

taxonomy richness

2025-11-19

Load data

```
laselva <- read_excel("laselva.xlsx", sheet = "alldata")
```

Convert Date to proper Date object

```
laselva$Date <- dmy(paste0("01-", laselva$Date)) # e.g., "Jan-1997" -> "1997-01-01"
```

Extract Year and Month index

```
laselva$Year <- year(laselva$Date)
laselva$Month_idx <- month(laselva$Date)
head(laselva, 13)
```

```
## # A tibble: 13 x 13
##   stream Months Date      variable  value ONI_First  SOI ENSO temp_min
##   <chr>   <dbl> <date>    <chr>    <dbl>    <dbl> <dbl> <dbl>   <dbl>
## 1 carapa     1 1997-01-01 total_rich  31     -0.36  0.8 -0.72   20.2
## 2 carapa     2 1997-02-01 total_rich  20     -0.1   2.9 -0.3    19.6
## 3 carapa     3 1997-03-01 total_rich  18      0.28 -0.7  0.15   21.1
## 4 carapa     4 1997-04-01 total_rich  31      0.75 -1    0.71   20.5
## 5 carapa     5 1997-05-01 total_rich  22      1.22 -2.2  2.34   21.6
## 6 carapa     6 1997-06-01 total_rich  23      1.6  -2.3  2.26   22.7
## 7 carapa     7 1997-07-01 total_rich  27      1.9  -1.2  2.26   22.6
## 8 carapa     8 1997-08-01 total_rich  23      2.14 -2.4  2.2    23.4
## 9 carapa     9 1997-09-01 total_rich  23      2.33 -2.4  2.06   22.8
## 10 carapa    10 1997-10-01 total_rich  22      2.4  -2.4  2.14   22.7
## 11 carapa    11 1997-11-01 total_rich  17      2.39 -2    2.11   22.9
## 12 carapa    12 1997-12-01 total_rich  17      2.24 -1.6  2.3    22.5
## 13 carapa    13 1998-01-01 total_rich  32      1.93 -4.4  2.45   20.8
## # i 4 more variables: rain_51 <dbl>, rain_1.4 <dbl>, Year <dbl>,
## #   Month_idx <dbl>
```

Subset months (Feb, May, Sep) and remove 2024

```
laselva <- laselva[laselva$Month_idx %in% c(2,5,9) &
  laselva$Year != 2024, ]
head(laselva, 13)
```

```
## # A tibble: 13 x 13
##   stream Months Date      variable  value ONI_First  SOI ENSO temp_min
##   <chr>   <dbl> <date>    <chr>    <dbl>    <dbl> <dbl> <dbl>   <dbl>
## 1 carapa     2 1997-02-01 total_rich  20     -0.1   2.9 -0.3    19.6
## 2 carapa     5 1997-05-01 total_rich  22      1.22 -2.2  2.34   21.6
```

```
## 3 carapa      9 1997-09-01 total_rich 23      2.33 -2.4 2.06      22.8
## 4 carapa     14 1998-02-01 total_rich 24      1.44 -3.4 2.27      21.1
## 5 carapa     17 1998-05-01 total_rich 18     -0.13  0.4 0.42      22.3
## 6 carapa     21 1998-09-01 total_rich 25     -1.35  1.7 -1.29     22.5
## 7 carapa     26 1999-02-01 total_rich 21     -1.07  1.6 -1.15     20.3
## 8 carapa     29 1999-05-01 total_rich 23     -1.04  0.4 -1.26     21.7
## 9 carapa     33 1999-09-01 total_rich 41     -1.26 -0.1 -1.33     22.0
## 10 carapa    38 2000-02-01 total_rich 21     -1.07  2.7 -1.37     20.1
## 11 carapa    41 2000-05-01 total_rich 27     -0.64  0.6 -1.18     21.3
## 12 carapa    45 2000-09-01 total_rich 15     -0.63  1.4 -0.52     22.5
## 13 carapa    50 2001-02-01 total_rich 12     -0.44  2.8 -0.78     19.5
## # i 4 more variables: rain_51 <dbl>, rain_1.4 <dbl>, Year <dbl>,
## #   Month_idx <dbl>
```

```
tail(laselve,13)
```

```
## # A tibble: 13 x 13
##   stream Months Date      variable  value ONI_First  SOI  ENSO temp_min
##   <chr>   <dbl> <date>    <chr>    <dbl>    <dbl> <dbl> <dbl>    <dbl>
## 1 saltito   185 2012-05-01 total_rich    5   -0.01  0.1 -0.28    21.8
## 2 saltito   189 2012-09-01 total_rich   14    0.27  0.4 -0.19    22.3
## 3 saltito   194 2013-02-01 total_rich    5   -0.34 -0.4 -0.12    20.2
## 4 saltito   197 2013-05-01 total_rich    7   -0.41  1.3 -1.14    21.5
## 5 saltito   201 2013-09-01 total_rich   12   -0.18  0.5 -0.13    22.1
## 6 saltito   206 2014-02-01 total_rich    5   -0.27  0.1 -0.05    19.7
## 7 saltito   209 2014-05-01 total_rich    6    0.16  0.9  0      22.2
## 8 saltito   218 2015-02-01 total_rich    3    0.53  0.4  0.15    20.6
## 9 saltito   221 2015-05-01 total_rich    5    1.18 -1.2  1.9     22.7
## 10 saltito  225 2015-09-01 total_rich    3    2.42 -2.7  2.15    22.6
## 11 saltito  230 2016-02-01 total_rich    7    1.58 -3.2  1.32    20.3
## 12 saltito  233 2016-05-01 total_rich    4   -0.07  0.7  0.36    22.7
## 13 saltito  237 2016-09-01 total_rich    6   -0.69  2    -0.54    22.5
## # i 4 more variables: rain_51 <dbl>, rain_1.4 <dbl>, Year <dbl>,
## #   Month_idx <dbl>
```

