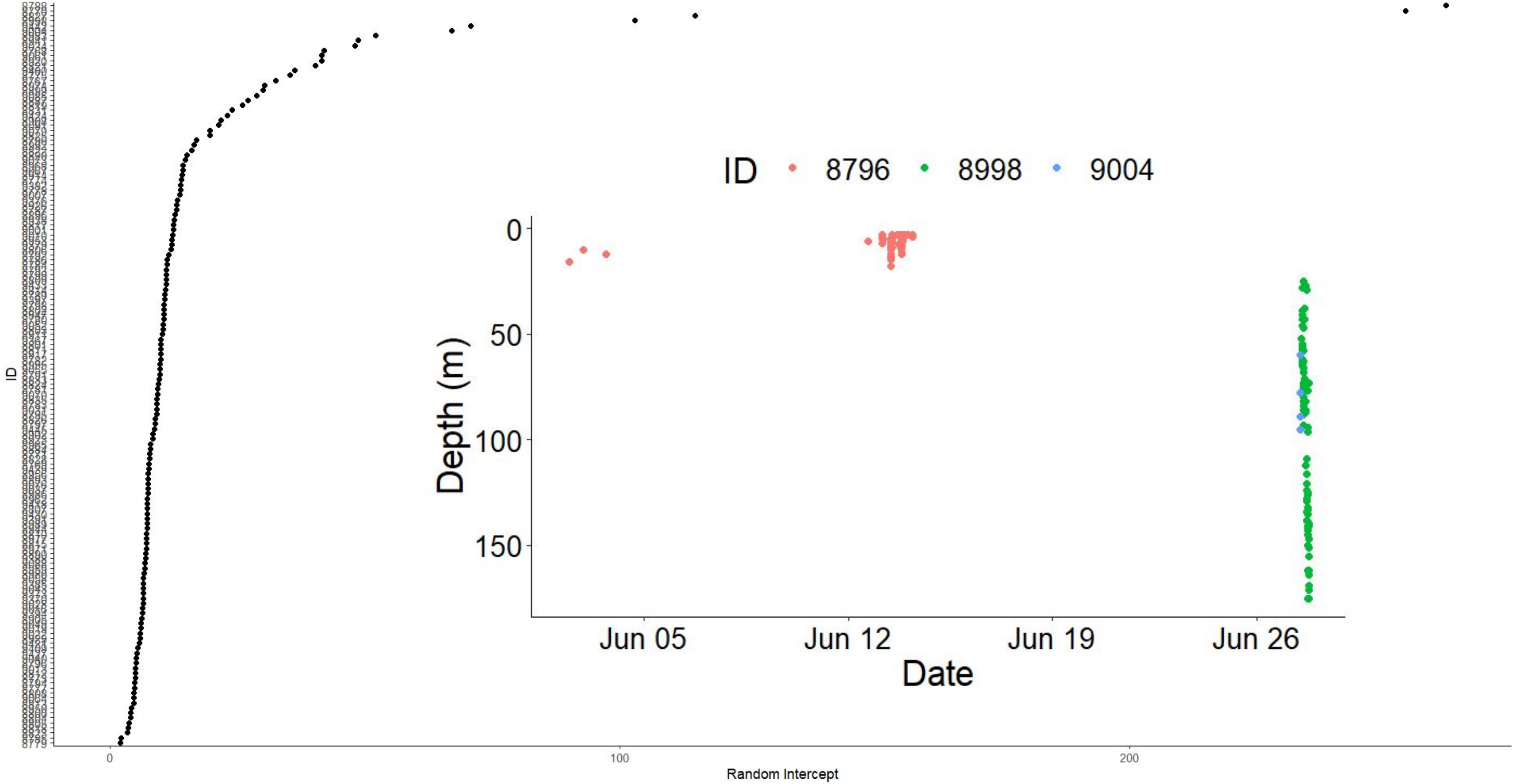
Supplementary materials accompanying this paper appear online.

Key Words: Smoothing; Stochastic partial differential equations; Generalized additive model; Spatial modelling; Basis-penalty smoothing.

