Rerun of Clements et al data original

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01/04/2022

—————————– Supplementary information to —————————-

——————— META-ANALYSIS REVEALS AN EXTREME “DECLINE EFFECT” ——————— ——————— IN OCEAN ACIDIFICATION IMPACTS ON FISH BEHAVIOUR ———————-

——– Jeff C. Clements, Josefin Sundin, Timothy D. Clark, Fredrik Jutfelt ——–

Get packages

```
library(pacman)

## Warning: package 'pacman' was built under R version 4.1.2

pacman::p_load(metafor, MCMCglmm, tidyverse, rotl, magrittr, kableExtra,
rmarkdown,gridExtra, psych, bindrcpp, pander)
library(BiocManager)

## Warning: package 'BiocManager' was built under R version 4.1.2

library(ggplot2)
library(viridis)

## Loading required package: viridisLite

library(patchwork)

## Warning: package 'patchwork' was built under R version 4.1.2
```

META-ANALYSIS - YEAR ONLINE - FULL DATASET

##attach dataset

```
decline<-read.csv(file.choose()) ##use dataset "S5 Data"
attach(decline)
```

#Note I noticed there is an issues in the S5 file published online as the file that was use. There is an issue with year of publishing and year online. This different to the full excel file published online. Without fixing the R code cannot run 2009 as there is nothing in 2009.

The S5 year of publishing and online also mismatches with the S10 file for creating Fig 1A. New S5.csv file created from full excel file published

```
head(decline)

##   obs study      authors year.online year.print if.at.pub X2017.if
if.group
## 1   1    a1 Munday et al        2009       2009     9.432    9.504
J
## 2   2    a1 Munday et al        2009       2009     9.432    9.504
J
## 3   3    a1 Munday et al        2009       2009     9.432    9.504
J
## 4   4    a1 Munday et al        2009       2009     9.432    9.504
J
## 5   5    a1 Munday et al        2009       2009     9.432    9.504
J
## 6   6    a1 Munday et al        2009       2009     9.432    9.504
J
##   avg.n            species climate cue cue.type life.stage ctrl.n
ctrl.mean
## 1    27 Amphiprion percula    Trop Yes  Habitat     Larvae     26
94.129
## 2    NA Amphiprion percula    Trop Yes  Habitat     Larvae     20
0.783
## 3    NA Amphiprion percula    Trop Yes  Habitat     Larvae     20
46.380
## 4    NA Amphiprion percula    Trop Yes  Habitat     Larvae     10
98.826
## 5    NA Amphiprion percula    Trop Yes      Kin     Larvae     30
0.912
## 6    NA Amphiprion percula    Trop Yes      Kin     Larvae     30
90.876
##   ctrl.sd oa.n oa.mean   oa.sd
## 1  2.9931   46  72.789 13.2730
## 2  3.5017   46  83.562 10.6211
## 3 14.0023   46  71.429 13.2730
## 4  1.8563   16  88.258  7.0440
## 5  2.9960   20  99.818  0.0045
## 6  3.9984   20  99.818  0.0045
```

##set factors

```
decline$year.online<-as.factor(decline$year.online)
decline$year.print<-as.factor(decline$year.print)
decline$obs<-as.factor(decline$obs)
decline$study<-as.factor(decline$study)
```

##view summary

```
summary(decline)
```

```
##       obs           study        authors            year.online    year.print
##  1      :  1   a3      : 48   Length:818         2018   :153   2018   :175
##  2      :  1   a87     : 40   Class :character   2015   :108   2015   : 98
##  3      :  1   a11     : 39   Mode  :character   2017   :101   2012   : 89
##  4      :  1   a90     : 36                      2012   : 97   2017   : 85
##  5      :  1   a22     : 30                      2014   : 83   2016   : 84
##  6      :  1   a31     : 28                      2013   : 58   2013   : 78
##  (Other):812   (Other):597                      (Other):218   (Other):209
##   if.at.pub           X2017.if            if.group             avg.n
##  Length:818         Length:818         Length:818         Min.   :  4.00
##  Class :character   Class :character   Class :character   1st Qu.: 12.50
##  Mode  :character   Mode  :character   Mode  :character   Median : 18.00
##                                                           Mean   : 32.62
##                                                           3rd Qu.: 30.00
##                                                           Max.   :568.00
##                                                           NA's   :727
##    species            climate              cue              cue.type
##  Length:818         Length:818         Length:818         Length:818
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##   life.stage            ctrl.n      ctrl.mean            ctrl.sd
##  Length:818         Min.   :  4   Min.   :   -69.78   Min.   :    0.000
##  Class :character   1st Qu.: 10   1st Qu.:     1.03   1st Qu.:    1.176
##  Mode  :character   Median : 18   Median :     9.20   Median :    5.560
##                     Mean   : 29   Mean   :   438.64   Mean   :  104.430
##                     3rd Qu.: 30   3rd Qu.:    44.01   3rd Qu.:   21.640
##                     Max.   :752   Max.   :154936.88   Max.   :25490.446
##
##       oa.n           oa.mean              oa.sd
##  Min.   :  2.00   Min.   :   -59.67   Min.   :    0.00
##  1st Qu.: 11.00   1st Qu.:     1.14   1st Qu.:    1.15
##  Median : 18.00   Median :    12.12   Median :    7.10
##  Mean   : 28.93   Mean   :   438.34   Mean   :  114.41
##  3rd Qu.: 30.75   3rd Qu.:    43.51   3rd Qu.:   22.43
##  Max.   :755.00   Max.   :157061.25   Max.   :36812.37
##
```