Make stream a factor

```
laselve$stream <- factor(laselve$stream)
```

Create factor for AR1 (unique time points)

- Date (class Date) no funciona directamente en el AR1 de glmmTMB

```
laselve$time_f <- factor(laselve$Date,
                        levels = sort(unique(laselve$Date)))
head(laselve,13)
```

```
## # A tibble: 13 x 14
##   stream Months Date      variable  value ONI_First  SOI  ENSO temp_min
##   <fct>   <dbl> <date>    <chr>    <dbl>    <dbl> <dbl> <dbl>    <dbl>
## 1 carapa      2 1997-02-01 total_rich    20   -0.1  2.9 -0.3     19.6
## 2 carapa      5 1997-05-01 total_rich    22    1.22 -2.2  2.34     21.6
## 3 carapa      9 1997-09-01 total_rich    23    2.33 -2.4  2.06     22.8
## 4 carapa     14 1998-02-01 total_rich    24    1.44 -3.4  2.27     21.1
## 5 carapa     17 1998-05-01 total_rich    18   -0.13  0.4  0.42     22.3
```

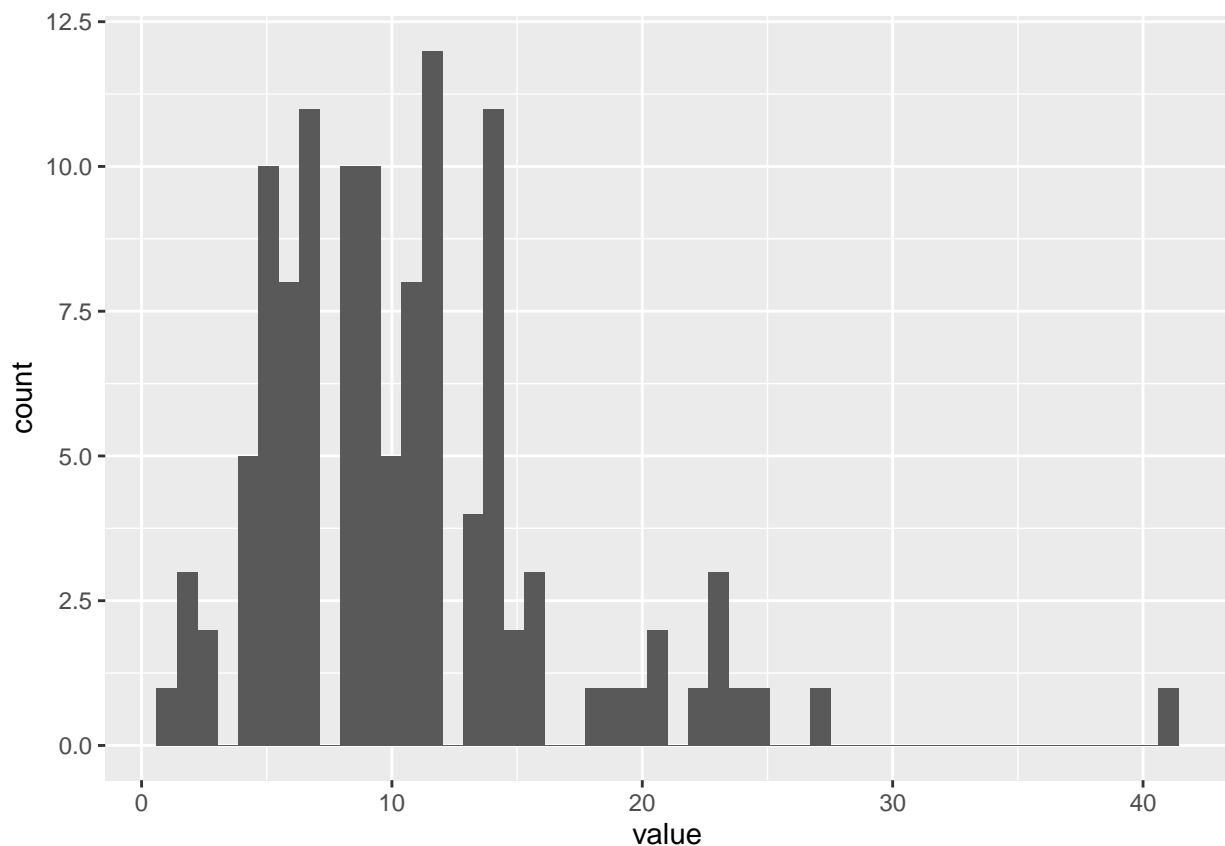
```
## 6 carapa      21 1998-09-01 total_rich    25      -1.35    1.7 -1.29    22.5
## 7 carapa      26 1999-02-01 total_rich    21      -1.07    1.6 -1.15    20.3
## 8 carapa      29 1999-05-01 total_rich    23      -1.04    0.4 -1.26    21.7
## 9 carapa      33 1999-09-01 total_rich    41      -1.26   -0.1 -1.33    22.0
## 10 carapa     38 2000-02-01 total_rich    21      -1.07    2.7 -1.37    20.1
## 11 carapa     41 2000-05-01 total_rich    27      -0.64    0.6 -1.18    21.3
## 12 carapa     45 2000-09-01 total_rich    15      -0.63    1.4 -0.52    22.5
## 13 carapa     50 2001-02-01 total_rich    12      -0.44    2.8 -0.78    19.5
## # i 5 more variables: rain_51 <dbl>, rain_1.4 <dbl>, Year <dbl>,
## #   Month_idx <dbl>, time_f <fct>
```

Quick summary

```
summary(laselve$value)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       1.0      7.0      9.0    10.6    13.0    41.0
```

```
ggplot(laselve, aes(value)) +
  geom_histogram(bins = 50)
```



