Ecological forecasting with dynamic GAMs

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“Because all decision making is based on what will happen in the future, either under the status quo or different decision alternatives, decision making ultimately depends on forecasts”

Dietze et al. 2018

Properties of ecological series

Temporal autocorrelation

Lagged effects

Non-Gaussian data and missing observations

Measurement error

Time-varying effects

Nonlinearities

Multi-series clustering

Properties of ecological series

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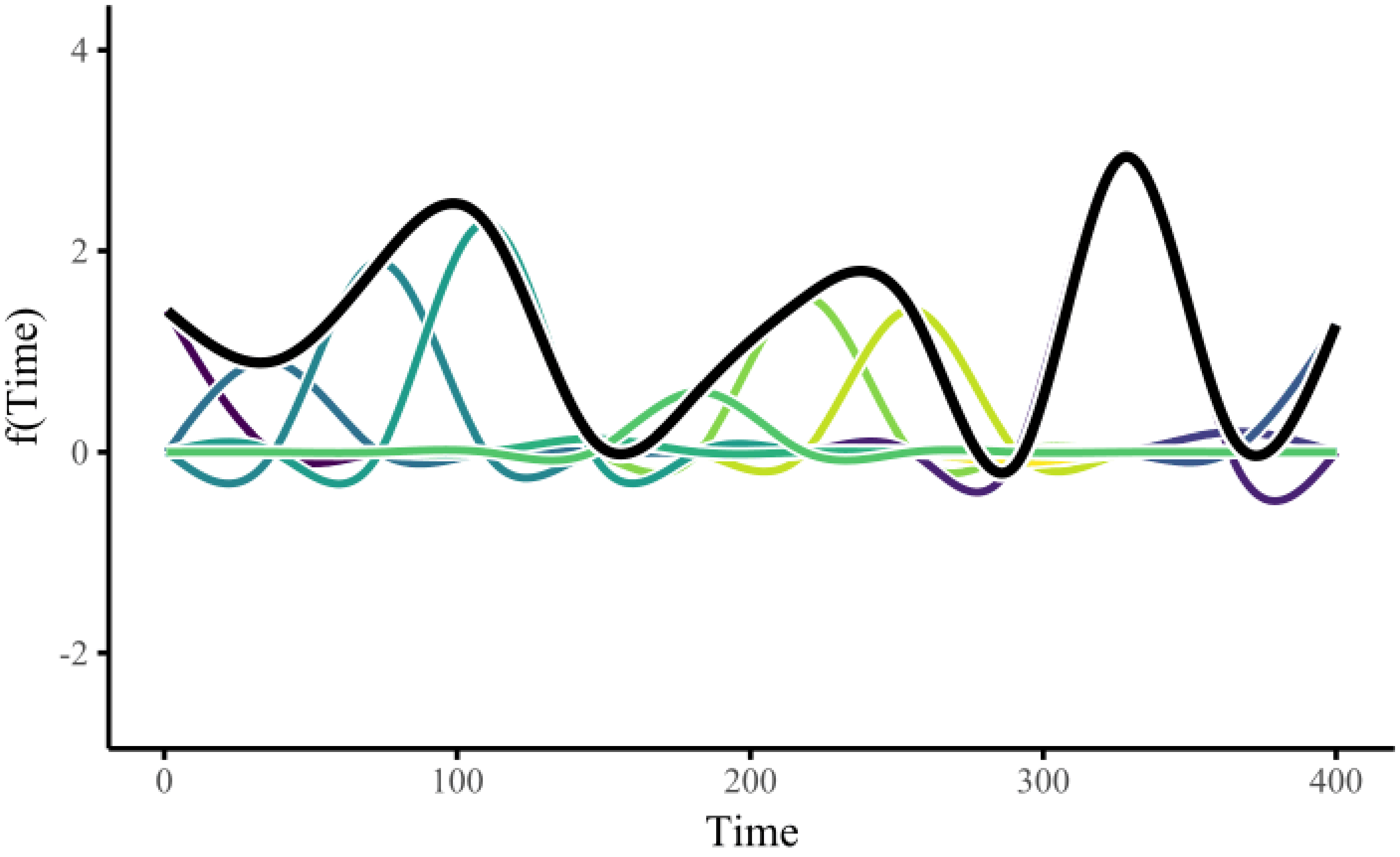
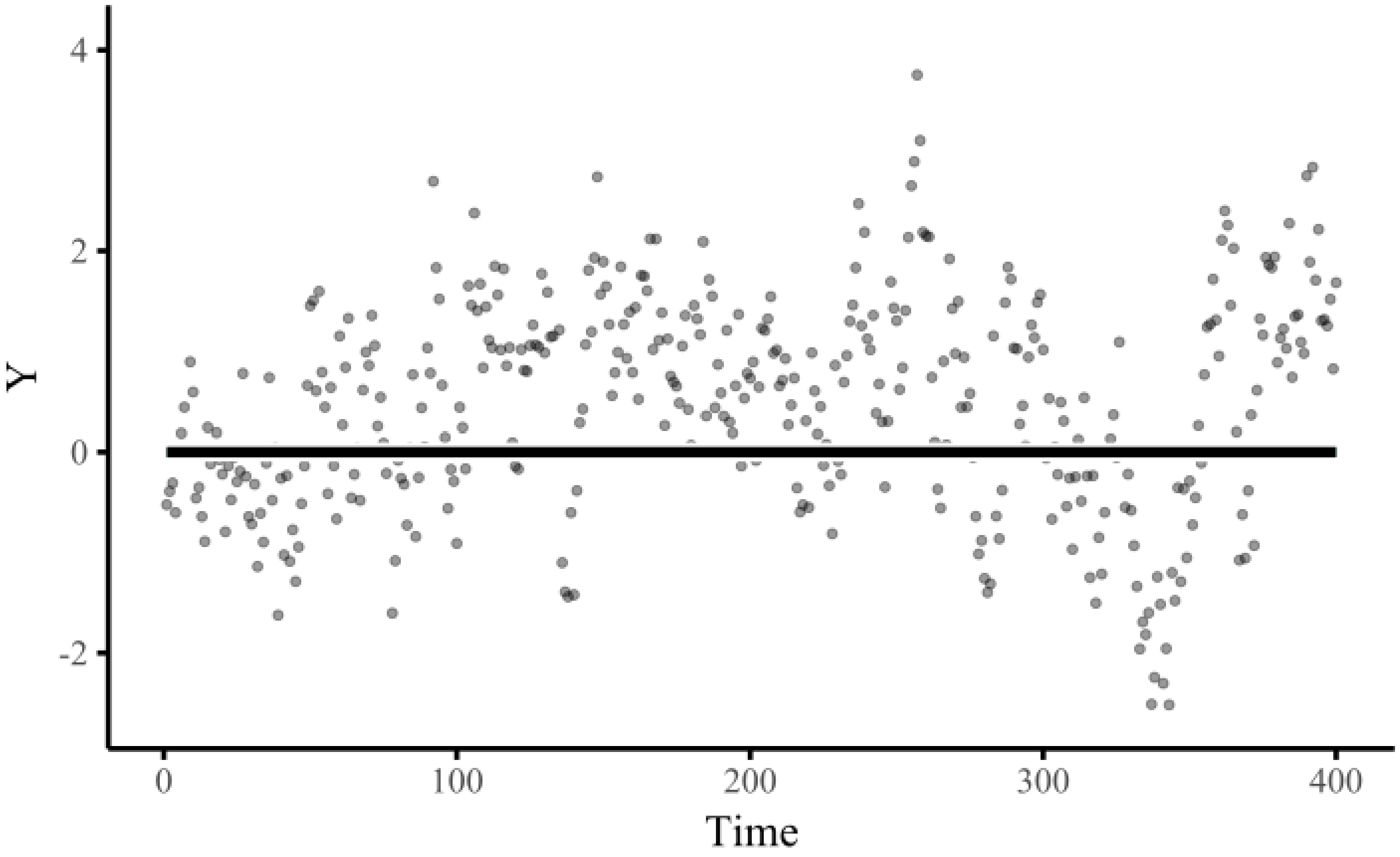
GAMs use splines...



