

# General information about GAMs

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## Model construction

### s (Both GAMs)

s = represent smooth function

```
gam(value ~s(date,...
```

### Define knots (Both GAMs)

k = knots. 12 month per year or 24 sampling event per year.

Seleccione 12 por Simpson, del siguiente enlace:

<https://fromthebottomoftheheap.net/2014/05/09/modelling-seasonal-data-with-gam/>

### bs= basis spline (Both GAMs)

bs= basis spline.

Smooth classes are invoked directly by s terms.

<https://stat.ethz.ch/R-manual/R-devel/library/mgcv/html/smooth.terms.html>

```
brms::brm(bf(value ~ s(date, bs="cs"...))
```

### Cubic regression splines & A cyclic cubic regression spline.

bs="cr". These have a cubic spline basis defined by a modest sized set of knots spread evenly through the covariate values.

bs="cs" specifies a shrinkage version of "cr".

bs="cc" specifies a cyclic cubic regression splines. i.e. a penalized cubic regression splines whose ends match, up to second derivative.

### P-splines

bs="ps".

**bf (Bayesian GAMs)** Note that we use the bf() argument to specify this nonlinear model.

## Output

Hay que ver el Smooth Terms: `-> sds(sdate_1) -> sds(stimes_1)` is the variance parameter, which has the effect of controlling the wiggleness of the smooth - the larger this value the more wiggly the smooth. <https://fromthebottomoftheheap.net/2018/04/21/fitting-gams-with-brms/>

## Check models

### `pp_check()`

The `pp_check` allows for graphical posterior predictive checking. We can generate figures to compare the observed data to simulated data from the posterior predictive distribution. This is a great graphical way to evaluate your model.

[https://tem11010.github.io/regression\\_brms/](https://tem11010.github.io/regression_brms/)

Here, `nsamples` refers to the number of draws from the posterior distribution to use to calculate `yrep` values.

```
pp_check(model, nsamples=100)
```

### `bayes_r2`

Bayes R<sup>2</sup> quantifies the expected fit or variance explained by a model

We can also get an R-squared estimate for our model, thanks to a newly-developed method from Andrew Gelman, Ben Goodrich, Jonah Gabry and Imad Ali, with an explanation here. [http://www.stat.columbia.edu/~gelman/research/unpublished/bayes\\_R2.pdf](http://www.stat.columbia.edu/~gelman/research/unpublished/bayes_R2.pdf) [https://tem11010.github.io/regression\\_brms/](https://tem11010.github.io/regression_brms/)

`r2(cc.qp_A.Bayes_mod)` Existe esta otra, pero usare la de Gelman

```
bayes_R2(model)
```

## AIC

AIC and DIC are not recommended in particular not with Bayesian models. So it is not necessarily surprising that the results differ (buerkner).

<https://discourse.mc-stan.org/t/waic-aicc-and-dic-differences-in-a-bernoulli-glmm-in-brms-vs-glmmtnb/5966>