1. INTRODUCTION

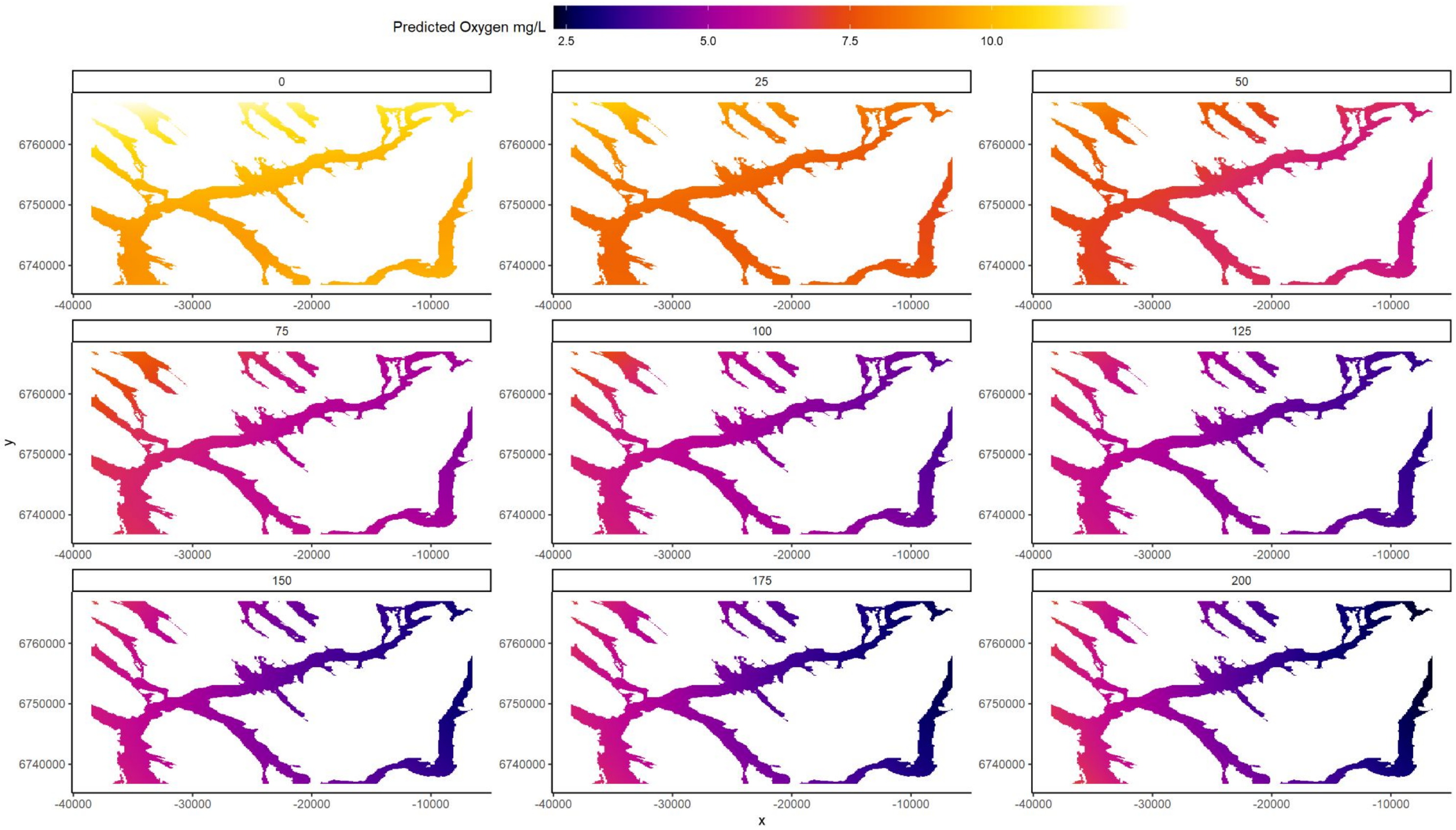


FAQ: Can mgcv incorporate random effects?

