Microeconomic adaptation to severe climate disturbances on Australian coral reefs (Ambio)

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1 Publication details

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Online Resource 2
R Markdown documentation with data preparation and logistic regression models associated with adaptive responses to climate disturbances on coral reefs by Australian reef tourism operators.
R Markdown can be used in combination with Online Resource 3 (after being converted to a .csv file) to reproduce the findings represented in this study.

2 Preparations

Load the necessary libraries

```r
#library(tidyverse) #for data wrangling, includes dplyr and ggplot2
library(tidyverse) #for data wrangling
library(ggnewscale) #for plotting
library(performance) #for VIF estimation
library(GGally) #for plotting graphs
library(ggpubr) #for combining multiple plots
library(DHARMa) #for residuals and diagnostics
library(ppcor) #for estimating partial correlations
```

3 Introduction

We undertook an exploratory study to empirically assess adaptation to severe climate disturbances on Australian coral reefs by tourism operators. We focused on four primary research questions: (1) how did tourism operators in Australia respond to severe climate-related disturbances, specifically the coral bleaching events in 2016 and 2017 and severe cyclones in 2011 and 2017? (2) How applicable is the microeconomic adaptation framework developed by Bartelet et al. (2022a) towards adaptation to climate change by coral reef
tourism operators? (3) Did increasingly severe impacts reduce the adaptation alternatives that were available (Hoegh-Guldberg et al. 2019)? And (4) how did the contextual characteristics of the business affect the adaptation process?

4 Description of method

As described in greater detail in our manuscript, we conducted surveys with representatives of reef tourism companies (operators) in Australia. The surveys requested information on the actions that each operator took in response to a specific climate disturbance and a number of predictors linked to the disturbance, company, and representative characteristics.

5 Read in the data

```r
data = read.csv('ESM_2.csv')
glimpse(data)
```

### Rows: 58
### Columns: 20
- **$ X.** <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, ...
- **$ resp_age** <chr> "35 - 44", "35 - 44", "45 - 54", "25 - 34", "55 - 64", ...
- **$ resp_gender** <int> 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, ...
- **$ scuba_fraction** <dbl> 0.4, 1.0, 1.0, 0.2, 1.0, 0.2, 1.0, 0.4, 0.4, 0.2, ...
- **$ dist_type** <int> 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, ...
- **$ dist_severity** <dbl> 0.00, 0.00, 0.50, 0.25, 0.00, 1.00, 0.25, 0.25, 0.00, 0...
- **$ psgseats** <int> 1, 2, 1, 3, 1, 2, 2, 3, 8, 3, 5, 5, 2, 1, 1, 2, 5, 1, 2...
- **$ divbl** <int> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0...
- **$ chgsites** <int> 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1...
- **$ chgact** <int> 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1...
- **$ nrm** <int> 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1...
- **$ insurance** <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
- **$ monitor** <int> 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0...
- **$ relief** <int> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
- **$ support** <int> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
- **$ co2** <int> 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, ...
- **$ educate** <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, ...
- **$ none** <int> 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
- **$ topresponse** <chr> "none", "none", "chgsites", "nrm", "none", "relief", "n-

6 Response clusters

We now calculate the partial correlations between the adaptive responses that operators adopted in response to climate disturbances. These partial correlations reflect whether particular responses were more frequently implemented together than others. We used Spearman's Rank correlation because our responses are measures on a binary scale.

We found eight positive partial correlations between our individual adaptive responses that were significant at a p-level of 5% (Figure 1). Based on these significant associations, we decided to make some changes to...
the a priori classification of adaptive response as proposed in Table 3. Most notably we decided to merge the adaptive responses of operational change, product diversification, and livelihood diversification into a combined adaptive response cluster linked to changes in ‘operating model’ because they were all linked to responses on the business and operational side. Compared to our a priori categorization, we classified ‘spatial diversification’ as a separate adaptation cluster because it was frequently implemented and not significantly associated with any of the other adaptive responses.