...penalized to fit data

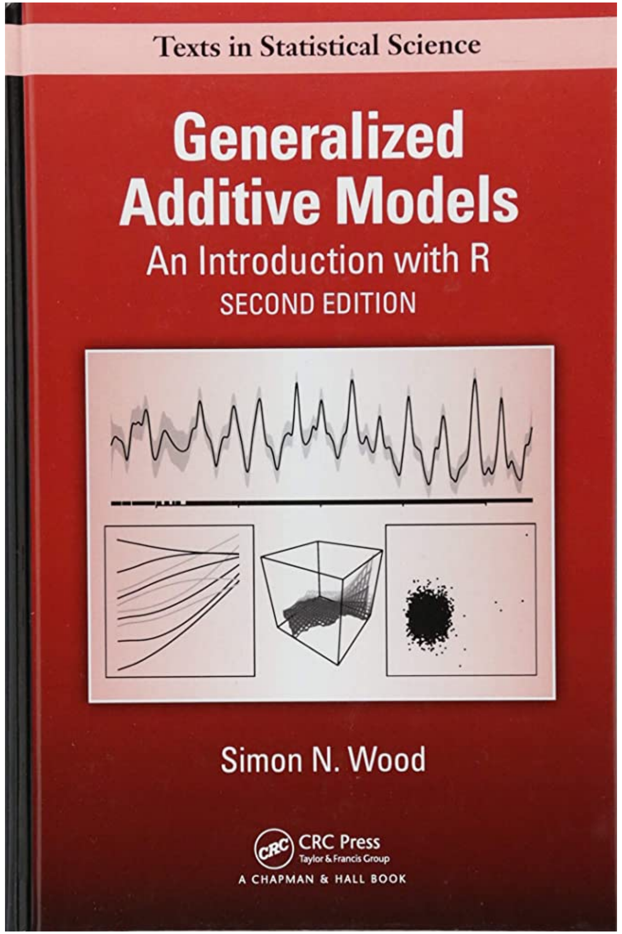


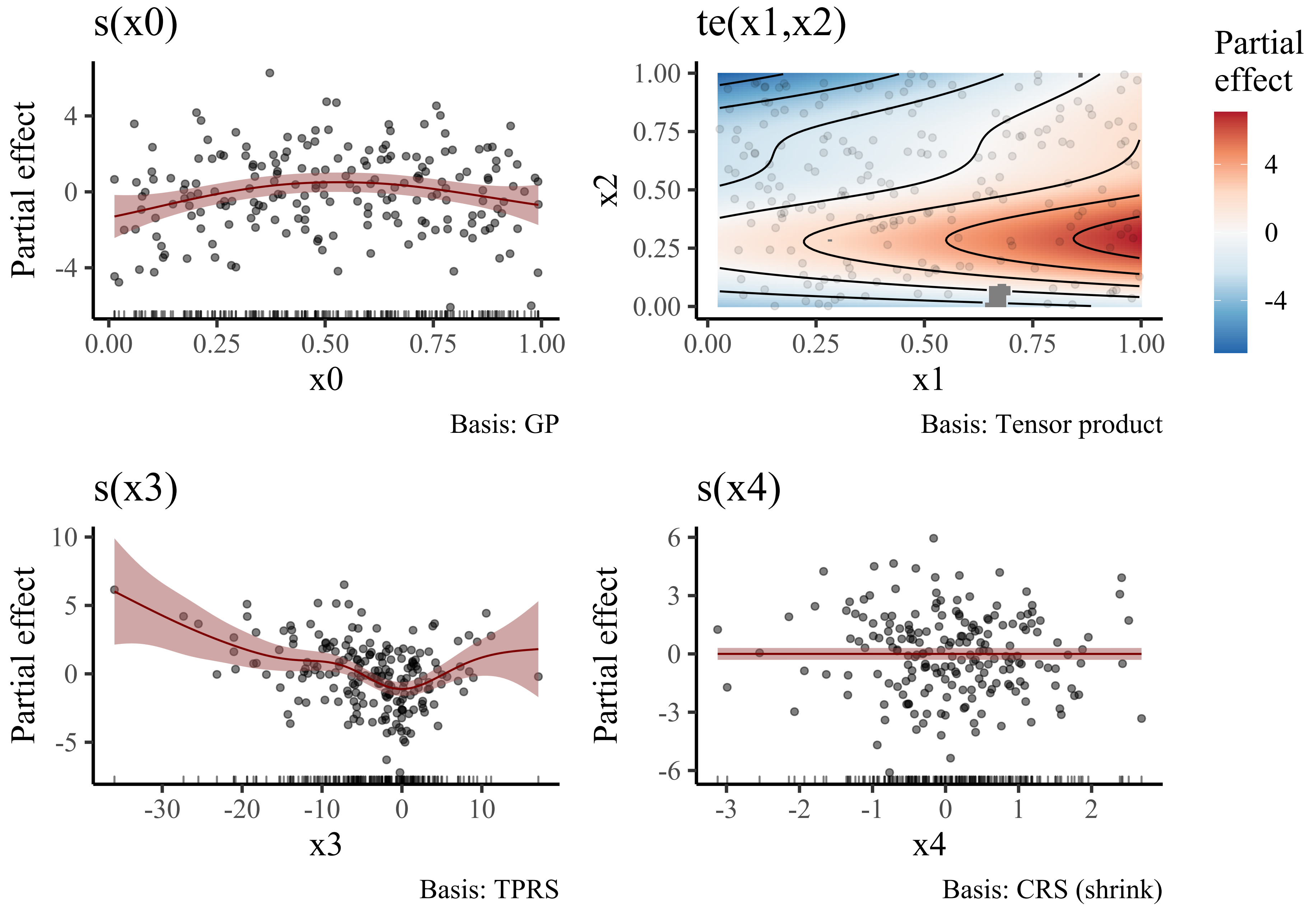
Easy to fit in R

$$\mathbb{E}(\boldsymbol{Y}_t|\boldsymbol{X}_t) = g^{-1}(\alpha + \sum_{j=1}^{J} f(x_{jt}))$$

Where:

- g^{-1} is the inverse of the link function
- α is the intercept
- $f(x)$ are potentially nonlinear functions of the J predictors




s(x0)
Partial effect
4
0
-4
0.00
0.25
0.50
0.75
1.00
x0
Basis: GP
te(x1,x2)
1.00
0.75
0.50
0.25
0.00
x2
x1
Basis: Tensor product
Partial effect
4
0
-4
s(x3)
10
5
0
-5
-30
-20
-10
0
10
x3
Basis: TPRS
s(x4)
6
3
0
-3
-6
-3
-2
-1
0
1
2
x4
Basis: CRS (shrink)

Need more on GAMs?

Gavin has you covered ☺

Generalized Additive Models with R and mgcv

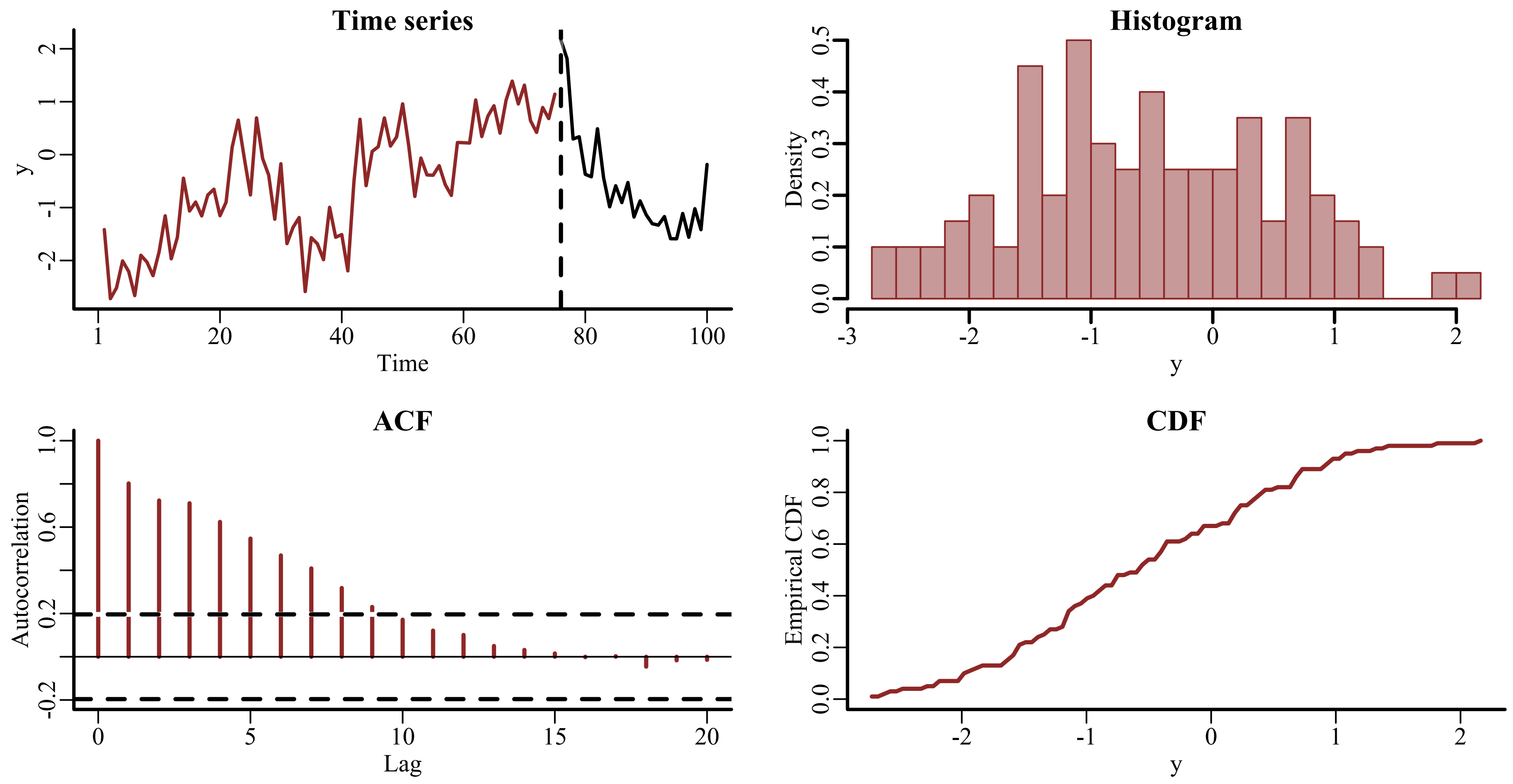
Gavin Simpson

January 3, 2022

GAMs are just fancy GLMs, where some (or all) of the predictor effects are estimated as (possibly nonlinear) smooth functions

But the complexity these smooth functions can handle is *enormous*

What's the catch?