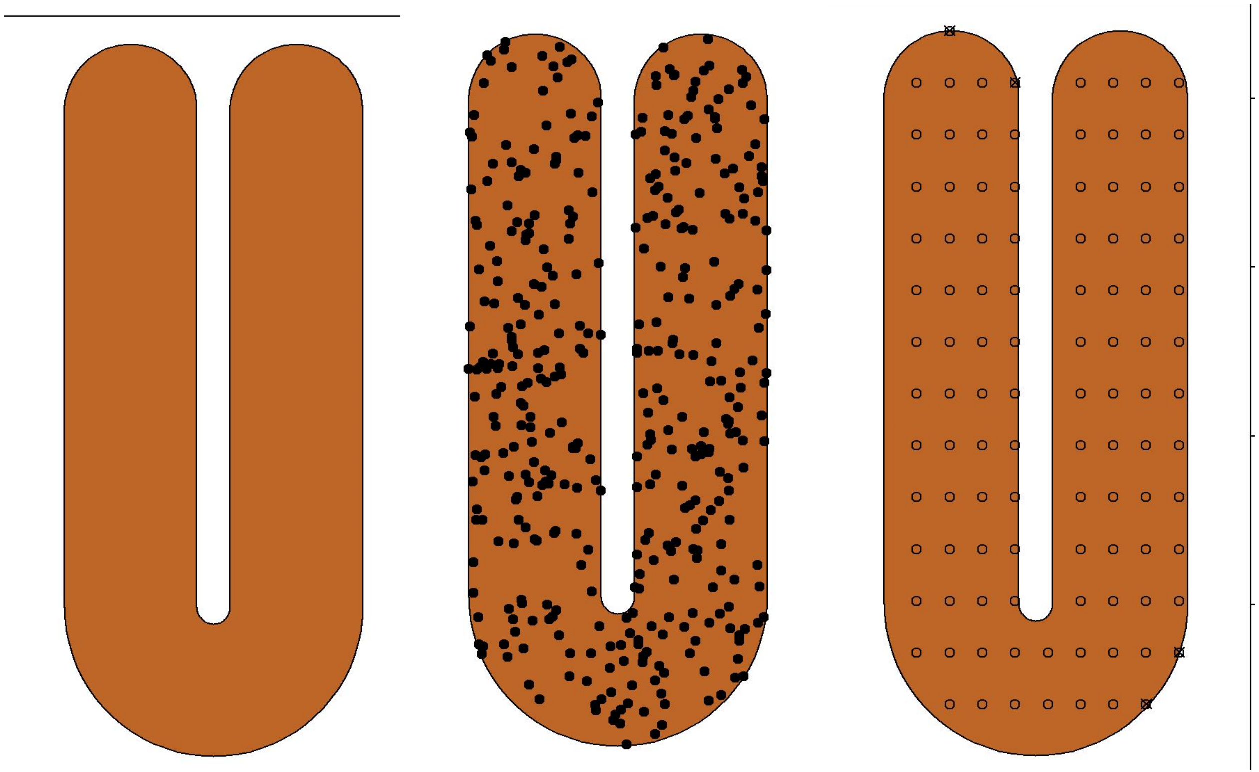


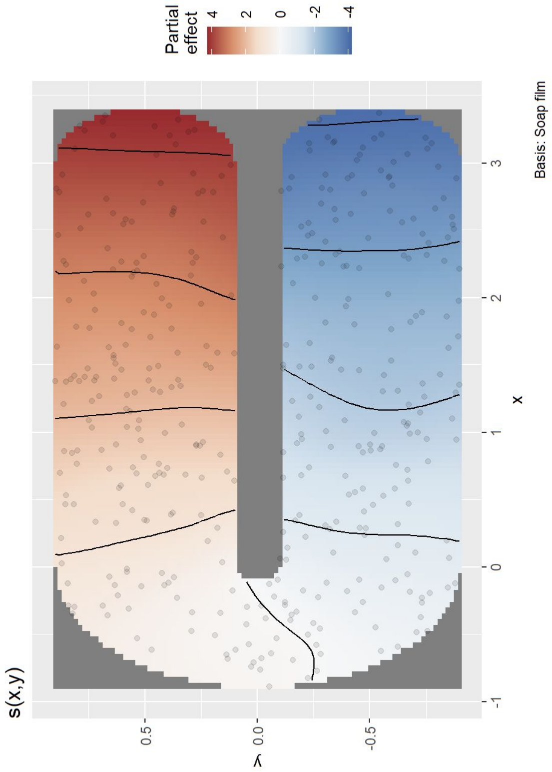
FAQ: Can we smooth in three spatial dimensions?

```
gam(oxygen ~ s(x, y, z), data=oxygen, method=”reml”)
```



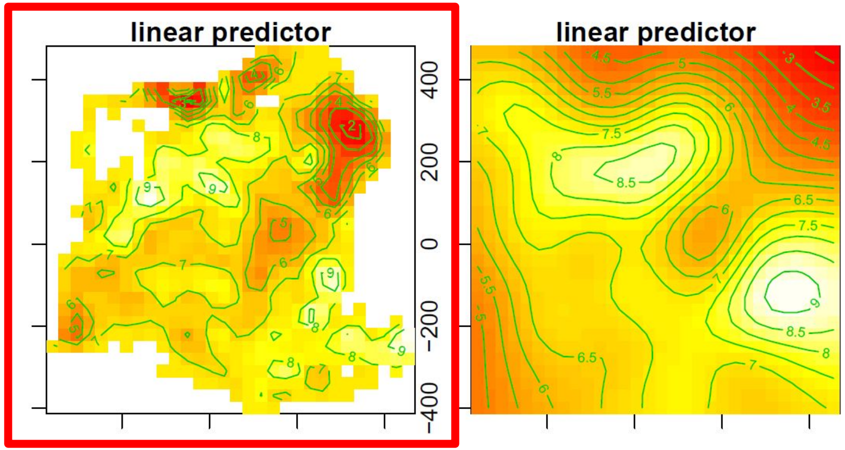
FAQ: Can we smooth around borders?





https://blog.benjaminhlina.com/posts/post-with-code/soapcheckr/

FAQ: Can we smooth around borders?