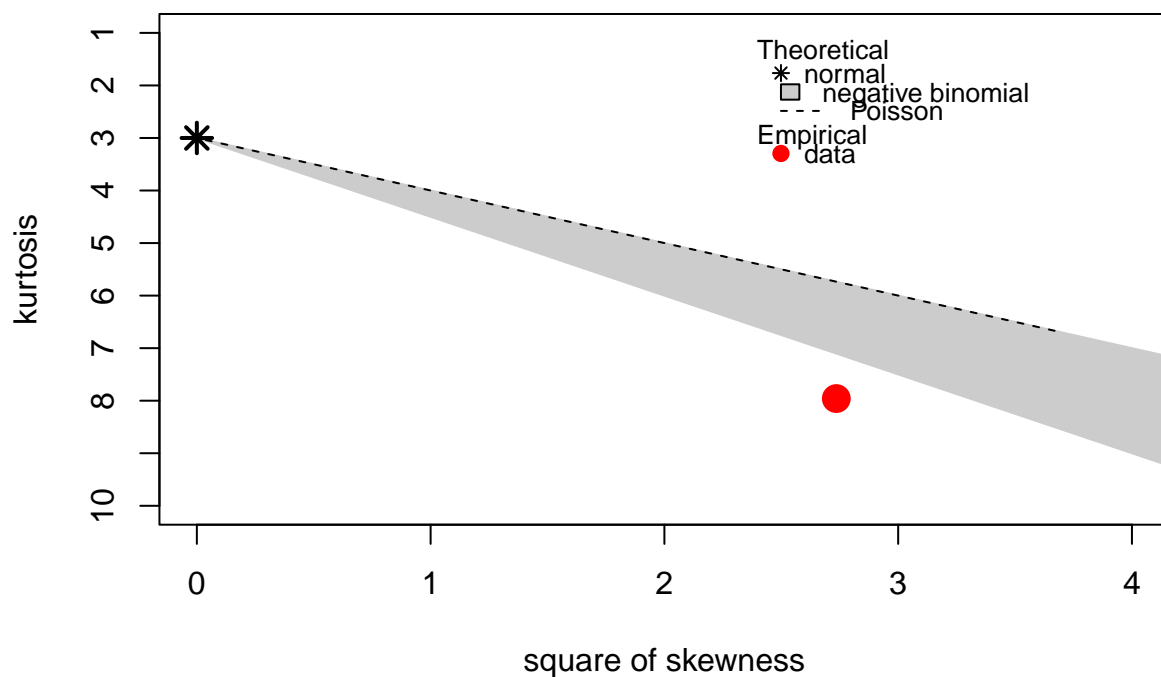
Distribution check

- We checked the distribution of the count variable (value) using `fitdistrplus::descdist()`.
- The summary shows:
 - Mean = 10.6
 - Variance (SD²) = 6.04² = 36.48

- So variance » mean
- Since the variance was much larger than the mean (variance » mean), **the data violated the Poisson assumption of mean = variance**. This level of overdispersion is typical of ecological count data, and **therefore a negative binomial** model provides a more appropriate and flexible error structure for the analysis.
- https://cran.r-project.org/web/packages/GlmSimulator/vignettes/count_data_and_overdispersion.html
- https://pacificpapermill.com/slideshows/PPM_Poisson_Regression.pdf

```
fitdistrplus::descdist(laselve$value, discrete = TRUE)
```

Cullen and Frey graph



```
## summary statistics
## -----
## min: 1    max: 41
## median: 9
## mean: 10.60169
## estimated sd: 6.041367
## estimated skewness: 1.653916
## estimated kurtosis: 7.959617
```

Fit negative binomial GLMM

- We use a negative binomial distribution because 'value' is **overdispersed count data**.
 - (variance » mean, assessed with `fitdistrplus::descdist()`).
- `glmmTMB` is ideal because it accommodates overdispersion, random effects, and correlation structures.

```

laselva <- laselva %>%
  group_by(stream) %>%
  arrange(Months, .by_group = TRUE) %>%
  mutate(time_factor = factor(row_number())) %>%
  ungroup()

# Ajustar el modelo AR1 usando time_factor
mod1 <- glmmTMB(
  value ~ ONI_First + SOI + ENSO + temp_min + rain_51 + stream +
    ar1(time_factor + 0 | stream), # AR1 por stream
  family = nbinom2,
  data = laselva
)

summary(mod1)