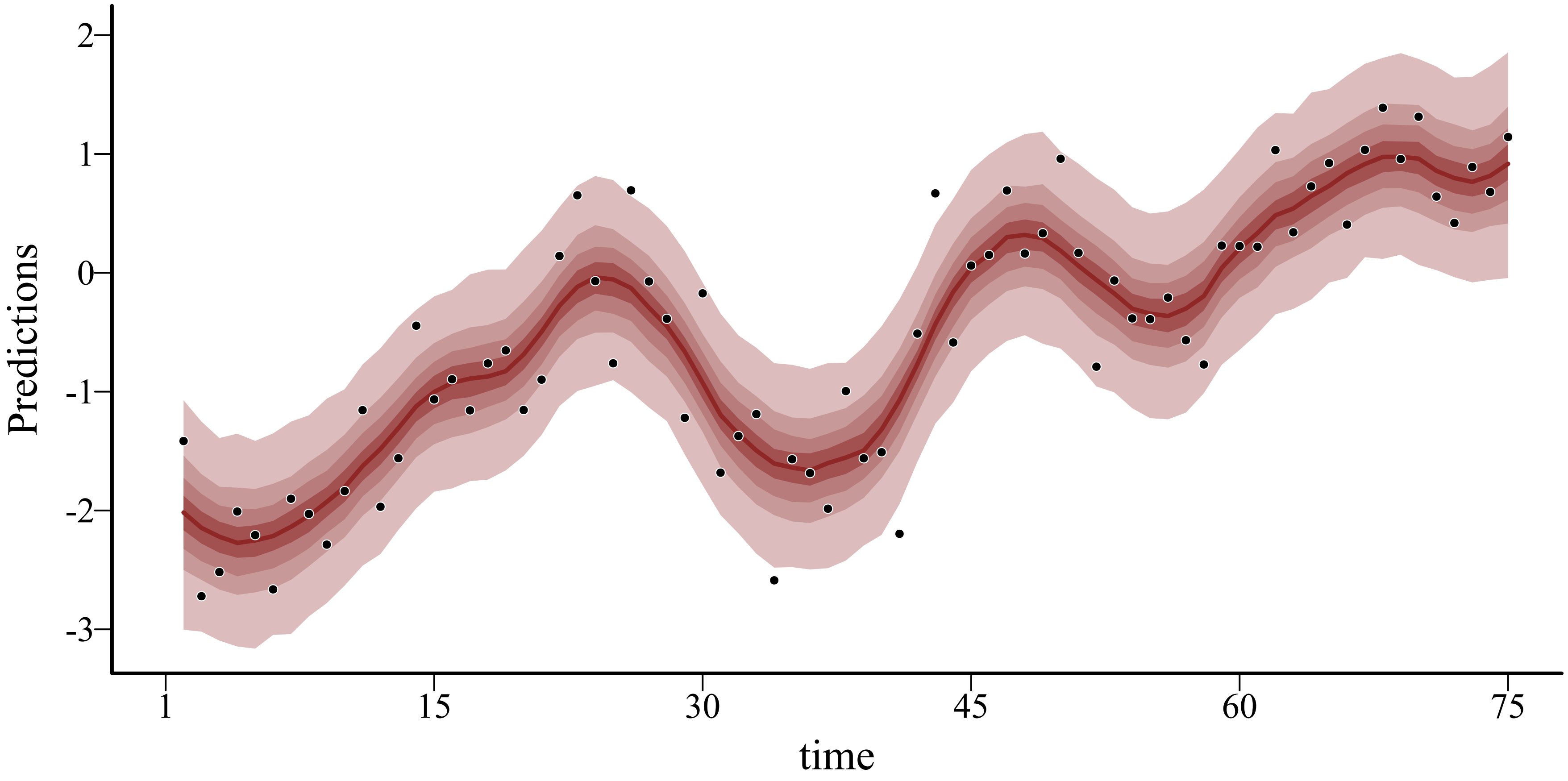


A spline of `time`

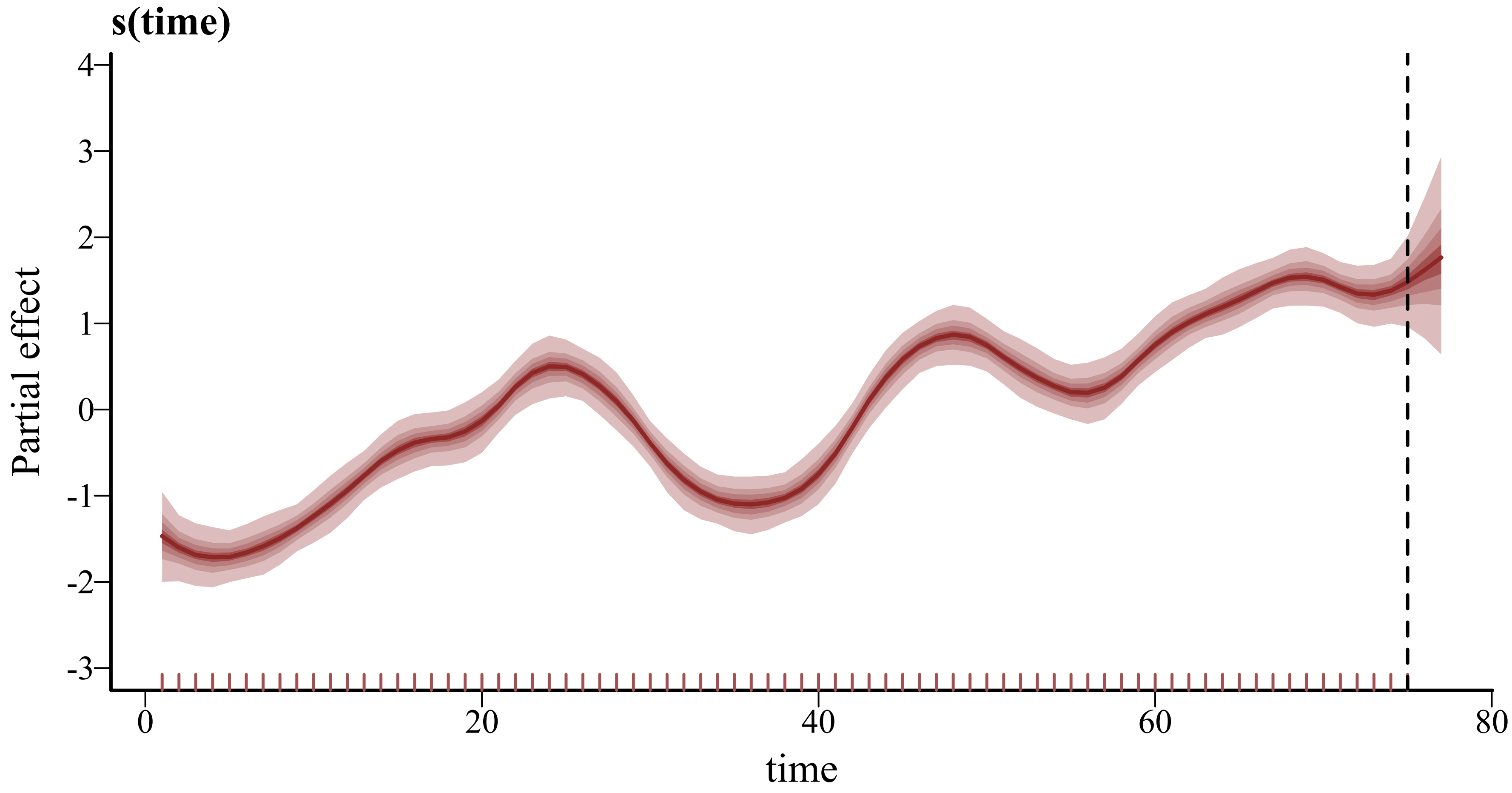
```r
library(mgcv)
model ← gam(y ~ s(time, k = 20, bs = 'bs', m = 2),
            data = data,
            family = gaussian())
```