PLOS | ONE

RESEARCH ARTICLE

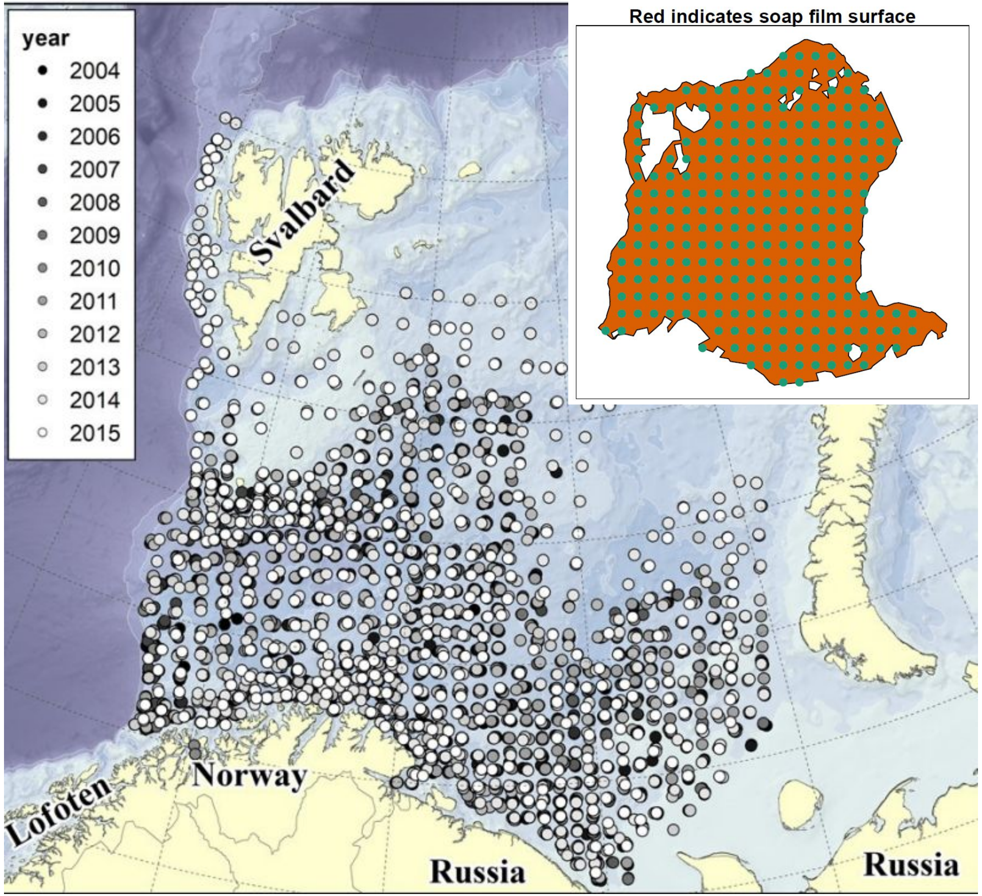
Seasonal dynamics of spatial distributions and overlap between Northeast Arctic cod (*Gadus morhua*) and capelin (*Mallotus villosus*) in the Barents Sea

Johanna Fall[1]*, Lorenzo Ciannelli[2], Georg Skaret[1], Edda Johannesen[1]

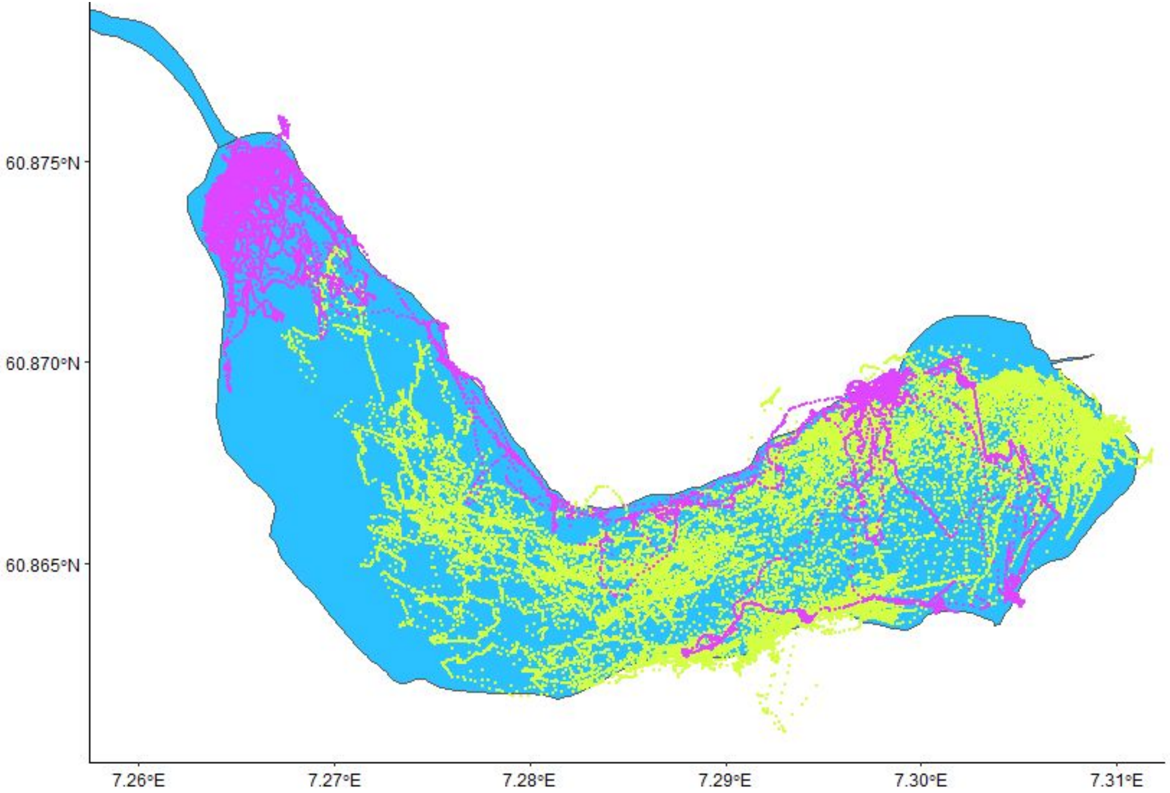
1 Institute of Marine Research, Bergen, Norway, **2** College of Earth, Ocean and Atmospheric Sciences, Oregon State University, Corvallis, Oregon, United States of America