We found that the adaptive responses of ‘monitoring (reefs and/or climate)’ and ‘restoration’ were significantly correlated, although our a priori classification had defined monitoring as a protective measure. We used the monitoring and restoration responses as separate responses in our consequent analysis because these were each implemented by a relatively large fraction of operators. In accordance with our a priori classification, the adaptive responses of ‘relief measures’ and ‘support-seeking’ were significantly correlated. Finally, one of the adaptive responses that was mentioned as other response by 16% of the participants was ‘visitor education’, i.e. informing and educating visitors about the causes and consequences of the climate disturbances. We merged the visitor education response with ‘climate action’ because they were significantly associated and because visitor education could potentially have an effect on future carbon emissions similar to a company taking climate action itself.

```
response_cor <- data[, c("divbl","relief", "support", "chgopmode", "chgact", "chgsites", "educate", "monitor", "nrm", "co2")]

pcor(response_cor, method="spearman")
```

## $estimate
##
##             divbl  relief  support  chgopmode  chgact  chgsites  educate  monitor   nrm    co2
## divbl       1.000000 0.24839999 -0.12827148  0.42408823 0.00162640 0.005038315 0.020557887 -0.14875325
## relief     0.24839999 1.00000000  0.63844626  0.12717991 -0.29182274 0.143035380 0.21496514  0.18759442
## support   -0.12827148  0.63844626  1.00000000 -0.21227795  0.39025149 0.006969280 0.09439283  0.83141793
## chgopmode  0.42408823  0.12717991 -0.21227795  1.00000000  0.54903986 0.009699280 0.04939283  0.18759442
## chgact    -0.00162640 -0.29182274  0.39025149  0.54903986  1.00000000 0.006969280 0.09439283  0.18759442
## chgsites -0.00503831 0.14303538  0.00696928  0.54903986  1.00000000 0.006969280 0.09439283  0.83141793
## educate   0.02055789 -0.31138278  0.02203716  0.09439283  0.09439283 1.000000000 -0.10499157  0.70770008
## monitor   -0.14875325 -0.01614644  0.02203716 -0.10499157 -0.10499157 1.000000000  0.00791957  0.70770008
## nrm       -0.00503831 0.02055789 -0.14875325 -0.28494906 -0.28494906 0.007919570 1.00000000  0.70770008
## co2      -0.02055789 -0.14875325  0.31743868  0.20770008  0.20770008 0.219029501 0.21902950 1.00000000

## $p.value
##
##   divbl  relief  support  chgopmode  chgact  chgsites  educate  monitor  nrm    co2
## divbl  0.00000000  8.196356e-02 3.746750e-01 2.146388e-03 9.910563e-01 0.28494906 -0.18862051
## relief 0.08196356  0.000000e+00 6.089877e-07 3.787870e-01 3.975336e-02 0.83141793 -0.18862051
## support 0.00696928 0.21496514  0.02203716  0.09439283 -0.10499157 0.00791957  0.70770008
## chgopmode 0.00000000 0.31743868  0.36417067  1.00000000  0.70770008 0.26086092  0.70770008
## chgact  0.005038315 0.02055789 -0.14875325 -0.28494906 -0.28494906 0.00791957  0.70770008
## chgsites 0.02055789 -0.31138278  0.02203716 -0.10499157 -0.10499157 1.00000000  0.00791957  0.70770008
## educate 0.02055789 -0.31138278  0.02203716 -0.10499157 -0.10499157 1.00000000  0.00791957  0.70770008
## nrm  0.02055789 -0.31138278  0.02203716 -0.10499157 -0.10499157 1.00000000  0.00791957  0.70770008
## co2  0.02055789 -0.31138278  0.02203716 -0.10499157 -0.10499157 1.00000000  0.00791957  0.70770008

## 3
W e then apply these clusters to our dataset before we start our analysis.

We then apply these clusters to our dataset before we start our analysis.
data_modified <- data %>%
  mutate(operational = ifelse(divbl + chgact + chgopmode > 0, 1, 0),
          coping = ifelse(relief + support + insurance > 0, 1, 0),
          climate = ifelse(co2 + educate > 0, 1, 0))

7 Predictor data preparation

For the predictors, we transformed the age of the company representative into a binary predictor (older versus younger), the business type (snorkel vs. scuba), and the company size (# passenger seats on boats) into a categorical predictor. We measured the number of passenger seats using nine multiple-choice options that ranged from ‘0-10 seats’ to ‘>500 seats’. Through visual inspection of the data, we identified three clusters that we consequently categorized as small (<20 seats), medium (20-200 seats), and large (>200 seats). We included company size as a categorical rather than an ordinal predictor because the effects were not ordered linearly for all response models. We used small-sized companies as the reference group.