A B-spline (`bs = 'bs'`) with `m = 2` sets the penalty on the second derivative

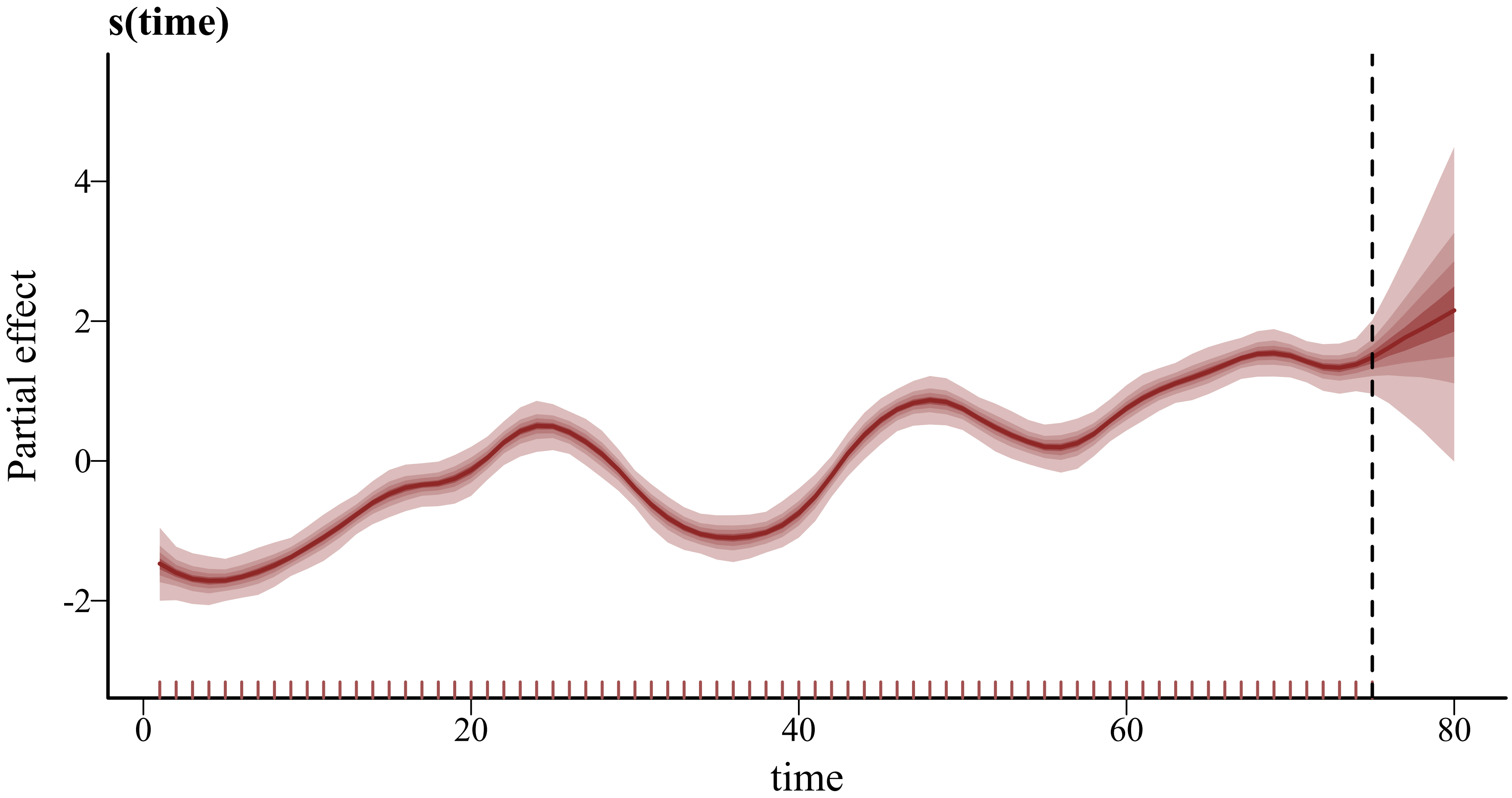
Hindcasts 😊



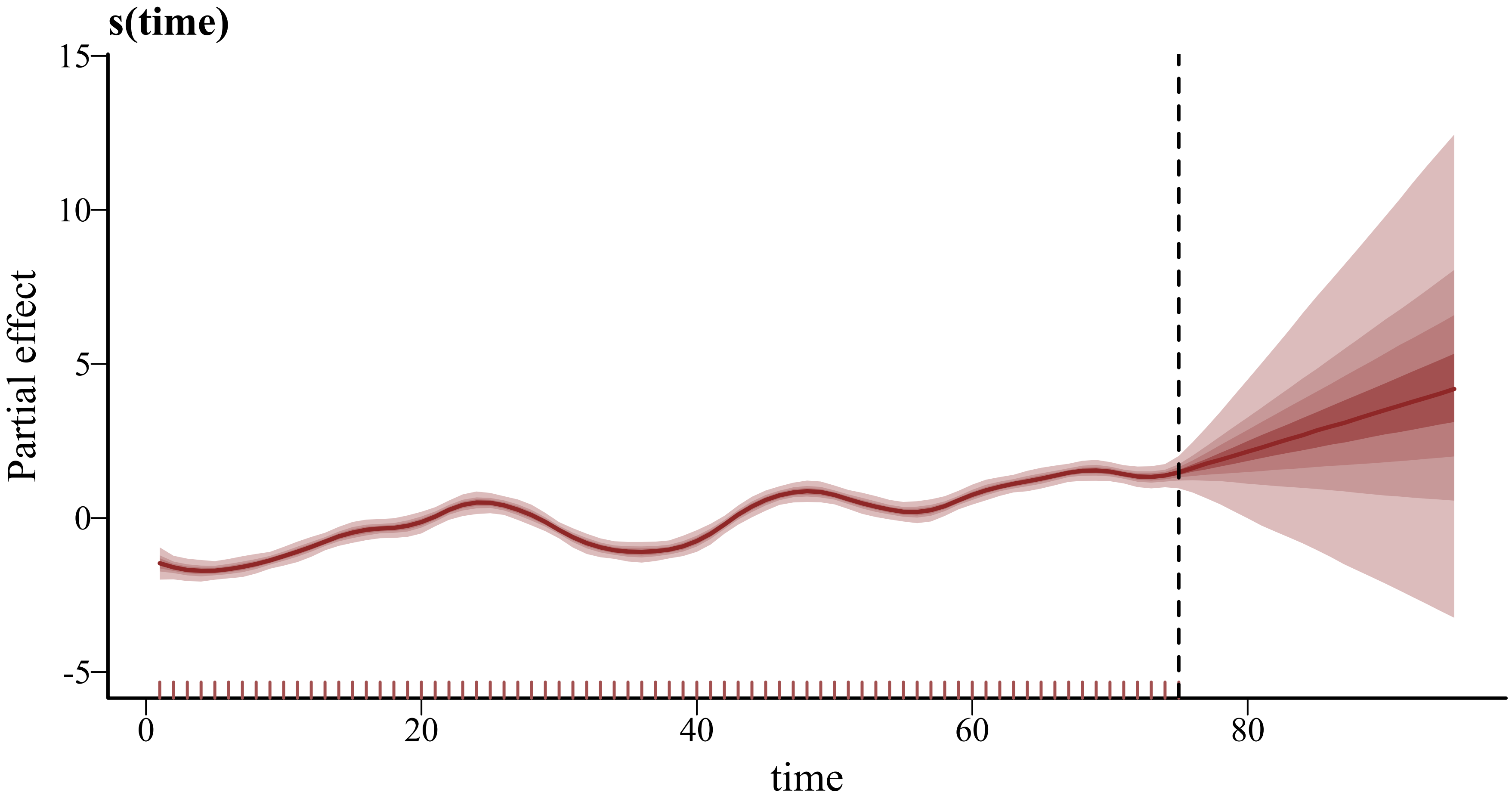
Extrapolate 2-steps ahead ☺



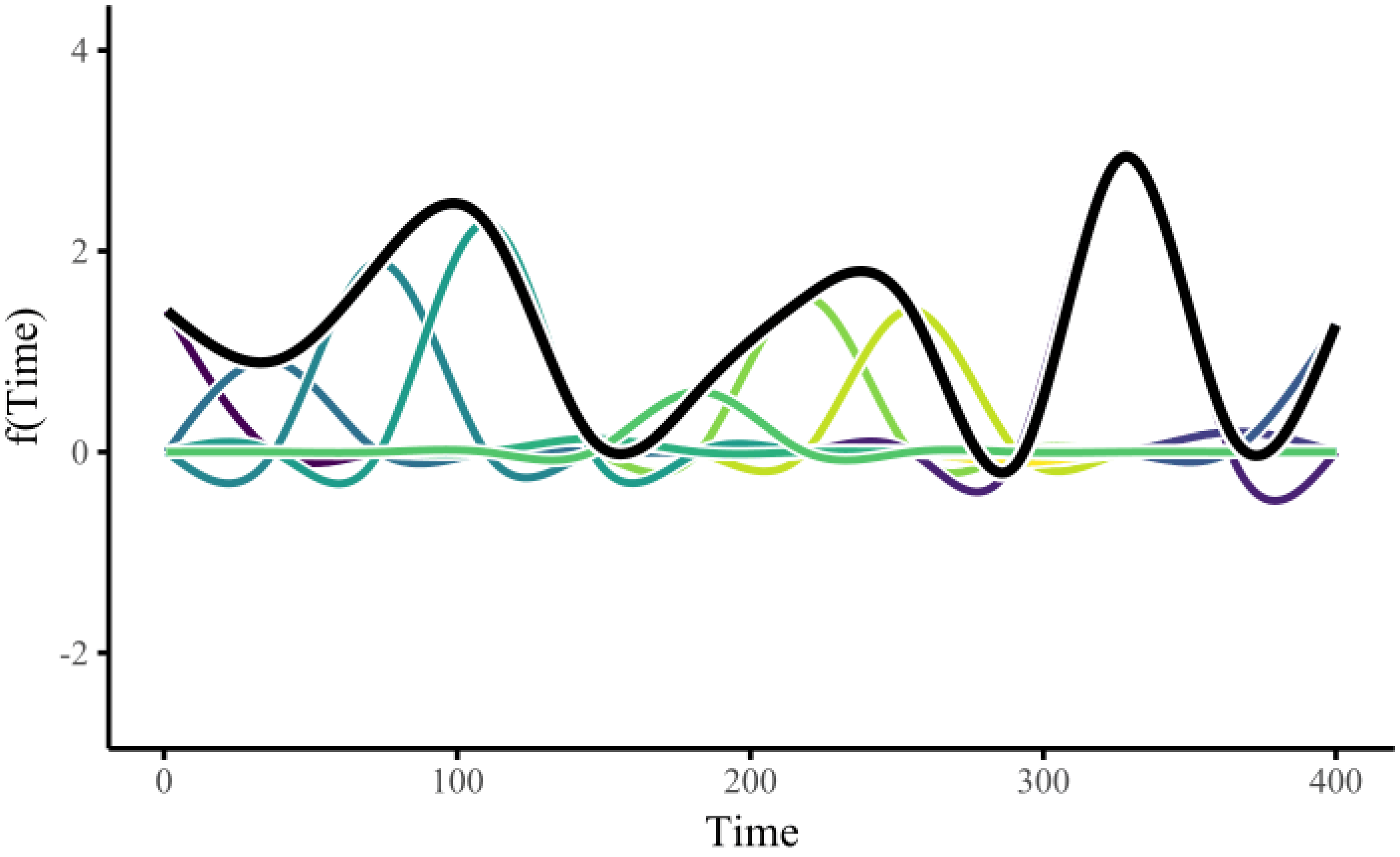
5-steps ahead ☹



20-steps ahead 😥



Basis functions ⇨ local knowledge



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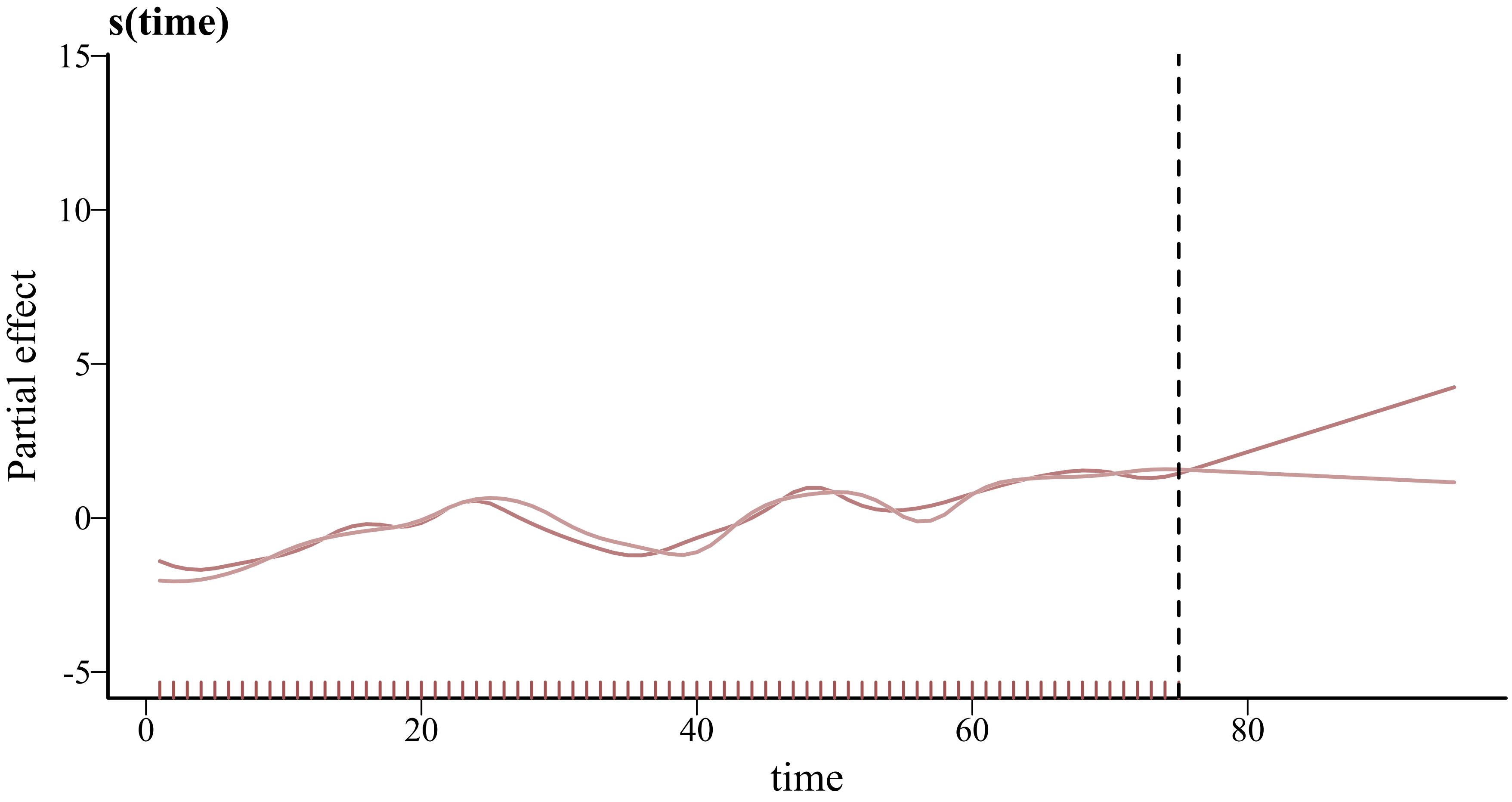

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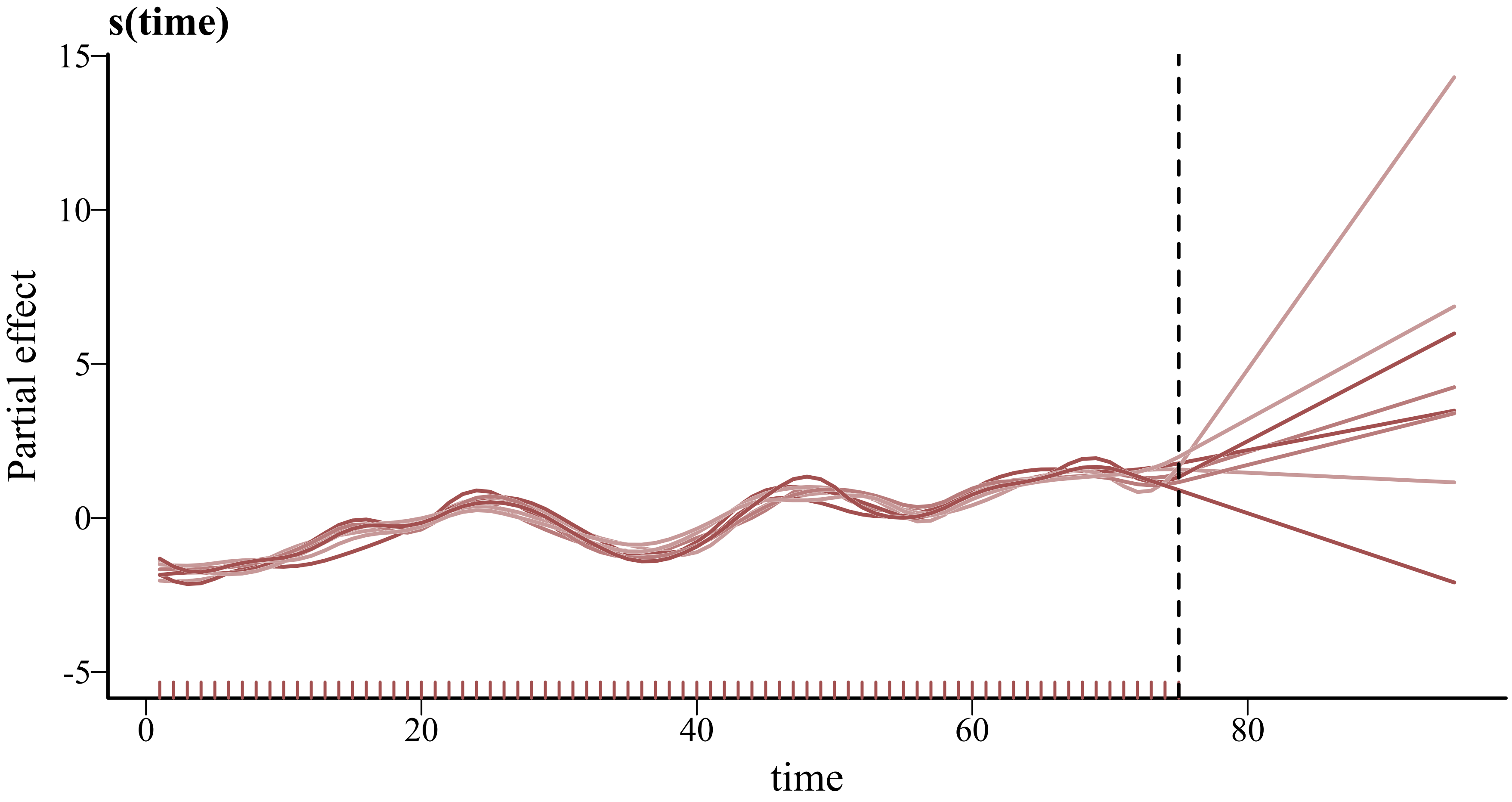