* johanna.fall@hi.no

Check for updates



My favourite example 1



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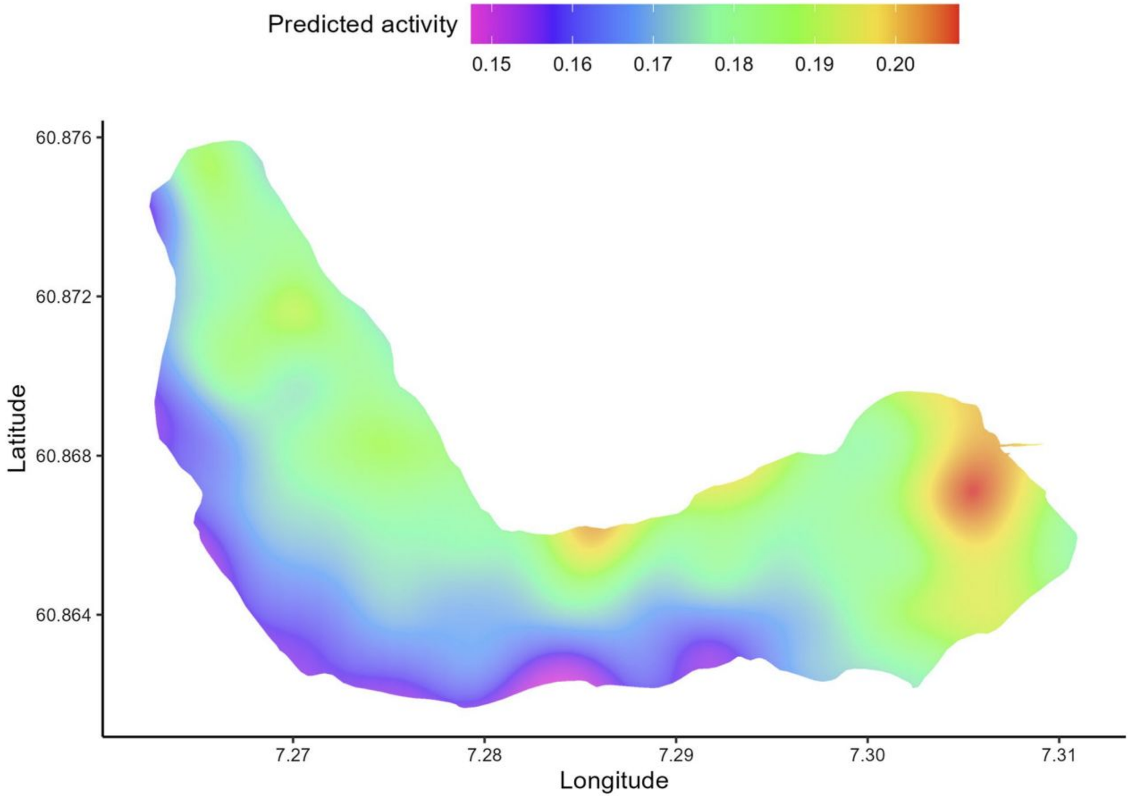
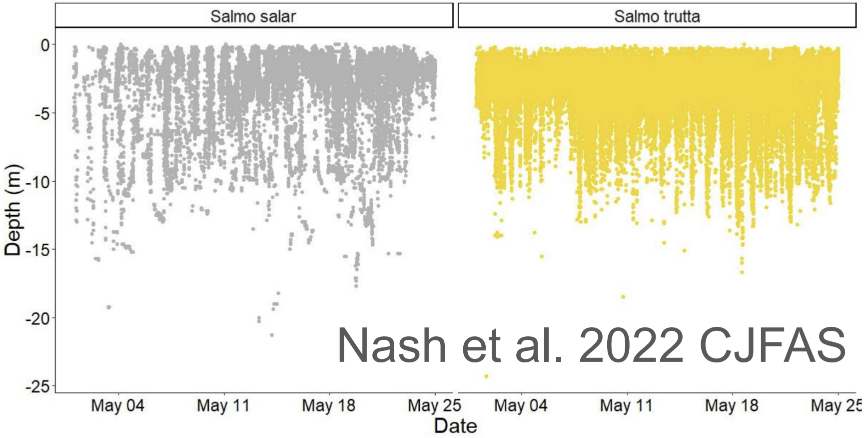
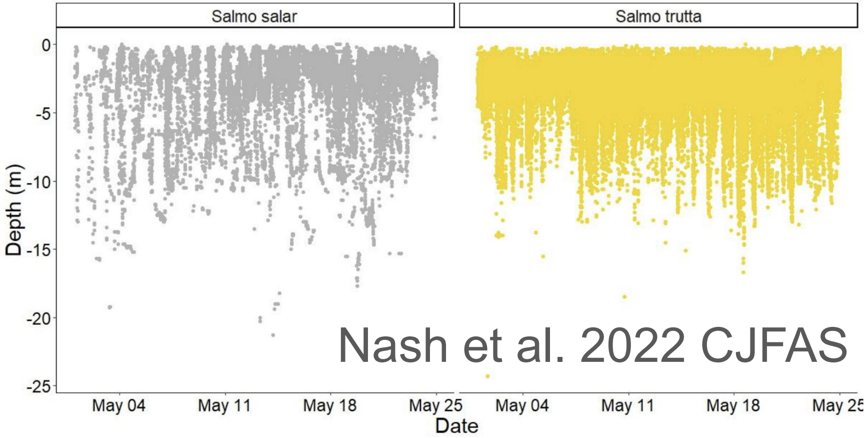
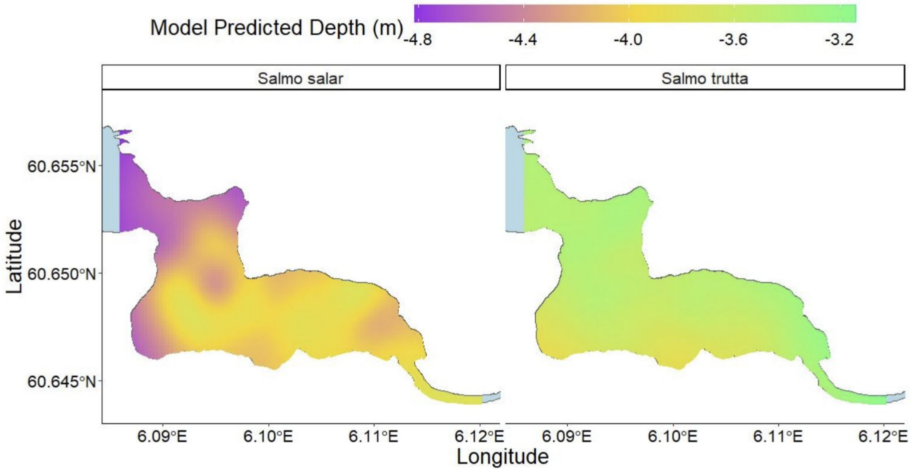