Business type (scuba vs. snorkeling)

Business size (# passenger seats)

For boats (‘psgseats’): 1 for 0 – 10 seats, 2 for 10 – 20 seats, 3 for 20 – 50 seats, 4 for 50 – 100 seats, 5 for 100 – 200 seats, 6 for 200 – 300 seats, 7 for 300 – 400 seats, 8 for 400 – 500 seats, and 9 for >500 seats.
ggplot(data_modified, aes(x=psgseats)) + ylab("Frequency") +
geom_bar() + geom_vline(xintercept = 2.5) +
geom_bar() + geom_vline(xintercept = 5.5) +
annotate("text", x=1.5, y=20, label= "Small") +
annotate("text", x=4, y=20, label= "Medium") +
annotate("text", x=7, y=20, label= "Large")

Representative gender

ggplot(data_modified, aes(x=resp_gender)) + ylab("Frequency") +
geom_bar() + geom_vline(xintercept = 0.5) +
annotate("text", x=0.2, y=35, label= "Male") +
annotate("text", x=0.75, y=35, label= "Female")
Representative age

```
ggplot(data_modified, aes(x=resp_age)) + ylab("Frequency") +
  geom_bar() + geom_vline(xintercept = 3.5) +
  annotate("text", x=2.5, y=22, label= "Younger") +
  annotate("text", x=4.5, y=22, label= "Older")
```
We now apply these modifications to our data using the code below.

Because all our predictors are on a binary scale, we standardized our only non-binary predictor (disturbance severity) using z-scores, by subtracting the mean and dividing by twice the standard deviation (Gelman, 2008). Dividing by twice the standard deviation standardizes each variable to have a mean of ‘0’ and a standard deviation of ‘0.5’; this technically standardizes all predictors on a binary scale. Coefficients for continuous predictors from the Bayesian models are now directly comparable and should be interpreted as the effect of a one-standard deviation change in the predictor variable on the response variable.

data_modified <- data_modified %>%
  mutate(scuba_binary = ifelse(scuba_fraction > 0.4, 1, 0),
         resp_age_binary = case_when(
            resp_age == '18 - 24' | resp_age == '25 - 34' | resp_age == '35 - 44' - 1,
            resp_age == '45 - 54' | resp_age == '55 - 64' | resp_age == '65+' - 0),
         psgseats_cat = case_when(
            psgseats == 1 | psgseats == 2 - 'small',
            psgseats == 3 | psgseats == 4 | psgseats == 5 - 'medium',
            psgseats == 6 | psgseats == 7 | psgseats == 8 | psgseats == 9 - 'large'),
         z.dist_severity = (dist_severity-mean(dist_severity))/(2*sd(dist_severity))
   )

ggplot(data_modified, aes(x=scuba_binary)) + geom_bar()
```r
ggplot(data_modified, aes(x=resp_age_binary)) +
  geom_bar()
```
ggplot(data_modified, aes(x=psgseats_cat)) + geom_bar()

| count | small | medium | large |
|-------|-------|--------|-------|
|       |       |        |       |

ggplot(data_modified, aes(x=z.dist_severity)) + geom_bar()
8 Analysis and model validation