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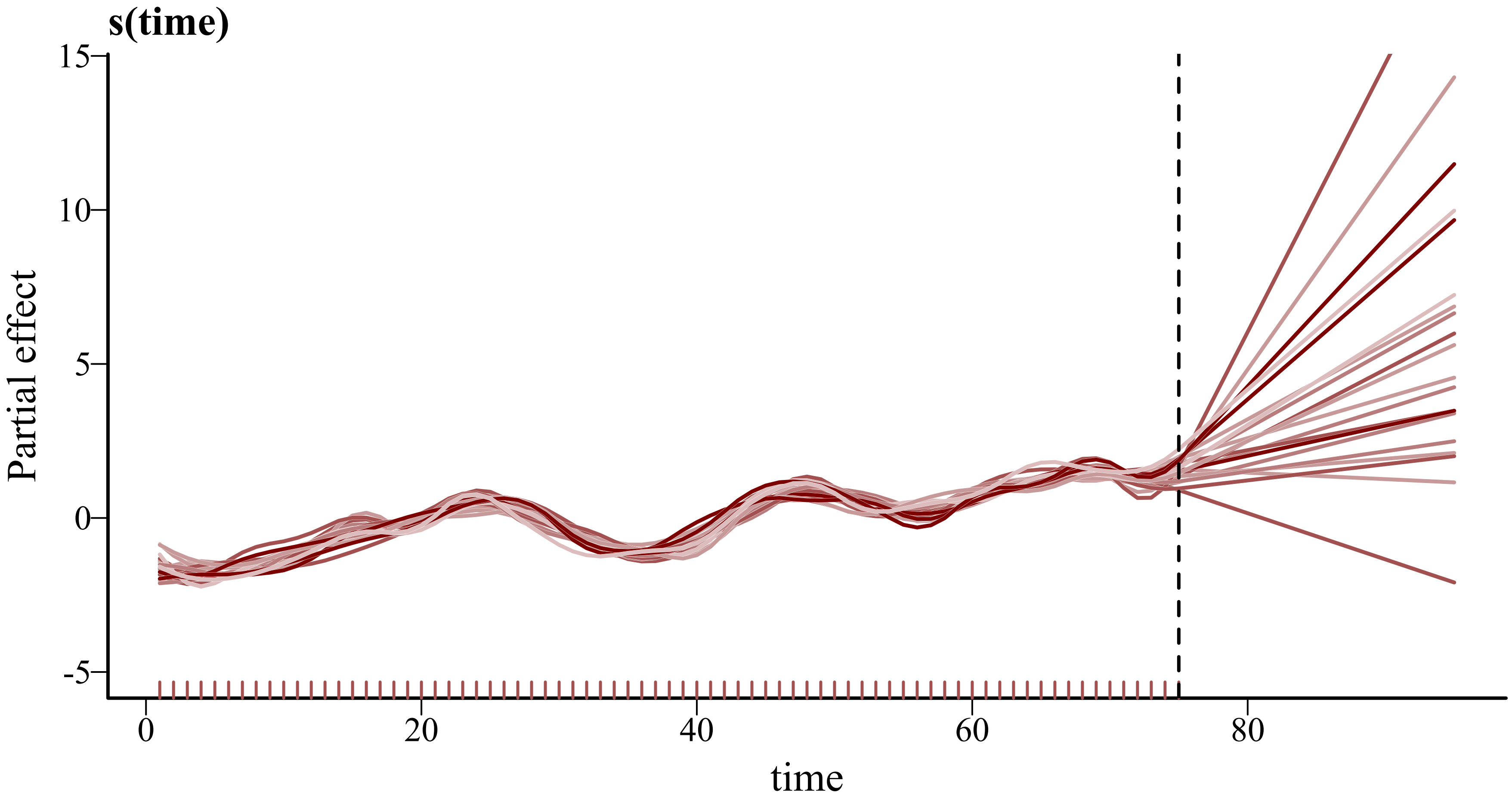
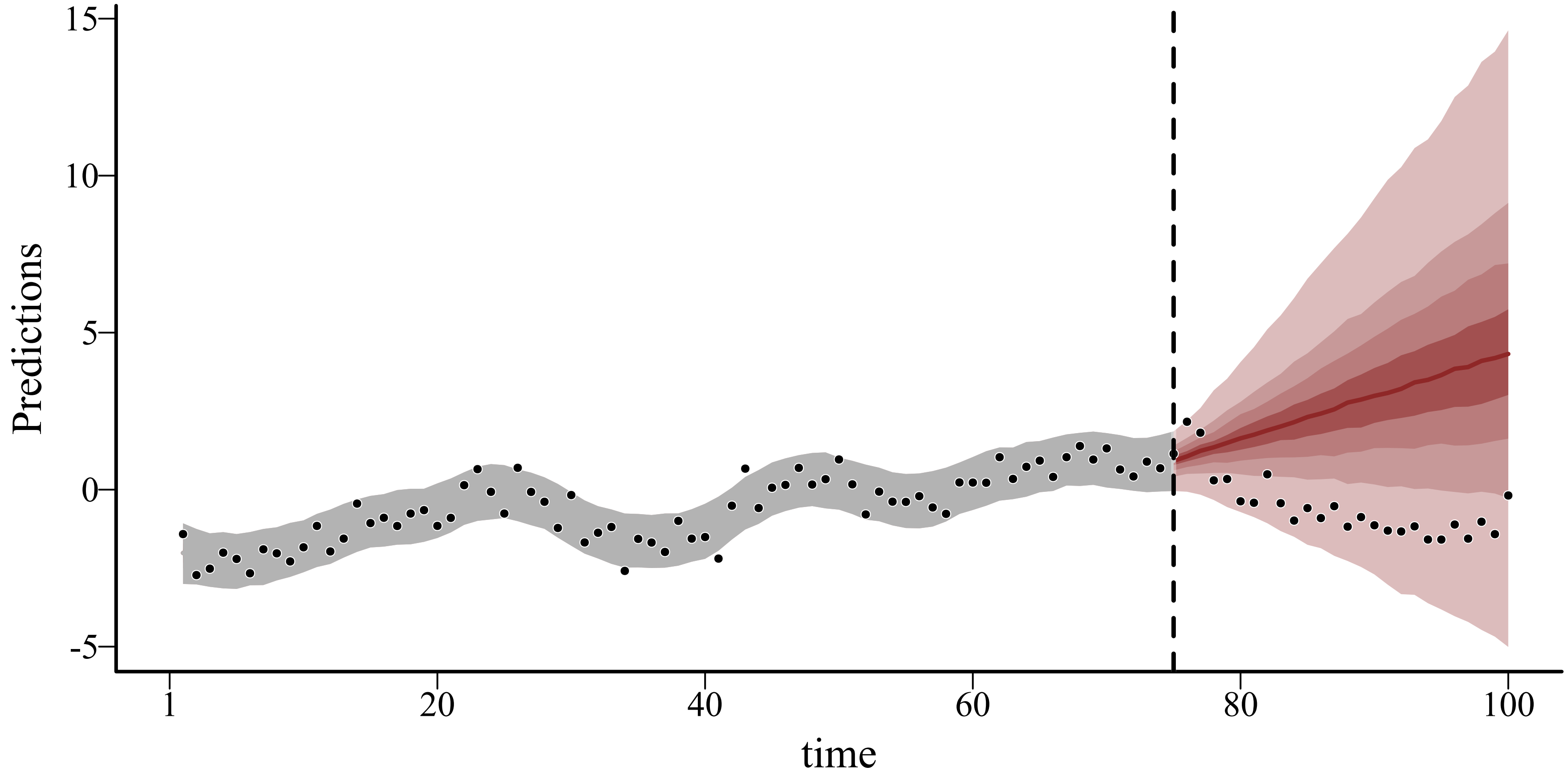
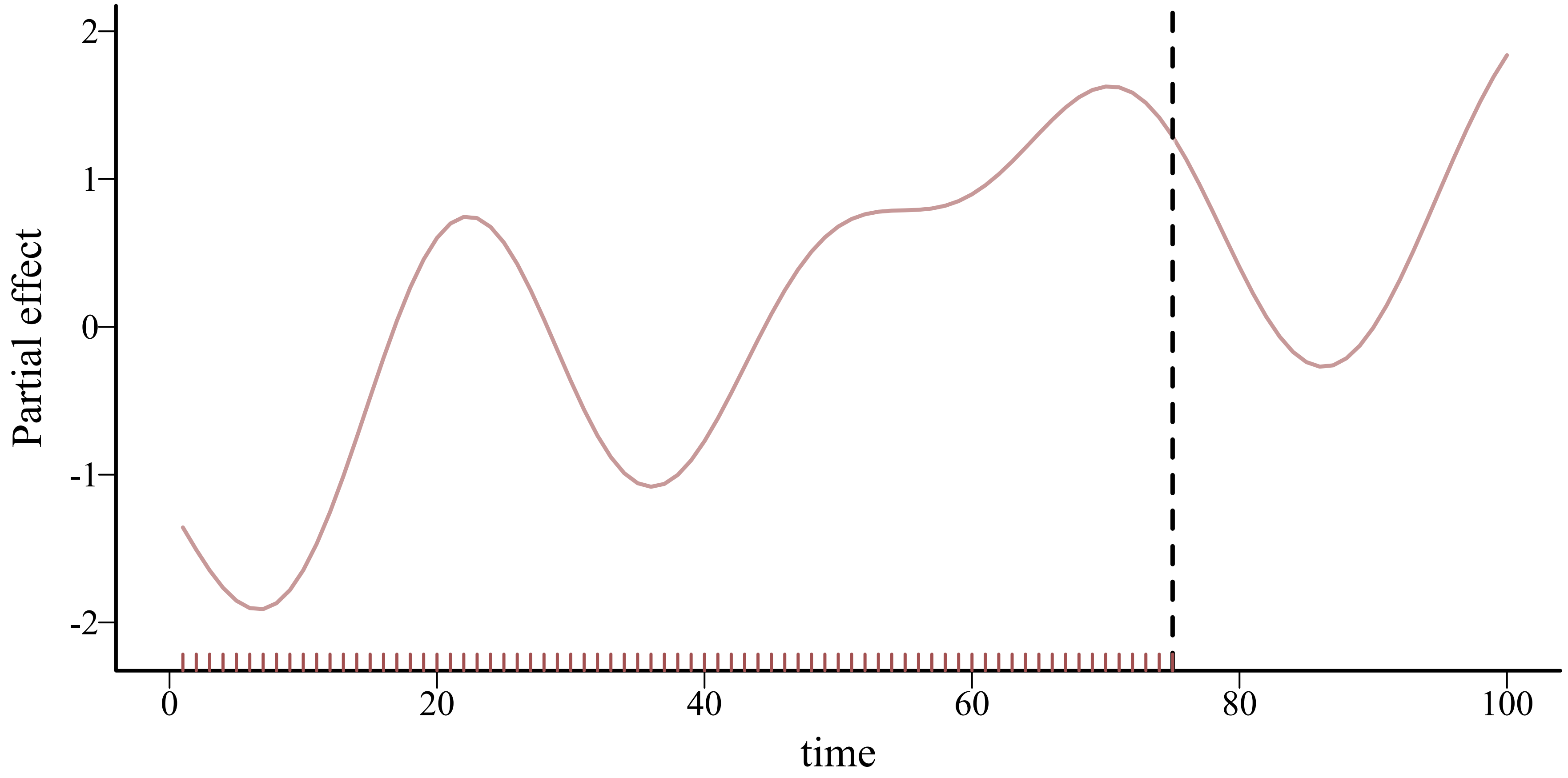