## Family: nbinom2 ( log )
## Formula:
## value ~ ONI_First + SOI + ENSO + temp_min + rain_51 + stream +
##       ar1(time_factor + 0 | stream)
## Data: laselva
##
##      AIC      BIC    logLik -2*log(L)  df.resid
##    655.0    682.7   -317.5    635.0      108
##
## Random effects:
##
## Conditional model:
##   Groups Name      Variance Std.Dev. Corr
##   stream time_factor1 0.2374   0.4872   0.96 (ar1)
## Number of obs: 118, groups:  stream, 2
##
## Dispersion parameter for nbinom2 family (): 5.7e+08
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   2.63522    0.76634   3.439 0.000584 ***
## ONI_First      0.04275    0.10472   0.408 0.683066
## SOI            -0.03227    0.02875  -1.122 0.261717
## ENSO           -0.09092    0.10314  -0.881 0.378072
## temp_min       -0.01040    0.03223  -0.323 0.747013
## rain_51        -0.02336    0.02126  -1.099 0.271764
## streamsaltito -0.10427    0.47642  -0.219 0.826752
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Results and limitations of the AR1 model

- The AR1 model fits but shows an unrealistically large dispersion parameter (5.7×10^8), and **AR1** assumptions are questionable because sampling was quarterly and not equally spaced across the year.

Why AR1 is not ideal here?

- Temporal spacing is irregular:
 - Feb → May → Sep → (next Feb)
 - **AR1 assumes constant t (equally spaced time steps). When spacing is uneven, AR1 overestimates correlation and produces unstable estimates (REFERENCE).**
- Only three sampling points per year.
 - AR1 needs longer, regularly sampled time series to be statistically meaningful.
- Each year begins again at “time = 1” This breaks the AR1 chain, making the correlation structure artificial. AR1 assumes uniform time steps and a continuous series, which is not the case here.

More appropriate alternative: Random intercept for Year