Logistic regression model for changes in operating model response

Model definition and VIF test

```r
opportunistic.glm <- glm(operational ~ z.dist_severity + dist_type +
scuba_binary + psgseats_cat +
resp_age_binary + resp_gender,
data=data_modified, family=binomial(link='logit'))
```

check_collinearity(opportunistic.glm)

```r
## # Check for Multicollinearity
##
## # Low Correlation
##
## Term  VIF  VIF 95% CI Increased SE Tolerance Tolerance 95% CI
## z.dist_severity 2.34 [1.75, 3.41] 1.53 0.43 [0.29, 0.57]
## dist_type 2.02 [1.54, 2.92] 1.42 0.49 [0.34, 0.65]
## scuba_binary 1.21 [1.05, 1.88] 1.10 0.82 [0.53, 0.95]
## psgseats_cat 1.48 [1.20, 2.14] 1.22 0.68 [0.47, 0.83]
## resp_age_binary 1.31 [1.10, 1.94] 1.15 0.76 [0.52, 0.91]
## resp_gender 1.16 [1.03, 1.92] 1.08 0.86 [0.52, 0.97]
```

Model validation
model.resid <- simulateResiduals(operational.glm)

plot(model.resid)

DHARMa residual

QQ plot residuals

Expected

Residual vs. predicted

No significant problems detected

Model summary

summary(operational.glm)

## Call:
## glm(formula = operational ~ z.dist.severity + dist_type + scuba_binary +
##     psgseats_cat + resp_age_binary + resp_gender, family = binomial(link = "logit"),
##     data = data_modified)
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.6688  -0.5682  -0.4287   0.6416   2.3081
## Coefficients:
##            Estimate Std. Error   z value  Pr(>|z|)  
## (Intercept)  -0.4891     0.8183   -0.5980      0.5500
## z.dist.severity  2.8165     1.0967    2.5678      0.0102  *
## dist_type     -0.2678     1.0174   -0.2627      0.7924
## scuba_binary  -0.3218     0.7801   -0.4117      0.6800
## psgseats_catmedium  -1.2541    0.8730  -1.4368      0.1505
## psgseats_catlarge  -0.7447    1.0627  -0.7006      0.4835
## resp_age_binary  0.1721     0.8022    0.2151      0.8301
## resp_gender    -0.2770     0.7556   -0.3667      0.7139
r2_operational <- 1 - (52.911 / 68.324)  # residual deviance / null deviance
r2_operational

## [1] 0.2255869

Logistic regression model for spatial diversification response

spatial.glm <- glm(chgsites ~ z.dist_severity + dist_type +
                     scuba_binary + psgseats_cat +
                     resp_age_binary + resp_gender,
                     data=data_modified, family=binomial(link='logit'))

check_collinearity(spatial.glm)

# # Check for Multicollinearity
# #
# # Low Correlation
# #
# # Term   VIF    VIF 95% CI Increased SE  Tolerance  Tolerance 95% CI
# z.dist_severity 1.88 [1.45, 2.71] 1.37 0.53 [0.37, 0.69]
# dist_type 1.69 [1.33, 2.44] 1.30 0.59 [0.41, 0.75]
# scuba_binary 1.09 [1.01, 2.36] 1.05 0.91 [0.42, 0.99]
# psgseats_cat 1.17 [1.03, 1.91] 1.08 0.86 [0.52, 0.97]
# resp_age_binary 1.35 [1.12, 1.98] 1.16 0.74 [0.51, 0.89]
# resp_gender 1.40 [1.15, 2.04] 1.18 0.71 [0.49, 0.87]

Model validation

model.resid <- simulateResiduals(spatial.glm)

plot(model.resid)
Model summary

summary(spatial.glm)

## Call:
## glm(formula = chgsites ~ z.dist_severity + dist_type + scuba_binary +
##     psgseats_cat + resp_age_binary + resp_gender, family = binomial(link = "logit"),
##     data = data_modified)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -2.2507 -0.6511 -0.3915  0.6022  2.1689
##
## Coefficients:
##     Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.0299    0.8041  -1.281  0.2002
## z.dist_severity   1.9412    1.0604   1.831  0.0672 .
## dist_type        1.1131    1.1526   0.966  0.3342
## scuba_binary    -0.5180    0.7669  -0.675  0.4994
## psgseats_catmedium 0.9663    0.7981   1.211  0.2260
## psgseats_catlarge -0.0305    1.0529  -0.029  0.9769
## resp_age_binary   -0.9604    0.8251  -1.164  0.2444
## resp_gender       1.0192    0.8382   1.216  0.2240
##
## (Dispersion parameter for binomial family taken to be 1)
r2_spatial <- 1 - (50.789 / 76.992)  # residual deviance / null deviance
r2_spatial