Forecasts 😨



We need *global knowledge*



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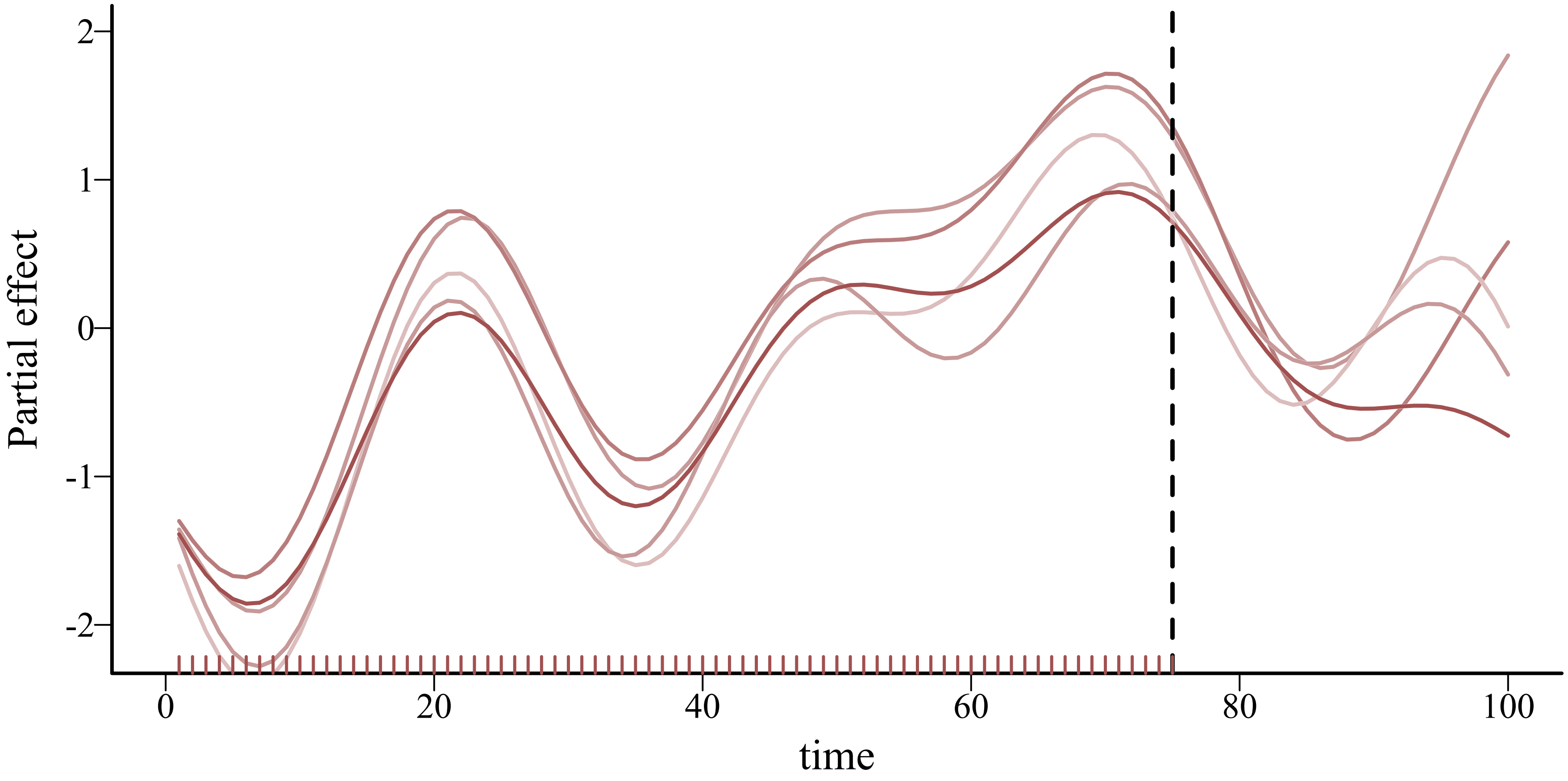

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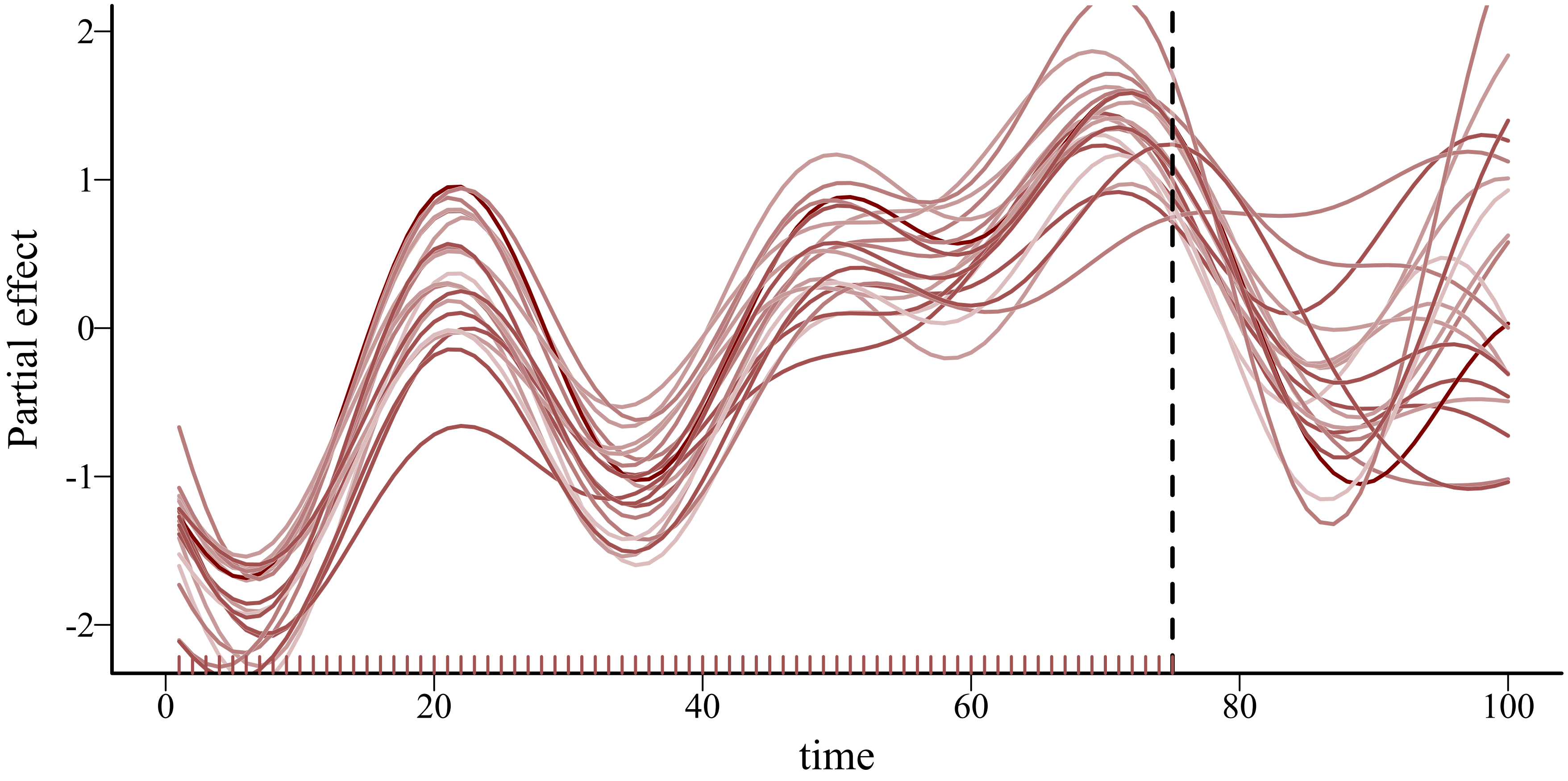

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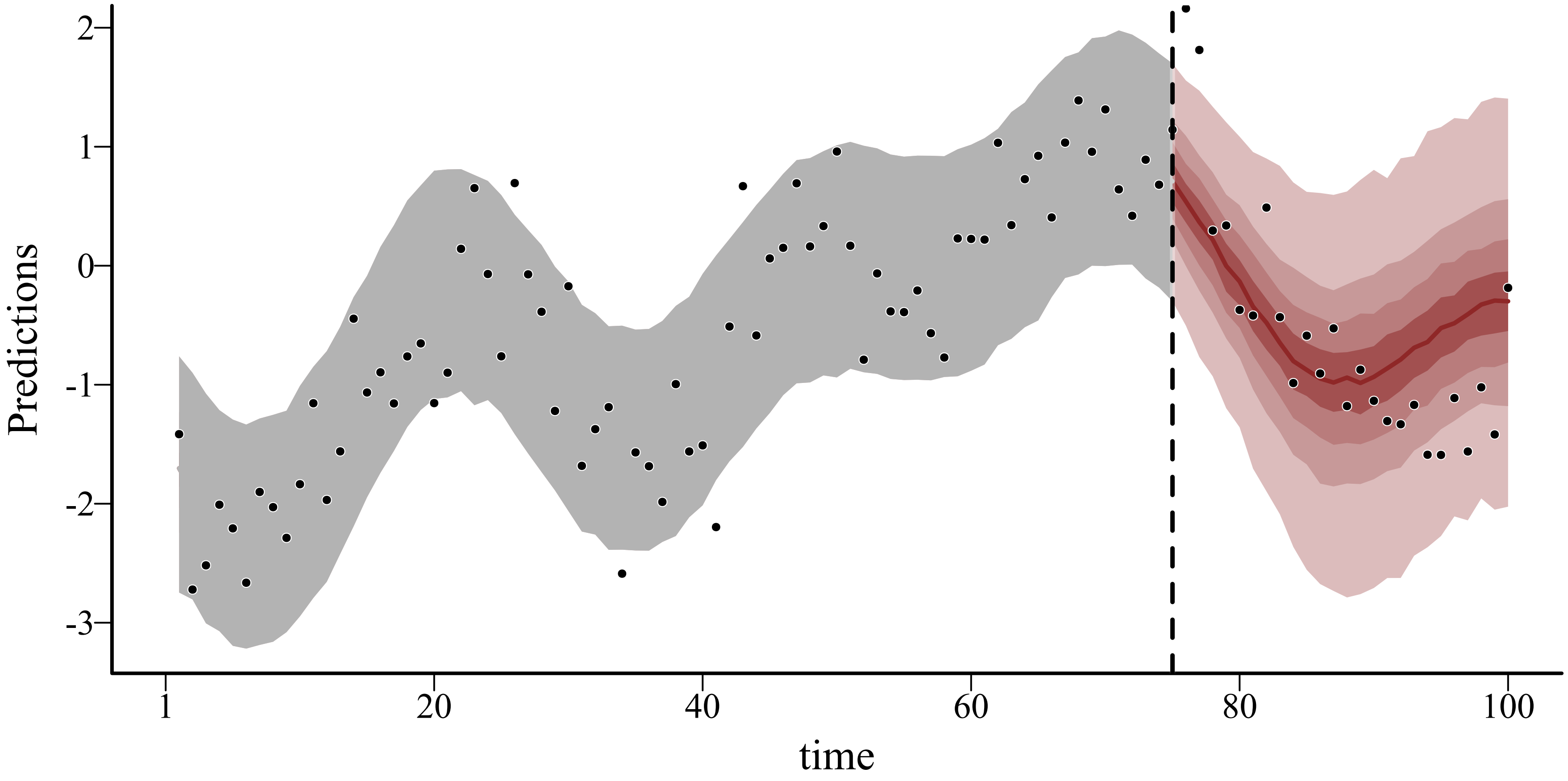


Dynamic GAMs

$$\mathbb{E}(\boldsymbol{Y_t}|\boldsymbol{X_t}) = g^{-1}(\alpha + \sum_{j=1}^{J} f(x_{jt}) + z_t)$$