```
mod2 <- glmmTMB(
  value ~ ONI_First + SOI + ENSO + temp_min + rain_51 + stream +
    (1 | Year), # random intercept for Year
  family = nbinom2,
  data = laselva
)

summary(mod2)

## Family: nbinom2 ( log )
## Formula:
## value ~ ONI_First + SOI + ENSO + temp_min + rain_51 + stream +      (1 | Year)
## Data: laselva
##
##          AIC          BIC      logLik -2*log(L)  df.resid
##        697.1         722.1     -339.6      679.1       109
##
## Random effects:
##
## Conditional model:
##   Groups Name      Variance Std.Dev.
##   Year  (Intercept) 0.1448   0.3806
## Number of obs: 118, groups: Year, 20
##
## Dispersion parameter for nbinom2 family (): 21.8
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   2.75566    0.81828   3.368 0.000758 ***
## ONI_First     -0.05673    0.13726  -0.413 0.679381
## SOI           -0.04780    0.03880  -1.232 0.217946
## ENSO          -0.01627    0.12659  -0.129 0.897717
## temp_min      -0.01874    0.03813  -0.492 0.623032
## rain_51       -0.01892    0.02759  -0.686 0.492801
## streamsaltito -0.08103    0.07087  -1.143 0.252870
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Why model2 is more appropriate

- 1) Accounts for repeated measures / grouped structure

- Multiple observations occur within each year, and those observations are not independent.
- 2) Captures unmeasured annual variation
- Each year may differ due to unrecorded events (storms, droughts).
 - The random intercept lets each year shift the baseline taxon_rich/abundance/...
- 3) Controls temporal dependence indirectly
- **Quarterly sampling is not evenly spaced, so classical AR1 is inappropriate.**
 - A random intercept groups observations within each year so that measurements taken in the same year are more similar to each other than to those from other years, partially accounting for temporal autocorrelation without misusing an AR1 structure.

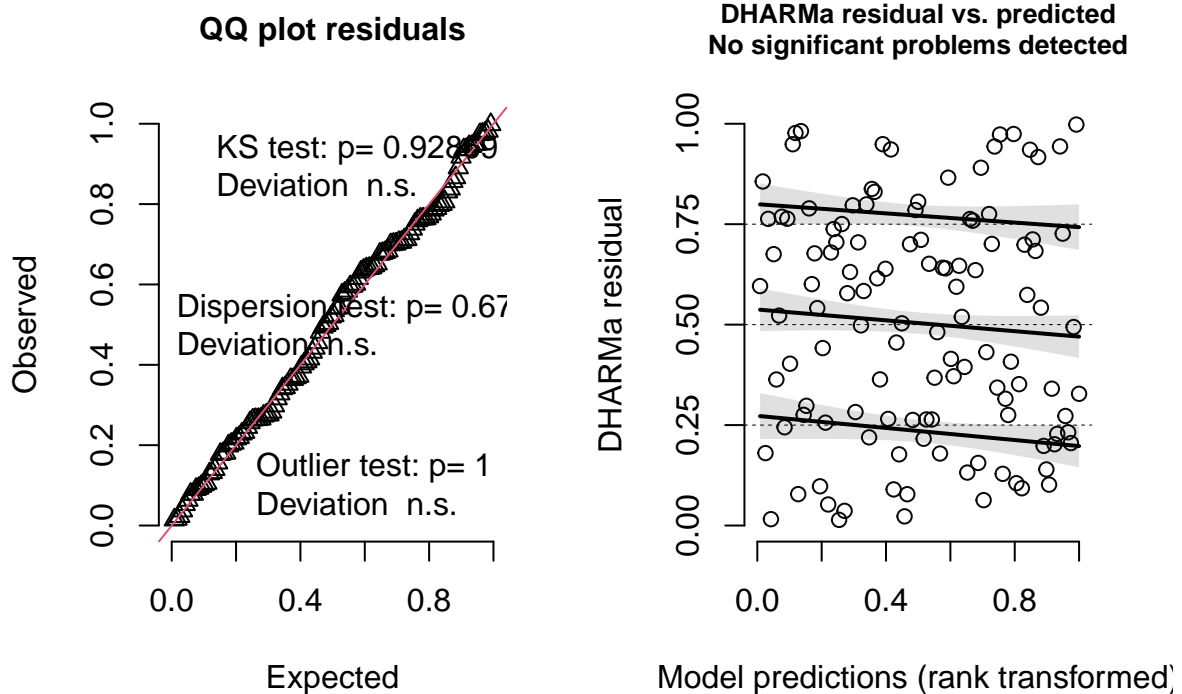
Residuals diagnostics

```
res <- simulateResiduals(mod2, n = 1000)
```