## [1] 0.3403341

Logistic regression model for monitoring response

monitor.glm <- glm(monitor ~ z.dist_severity + dist_type + 
    scuba_binary + psgseats_cat + 
    resp_age_binary + resp_gender, 
    data=data_modified, family=binomial(link='logit'))

check_collinearity(monitor.glm)

Model validation

model.resid <- simulateResiduals(monitor.glm)

plot(model.resid)
Model summary

summary(monitor.glm)

## Call:
## glm(formula = monitor ~ z.dist_severity + dist_type + scuba_binary +
## psgeats_cat + resp_age_binary + resp_gender, family = binomial(link = "logit"),
## data = data_modified)
##
## Deviance Residuals:
##    Min     1Q   Median     3Q    Max
## -2.0911 -0.9425  0.5485  0.9662  1.7773
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.37854   0.71545  -0.529  0.5967
## z.dist_severity  1.91728   0.95157   2.015  0.0439 *
## dist_type    -0.71252   1.07601  -0.662  0.5079
## scuba_binary   0.44154   0.65833   0.671  0.5024
## psgeats_catmedium  0.91491   0.67280   1.360  0.1739
## psgeats_catlarge   0.90931   0.90901   1.000  0.3171
## resp_age_binary  0.06033   0.67702   0.089  0.9290
## resp_gender     0.11040   0.64284   0.172  0.8636
##
## Signif. codes:  < ***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

## (Dispersion parameter for binomial family taken to be 1)
# Null deviance: 80.129 on 57 degrees of freedom
# Residual deviance: 69.348 on 50 degrees of freedom
# AIC: 85.348

## Number of Fisher Scoring iterations: 4

\[
r_2_{\text{monitor}} \leftarrow 1 - \left( \frac{69.348}{80.129} \right) \quad \# \text{residual deviance / null deviance}
\]

## [1] 0.1345455

Logistic regression model for restoration response

\[
nrm.glm \leftarrow \text{glm}(nrm \sim z.\text{dist.severity} + \text{dist.type} +
    \text{scuba.binary} + \text{psgseats.cat} +
    \text{resp.age.binary} + \text{resp.gender},
    \text{data}=\text{data_modified}, \text{family} = \text{binomial(} \text{link} = \text{'logit'})\)
\]

\[
\text{check_collinearity(nrm.glm)}
\]

## # Check for Multicollinearity
## # Low Correlation
##
## | Term            | VIF | VIF 95% CI | Increased SE | Tolerance | Tolerance 95% CI |
##|-----------------|-----|------------|--------------|-----------|-----------------|
##| z.\text{dist.severity} | 3.79 | [2.70, 5.61] | 1.95 | 0.26 | [0.18, 0.37] |
##| \text{dist.type} | 3.13 | [2.26, 4.60] | 1.77 | 0.32 | [0.22, 0.44] |
##| \text{scuba.binary} | 1.21 | [1.05, 1.88] | 1.10 | 0.83 | [0.53, 0.95] |
##| \text{psgseats.cat} | 1.23 | [1.06, 1.88] | 1.11 | 0.81 | [0.53, 0.94] |
##| \text{resp.age.binary} | 1.76 | [1.37, 2.53] | 1.33 | 0.57 | [0.40, 0.73] |
##| \text{resp.gender} | 1.50 | [1.21, 2.17] | 1.22 | 0.67 | [0.46, 0.82] |

Model validation

\[
\text{model.resid} \leftarrow \text{simulateResiduals(nrm.glm)}
\]

\[
\text{plot(model.resid)}
\]
Model summary

summary(nrm.glm)