Where:

g^{-1} is the inverse of the link function

α is the intercept

$f(x)$ are potentially nonlinear functions of the J predictors

z_t is a ***latent dynamic process***

Modelling with the `mvgam`

Bayesian framework to fit Dynamic GLMs and Dynamic GAMs

- Hierarchical intercepts, slopes and smooths
- Latent dynamic processes
- State-Space models with measurement error

Built off the `mgcv` to construct penalized smoothing splines

Convenient and familiar formula interface

Uni- or multivariate series from a range of response distributions

Uses Stan for efficient Hamiltonian Monte Carlo sampling

Observation families

`gaussian()`, `student-t()` ⇨ real values in $(-\infty, \infty)$

`lognormal()`, `Gamma()` ⇨ positive real values in $[0, \infty)$

`betar()` ⇨ real values (proportional) in $[0, 1]$

`poisson()`, `nb()` ⇨ non-negative integers in $(0, 1, 2, \ldots)$

Extended predictor effects

`s()` ⇨ Smoothing spline of one or more covariates

`s(bs = 're')` ⇨ Hierarchical slopes or intercepts

`te(), ti(), t2()` ⇨ Tensor product smoothing spline of two or more covariates

`gp()` ⇨ Gaussian Process function (with squared exponential kernel) of one covariate

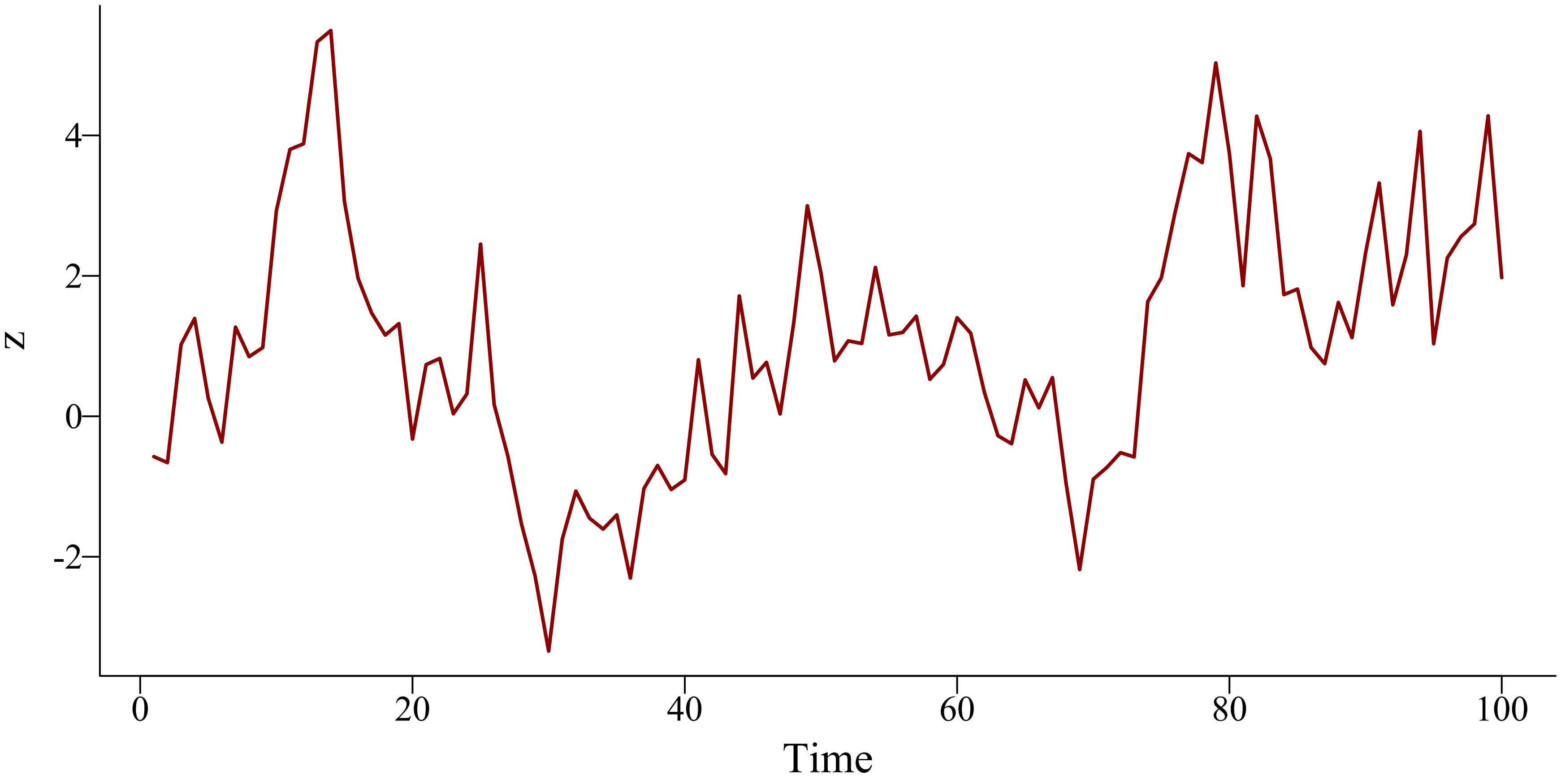
`dynamic()` ⇨ Time-varying effect of one covariate

We can fit models that include random effects, nonlinear effects and complex multidimensional smooth functions. All these effects can operate *on both process and observation models*

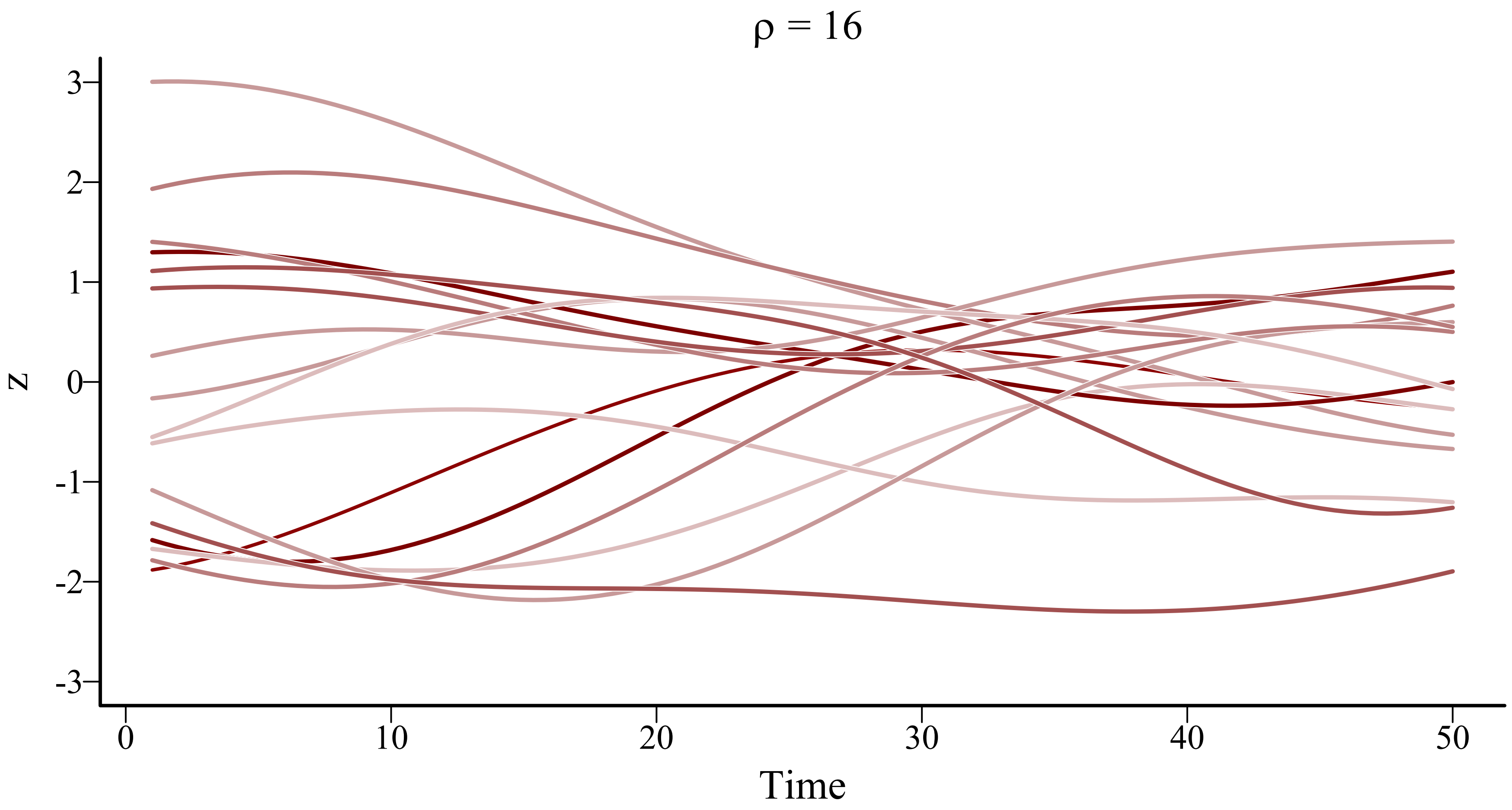
Can incorporate unobserved temporal dynamics; do not need to regress the outcome on its own past values

Very advantageous for ecological time series. But what kinds of dynamic processes are available in the `mvgam` 📦?

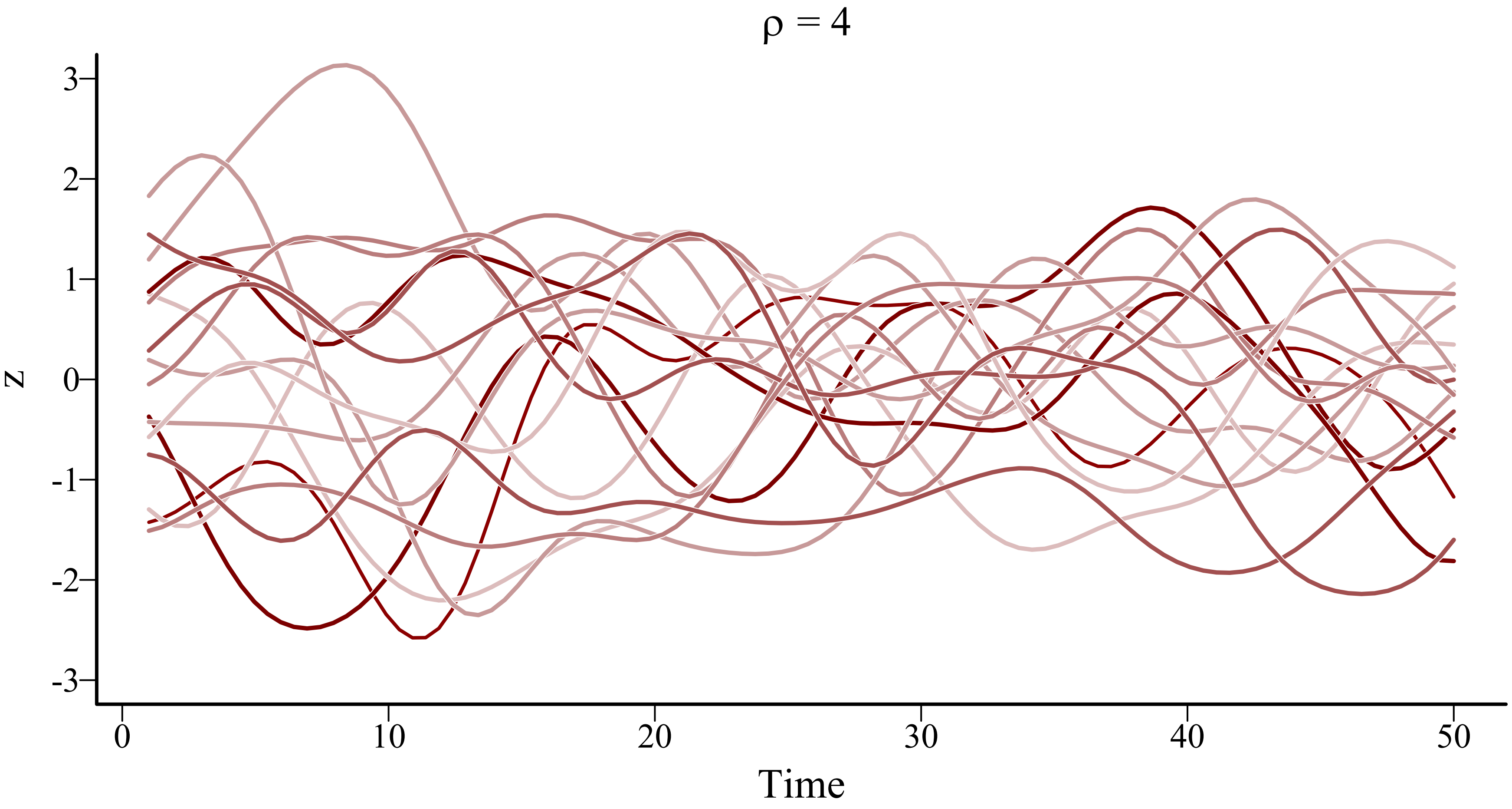
Random Walk or AR(1-3)