plots Residuals

```
plot(res)
```

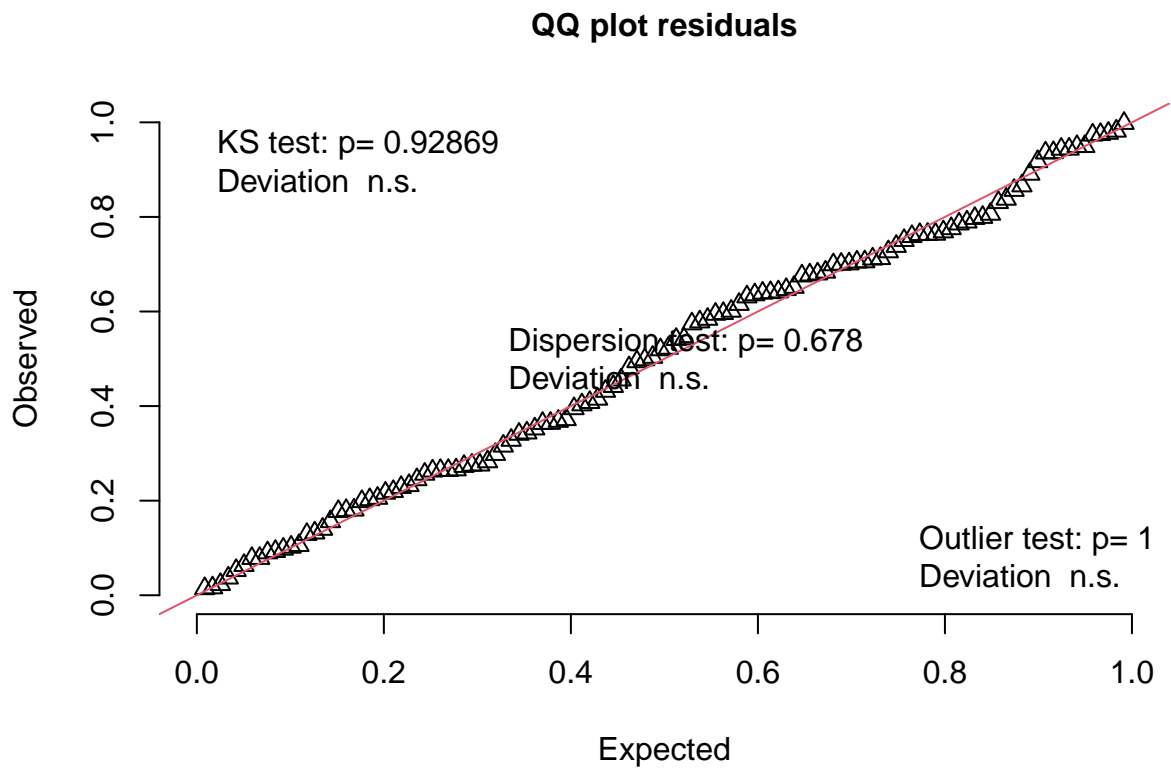
DHARMA residual



Uniformity test

- The Kolmogorov–Smirnov test on the DHARMA scaled residuals shows no deviation from the expected uniform distribution ($D = 0.050$, $p = 0.929$). **This indicates that the model's residuals are well behaved and that there is no evidence of major distributional misspecification.**

```
testUniformity(res)
```