## Call:
## glm(formula = nrm ~ z.dist_severity + dist_type + scuba_binary +
##     psgseats_cat + resp_age_binary + resp_gender, family = binomial(link = "logit"),
##     data = data_modified)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
##    -1.7498  -0.7521  -0.3551   0.6881   2.2851
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)       0.2975     0.8547  0.348  0.72779
## z.dist_severity   4.1055     1.3922  2.949  0.00319 **
## dist_type         -2.7922     1.3456 -2.075  0.03798 *
## scuba_binary      -0.7549     0.7841 -0.963  0.33569
## psgseats_catmedium 0.6210     0.7973  0.779  0.43605
## psgseats_catlarge 1.4673     1.0578  1.387  0.16540
## resp_age_binary   1.3234     0.8990  1.472  0.14097
## resp_gender       -2.1158     0.8485 -2.493  0.01265 *
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

DHARMa residual

QQ plot residuals
Expected
Observed
KS test: p= 0.62516
Deviation  n.s.
Outlier test: p= 1
Deviation  n.s.
Dispersion test: p= 0.728
Deviation  n.s.

Residual vs. predicted
No significant problems detected

DHARMa residual
Null deviance: 78.672 on 57 degrees of freedom
Residual deviance: 53.795 on 50 degrees of freedom
AIC: 69.795

Number of Fisher Scoring iterations: 5

\[
\text{r2_nrm} \leftarrow 1 - \left( \frac{53.795}{78.672} \right) \quad \# \text{residual deviance / null deviance}
\]

\[
\text{r2_nrm} \quad \# [1] 0.3162116
\]

Logistic regression model for climate action

\[
\text{climate.glm} \leftarrow \text{glm}(\text{climate} \sim \text{z.dist.severity} + \text{dist.type} + \\
\quad \text{scuba.binary} + \text{psgseats.cat} + \\
\quad \text{resp.age.binary} + \text{resp.gender}, \\
\quad \text{data}=\text{data_modified}, \text{family}=\text{binomial(link='logit'})
\]

check_collinearity(climate.glm)

# Check for Multicollinearity
# Low Correlation

# Term VIF VIF 95% CI Increased SE Tolerance Tolerance 95% CI
# z.dist.severity 2.21 [1.67, 3.21] 1.49 0.45 [0.31, 0.60]
# dist.type 2.17 [1.64, 3.14] 1.47 0.46 [0.32, 0.61]
# scuba.binary 1.27 [1.08, 1.91] 1.13 0.79 [0.52, 0.93]
# psgseats.cat 1.31 [1.10, 1.93] 1.14 0.77 [0.52, 0.91]
# resp.age.binary 1.33 [1.11, 1.95] 1.15 0.75 [0.51, 0.90]
# resp.gender 1.19 [1.04, 1.89] 1.09 0.84 [0.53, 0.96]

Model validation

model.resid \leftarrow \text{simulateResiduals(climate.glm)}

plot(model.resid)
Model summary

summary(climate.glm)

## Call:
## glm(formula = climate ~ z.dist_severity + dist_type + scuba_binary +
##     psgseats_cat + resp_age_binary + resp_gender, family = binomial(link = "logit"),
##     data = data_modified)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7764  -0.8489  -0.5892   0.9329   2.1973
##
## Coefficients:
##                Estimate Std. Error z value  Pr(>|z|)
## (Intercept)  -0.21515   0.72096  -0.298 0.765457
## z.dist_severity 1.26144   0.88851   1.420 0.155732
## dist_type    -1.26296   1.03177  -1.224 0.220833
## scuba_binary  0.99290   0.68373   1.452 0.146485
## psgseats_catmedium 0.67397   0.70596   0.955 0.339690
## psgseats_catlarge 1.06498   0.95577   1.114 0.265164
## resp_age_binary -1.46698   0.69895  -2.099 0.035804 *
## resp_gender    0.07798   0.66156   0.118 0.906200
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

## Residual vs. predicted
## DHARMa residuals
## Quantile deviations detected (rank adjusted quantile test)
## Null deviance: 79.298 on 57 degrees of freedom
## Residual deviance: 66.292 on 50 degrees of freedom
## AIC: 82.292
##
## Number of Fisher Scoring iterations: 4

```r
r2_climate <- 1 - (66.292 / 79.298)  # residual deviance / null deviance
r2_climate
```

## [1] 0.1640142