My favourite example 2



My favourite example 2





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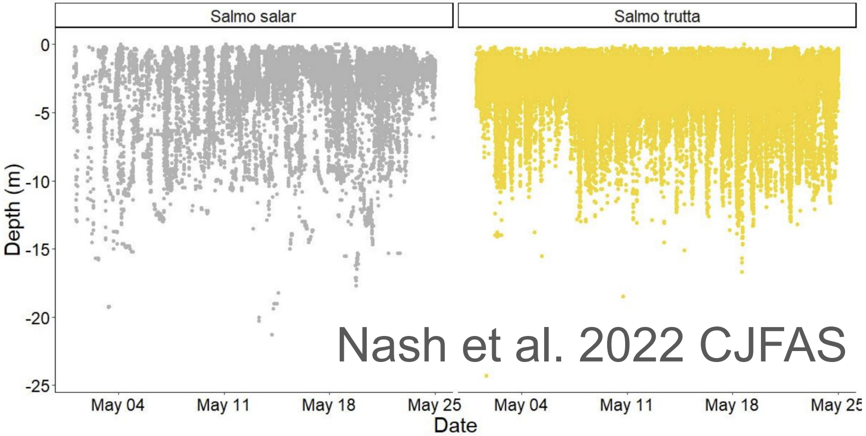
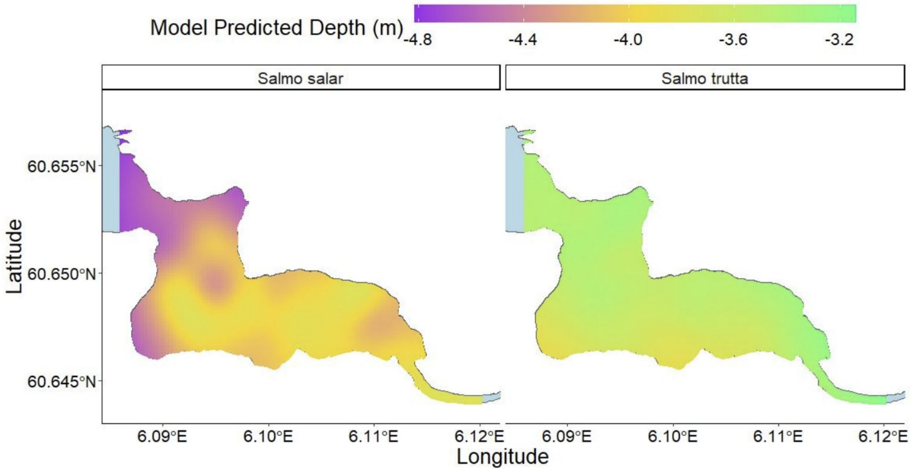
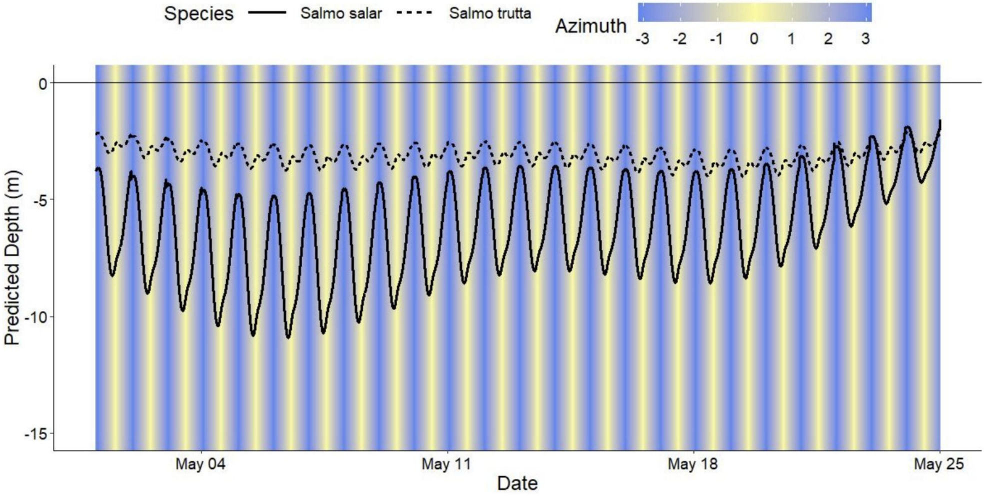