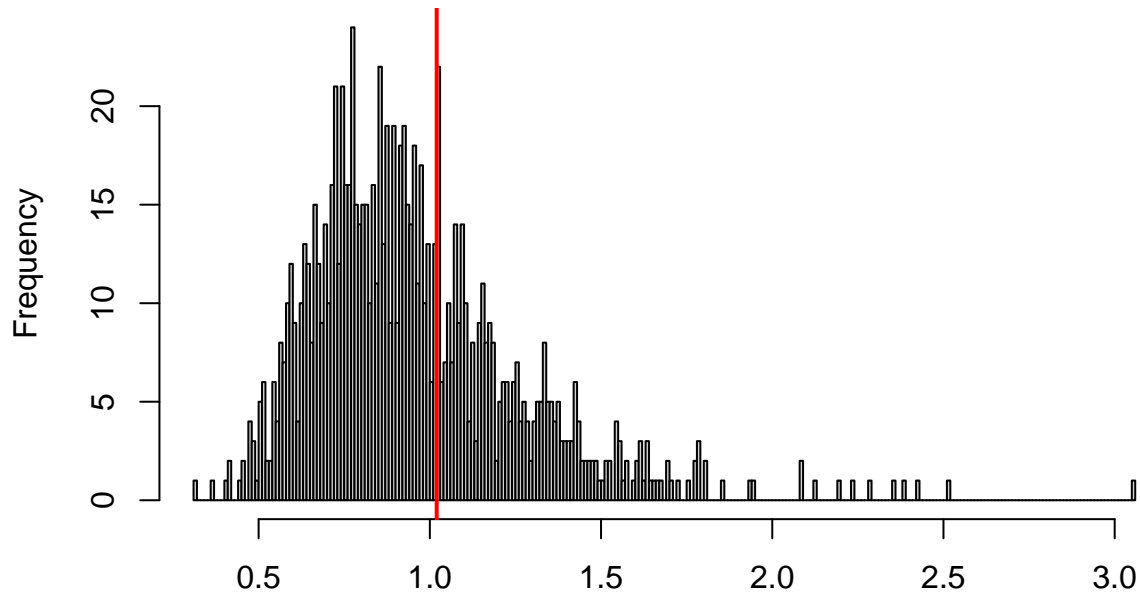
```
##
## Asymptotic one-sample Kolmogorov-Smirnov test
##
## data: simulationOutput$scaledResiduals
## D = 0.050081, p-value = 0.9287
## alternative hypothesis: two-sided
```

Dispersion test

- The DHARMA dispersion test indicates that the model does not show evidence of overdispersion. The dispersion value is close to 1 (1.0662) and the high p-value (0.678) means we cannot reject the null hypothesis of correct dispersion. This suggests that the negative binomial GLMM adequately captures the variance structure of the count data.

```
testDispersion(res)
```


DHARMA nonparametric dispersion test via sd of residuals fitted vs. simulated



Simulated values, red line = fitted model. p-value (two.sided) = 0.678

```
##
## DHARMA nonparametric dispersion test via sd of residuals fitted vs.
## simulated
##
## data: simulationOutput
## dispersion = 1.0662, p-value = 0.678
## alternative hypothesis: two.sided
```