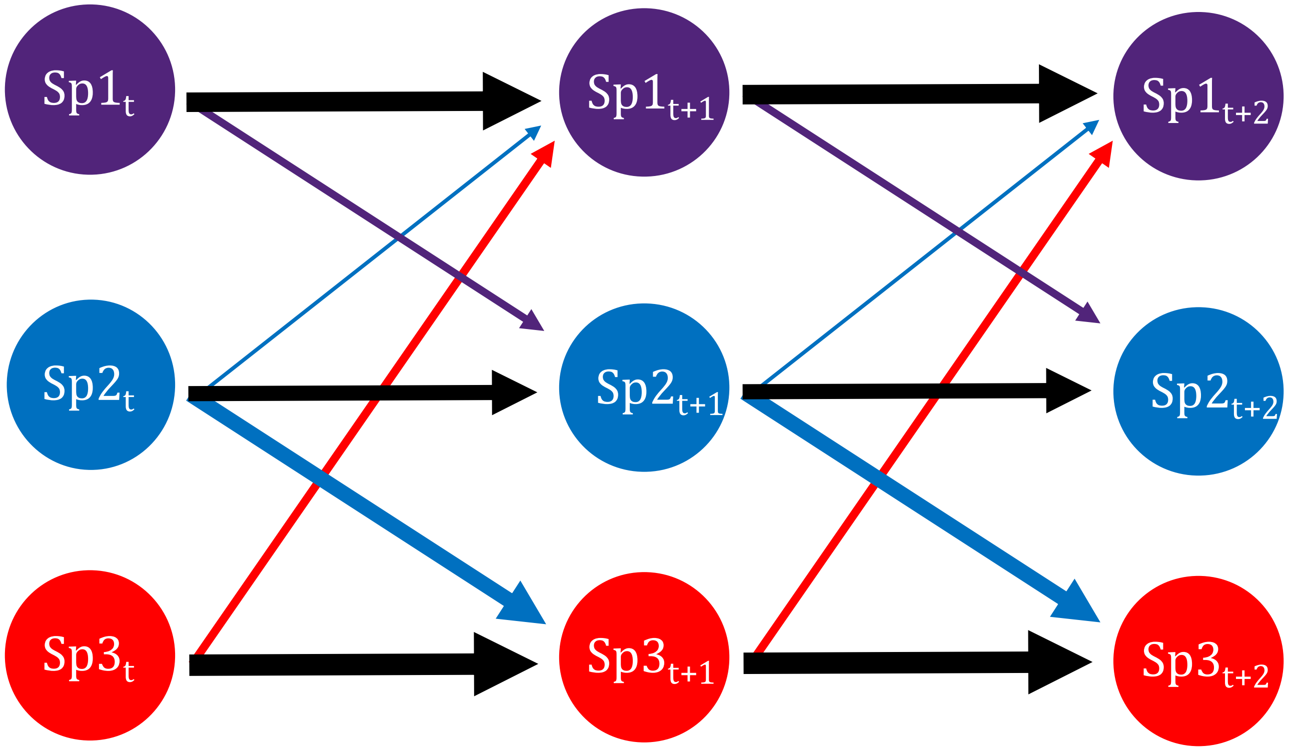
Gaussian Process...



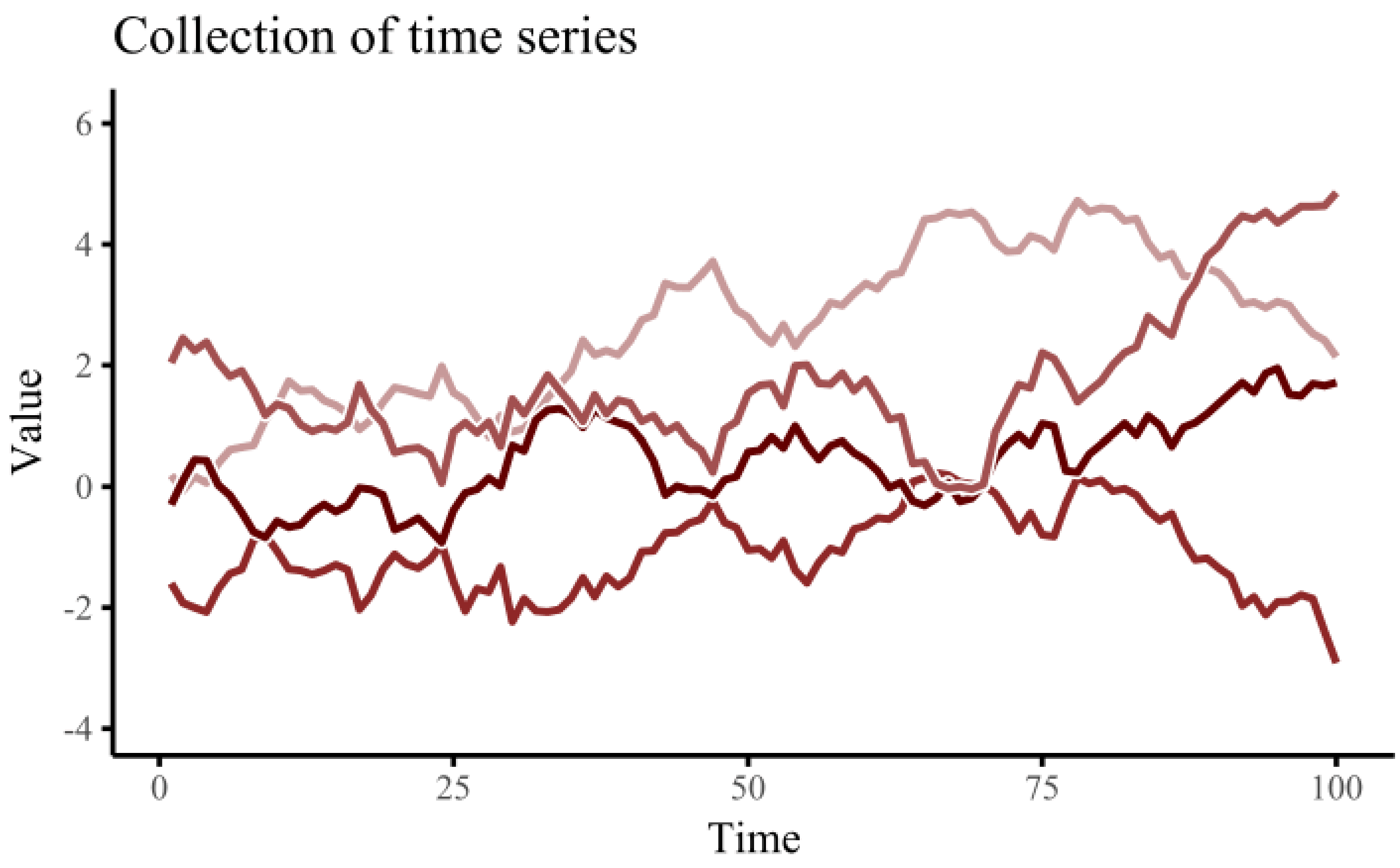
...where length scale ⇨ *memory*



VAR1 ⇨ Granger causality



Factors ⇨ induced correlations



Example of the interface

```r
model <- mvgam(
  formula = y ~
    s(series, bs = 're') +
    s(x0, series, bs = 're') +
    x1 +
    gp() +
    te(x3, x4, bs = c('cr', 'tp')),
  data = data,
  family = poisson(),
  trend_model = 'AR1',
  burnin = 500,
  samples = 500,
  chains = 4,
  parallel = TRUE
  )
```

Example data (long format)

y	series	time
2	species_1	1
0	species_2	1
NA	species_3	1
NA	species_4	1
1	species_1	2
0	species_2	2
3	species_3	2
5	species_4	2

Response (NAs allowed)

y	series	time
2	species_1	1
0	species_2	1
NA	species_3	1
NA	species_4	1
1	species_1	2
0	species_2	2
3	species_3	2
5	species_4	2

Series indicator (as `factor`)

y	series	time
2	species_1	1
0	species_2	1
NA	species_3	1
NA	species_4	1
1	species_1	2
0	species_2	2
3	species_3	2
5	species_4	2

Time indicator

y	series	time
2	species_1	1
0	species_2	1
NA	species_3	1
NA	species_4	1
1	species_1	2
0	species_2	2
3	species_3	2
5	species_4	2

Any other predictors

y	series	time	x0	x1	x2	x3	x4
2	species_1	1	-0.38	A	0.20	1.18	-0.72
0	species_2	1	-0.71	A	-2.67	1.02	0.67
NA	species_3	1	0.05	B	-0.33	0.12	1.50
NA	species_4	1	0.77	B	0.65	0.86	-0.49
1	species_1	2	0.29	A	-0.25	1.18	-0.82
0	species_2	2	0.34	A	-0.15	2.12	0.20
3	species_3	2	-0.38	B	-0.81	1.33	-1.15
5	species_4	2	1.32	B	0.22	-0.72	1.36

Types of `mvgam` predictions

$$\mathbb{E}(Y_t)$$

$$Y_t \sim \text{Poisson}(\lambda_t)$$

$$\log(\lambda_t) = \alpha + f(season)_t + z_t$$

type = ‘expected’

gives draws from the expected value of the posterior predictive distribution (i.e. the average of type = ‘response’)

In Poisson regression, this is the inverse of λ_t (i.e. $\exp(\lambda_t)$)

type = ‘response’

gives draws from a random Poisson distribution using λ_t

type = ‘link’

gives posterior draws from the linear predictor on the log scale

modified from Heiss 2022

Workflow in `mvgam` 📦

Fit models that can include nonlinear splines, GPs, and multivariate dynamic processes to ecological time series

Use posterior predictive checks and Randomized Quantile (Dunn-Smyth) residuals to assess model failures

Use `marginaleffects` 📦 to generate interpretable (and reportable) model predictions

Produce probabilistic forecasts

Evaluate forecasts from competing models with proper scoring rules

More resources

Vignette ⇨ Overview of the package

Vignette ⇨ Formatting data for use in `mvgam`

Vignette ⇨ Shared latent process models

Vignette ⇨ Time-varying effects

Vignette ⇨ Multivariate State-Space models

Motivating publication ⇨ Clark & Wells 2023 *Methods in Ecology and Evolution*