Nash et al. 2022 CJFAS





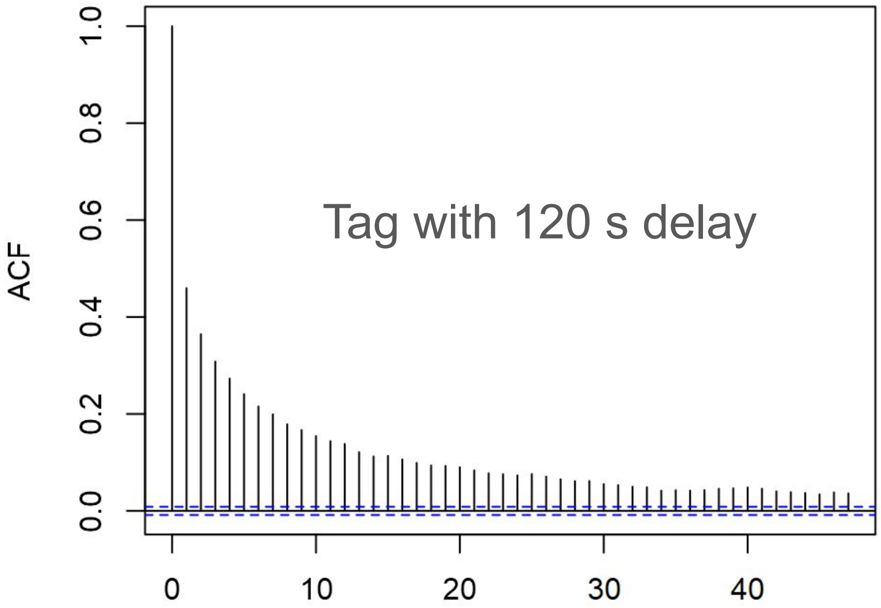
What can GAM theory teach us about designing studies

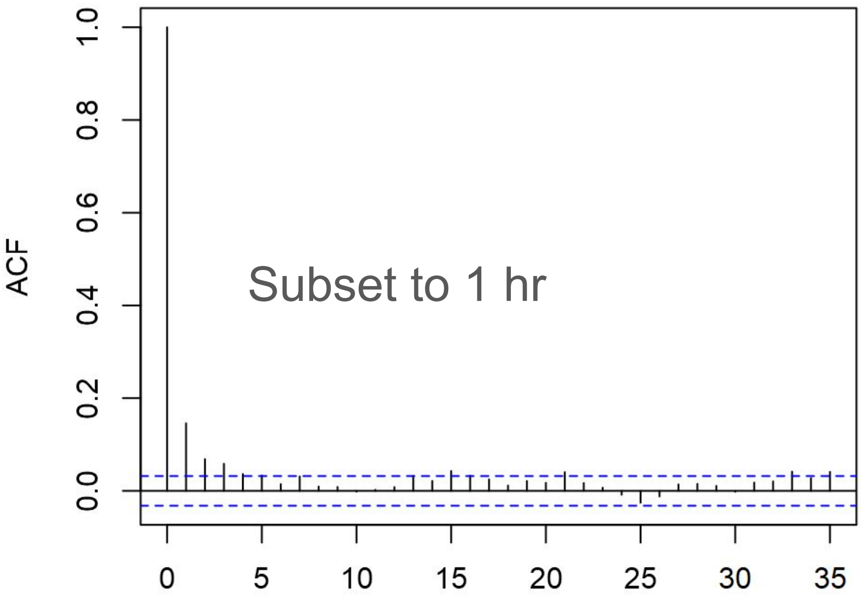
Lesson 1- sampling rates

- Transmitters provide immense volumes of data, particularly from sensors
- Depth, temp, accel are highly autocorrelated and often have to be subsampled
- When animals do not leave a study area, longer sampling intervals can be used