Model with <

```
mod3 <- glmmTMB(
  value ~ ONI_First + SOI + ENSO + temp_min + rain_1.4 + stream +
    (1 | Year), # random intercept for Year
  family = nbinom2,
  data = laselva
)
```

```
summary(mod3)
```

```
## Family: nbinom2 ( log )
## Formula:
## value ~ ONI_First + SOI + ENSO + temp_min + rain_1.4 + stream +      (1 | Year)
## Data: laselva
##
##      AIC      BIC    logLik -2*log(L)  df.resid
##      696.8      721.7    -339.4     678.8      109
```

```
##
## Random effects:
##
## Conditional model:
## Groups Name      Variance Std.Dev.
## Year (Intercept) 0.145    0.3808
## Number of obs: 118, groups: Year, 20
##
## Dispersion parameter for nbinom2 family (): 22
##
## Conditional model:
##      Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.559952   0.869982  2.942  0.00326 **
## ONI_First    -0.047061   0.138218 -0.340  0.73349
## SOI          -0.051418   0.039067 -1.316  0.18812
## ENSO         -0.032662   0.129020 -0.253  0.80015
## temp_min     -0.016909   0.038172 -0.443  0.65778
## rain_1.4      0.009279   0.010513  0.883  0.37747
## streamsaltito -0.081169   0.070755 -1.147  0.25131
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Mod4 Lo intenté, pero paso lo que creía. El número de ríos es demasiado pequeño para tratarlos como un efecto aleatorio. Con solo dos niveles, la varianza entre ríos no se puede estimar de forma estable. El modelo devuelve una varianza prácticamente cero (en el orden de $3.758e-10$) y un SD de $1.939e-05$, lo que dice que el componente aleatorio está esencialmente no identificado.

En cuanto a incluir Year como factor, el problema es que gran parte de la variabilidad interanual ya está representada en los predictores climáticos (ONI, SOI, ENSO, temperatura, lluvia). Al poner Year como efecto fijo, el modelo termina absorbiendo esa señal climática y dificulta detectar efectos independientes de los predictores. Por eso es que la mayoría de los años aparece como significativa: el factor Year está capturando toda la estructura temporal que ya explican las variables climáticas.

```
laselva$Year <- factor(laselva$Year)

mod4 <- glmmTMB(
  value ~ ONI_First + SOI + ENSO + temp_min + rain_51 + Year +
    (1 | stream), # stream como efecto aleatorio
  family = nbinom2,
  data = laselva
)

summary(mod4)
```

```
## Family: nbinom2 ( log )
## Formula:      value ~ ONI_First + SOI + ENSO + temp_min + rain_51 + Year +
##      (1 | stream)
## Data: laselva
##
##      AIC      BIC    logLik -2*log(L)  df.resid
##      675.2    750.0   -310.6    621.2      91
##
## Random effects:
##
## Conditional model:
```

```

## Groups Name      Variance Std.Dev.
## stream (Intercept) 3.758e-10 1.939e-05
## Number of obs: 118, groups: stream, 2
##
## Dispersion parameter for nbinom2 family (): 33.8
##
## Conditional model:
##      Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.46330    0.77376   4.476 7.61e-06 ***
## ONI_First    -0.01278    0.13509  -0.095 0.924641
## SOI          -0.04880    0.03957  -1.233 0.217432
## ENSO         -0.04871    0.12418  -0.392 0.694886
## temp_min     -0.01815    0.03611  -0.503 0.615281
## rain_51      -0.02195    0.02666  -0.823 0.410496
## Year1998     -0.22456    0.20430  -1.099 0.271698
## Year1999     -0.13876    0.26174  -0.530 0.596016
## Year2000     -0.28499    0.22508  -1.266 0.205455
## Year2001     -0.50026    0.22425  -2.231 0.025697 *
## Year2002     -0.67306    0.20382  -3.302 0.000959 ***
## Year2003     -0.63153    0.21249  -2.972 0.002959 **
## Year2004     -0.53009    0.20441  -2.593 0.009507 **
## Year2005     -0.84428    0.24846  -3.398 0.000679 ***
## Year2006     -0.91760    0.22997  -3.990 6.61e-05 ***
## Year2007     -0.83393    0.25535  -3.266 0.001092 **
## Year2008     -0.39888    0.22415  -1.780 0.075152 .
## Year2009     -0.92681    0.21861  -4.240 2.24e-05 ***
## Year2010     -1.37444    0.25978  -5.291 1.22e-07 ***
## Year2011     -1.05647    0.25739  -4.105 4.05e-05 ***
## Year2012     -1.02263    0.23542  -4.344 1.40e-05 ***
## Year2013     -1.13689    0.24462  -4.648 3.36e-06 ***
## Year2014     -1.44260    0.28504  -5.061 4.17e-07 ***
## Year2015     -1.36861    0.23048  -5.938 2.88e-09 ***
## Year2016     -1.19555    0.22927  -5.215 1.84e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```