Subsetting sensor data to reduce temporal autocorrelation

- Full time series highly autocorrelated
- Subset series has less autocorrelation





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Lesson 2- array design

- Using spatial smoothers allows us to interpolate some data
- Should consider how far is appropriate to smooth across based on changes in habitat and water chemistry
- Design receiver grids to limit excessive smoothing
- Where possible, use evenly gridded sampling designs

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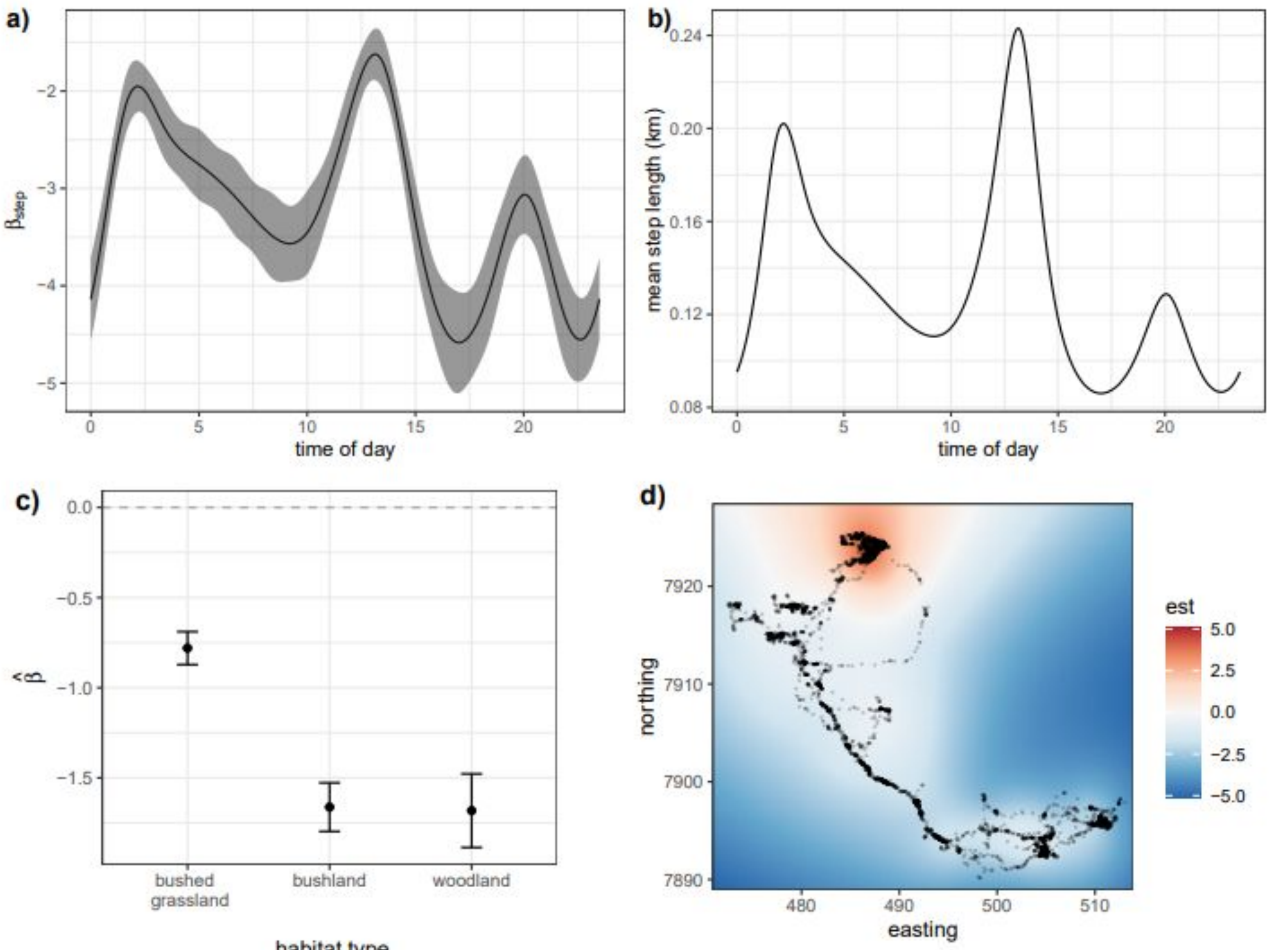
Novel areas and applications of GAMs

- Validating GAMs for step selection analysis
- Extending GAMs to include point process models
- Incorporating phylogenetic correlations to account for violation of independence
- Examples of three dimensional spatial fields

Step Selection



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