##subset by year

```
y2009 <- filter(decline, year.online == "2009")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2009$obs <- 1:nrow(y2009)
y2010 <- filter(decline, year.online == "2010")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
```

```
y2010$obs <- 1:nrow(y2010)
y2011 <- filter(decline, year.online == "2011")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2011$obs <- 1:nrow(y2011)
y2012 <- filter(decline, year.online == "2012")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2012$obs <- 1:nrow(y2012)
y2013 <- filter(decline, year.online == "2013")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2013$obs <- 1:nrow(y2013)
y2014 <- filter(decline, year.online == "2014")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2014$obs <- 1:nrow(y2014)
y2015 <- filter(decline, year.online == "2015")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2015$obs <- 1:nrow(y2015)
y2016 <- filter(decline, year.online == "2016")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2016$obs <- 1:nrow(y2016)
y2017 <- filter(decline, year.online == "2017")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2017$obs <- 1:nrow(y2017)
y2018 <- filter(decline, year.online == "2018")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2018$obs <- 1:nrow(y2018)
y2019 <- filter(decline, year.online == "2019")[,-
match(c("avg.n","cue.type","if.at.pub","X2017.if","if.group"), colnames
(decline))]
y2019$obs <- 1:nrow(y2019)
```

##comupte effect sizes for each year

```
lnRR2009 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
009,append=TRUE)
lnRR2010 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
010,append=TRUE)
lnRR2011 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
011,append=TRUE)
```

```
## Warning in log(m1i/m2i): NaNs produced

lnRR2012 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
012,append=TRUE)

## Warning in log(m1i/m2i): NaNs produced

lnRR2013 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
013,append=TRUE)

## Warning in log(m1i/m2i): NaNs produced

lnRR2014 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
014,append=TRUE)
lnRR2015 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
015,append=TRUE)

## Warning in log(m1i/m2i): NaNs produced

lnRR2016 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
016,append=TRUE)
lnRR2017 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
017,append=TRUE)

## Warning in log(m1i/m2i): NaNs produced

lnRR2018 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
018,append=TRUE)
lnRR2019 <- escalc(measure= "ROM",
m1i=oa.mean,sd1i=oa.sd,n1i=oa.n,m2i=ctrl.mean,sd2i=ctrl.sd,n2i=ctrl.n,data=y2
019,append=TRUE)

#Note log(m1i/m21i) produced NAs for 2011, 2012, 2013, 2015, 2017
```

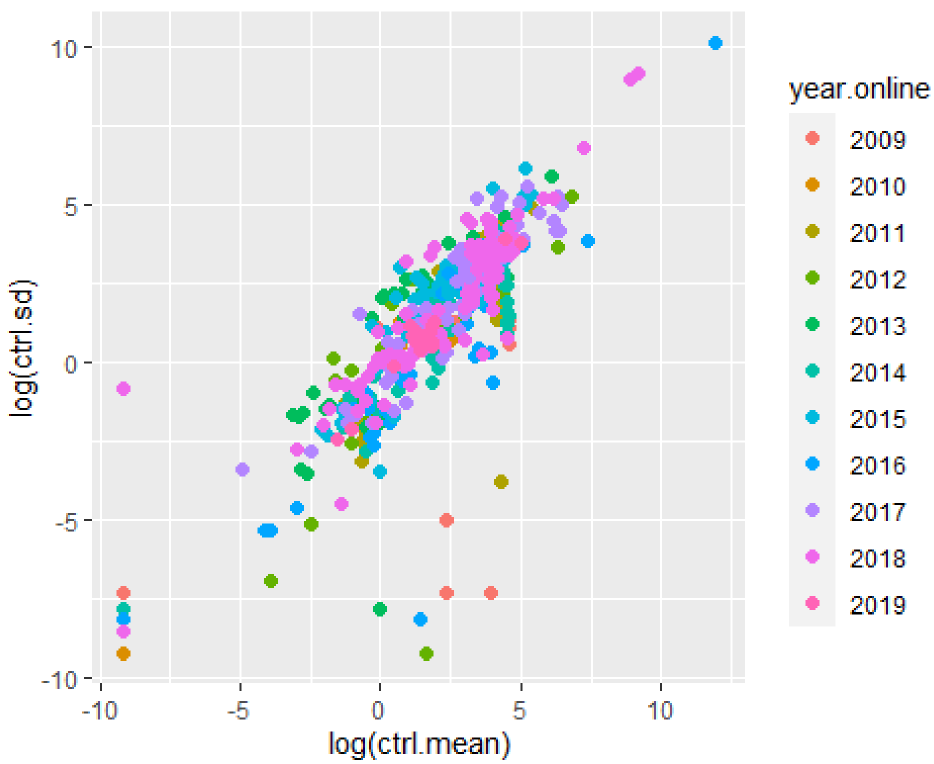
##remove NAs

```
lnRR2009clean<-na.omit(lnRR2009)
lnRR2010clean<-na.omit(lnRR2010)
lnRR2011clean<-na.omit(lnRR2011)
lnRR2012clean<-na.omit(lnRR2012)
lnRR2013clean<-na.omit(lnRR2013)
lnRR2014clean<-na.omit(lnRR2014)
lnRR2015clean<-na.omit(lnRR2015)
lnRR2016clean<-na.omit(lnRR2016)
lnRR2017clean<-na.omit(lnRR2017)
```

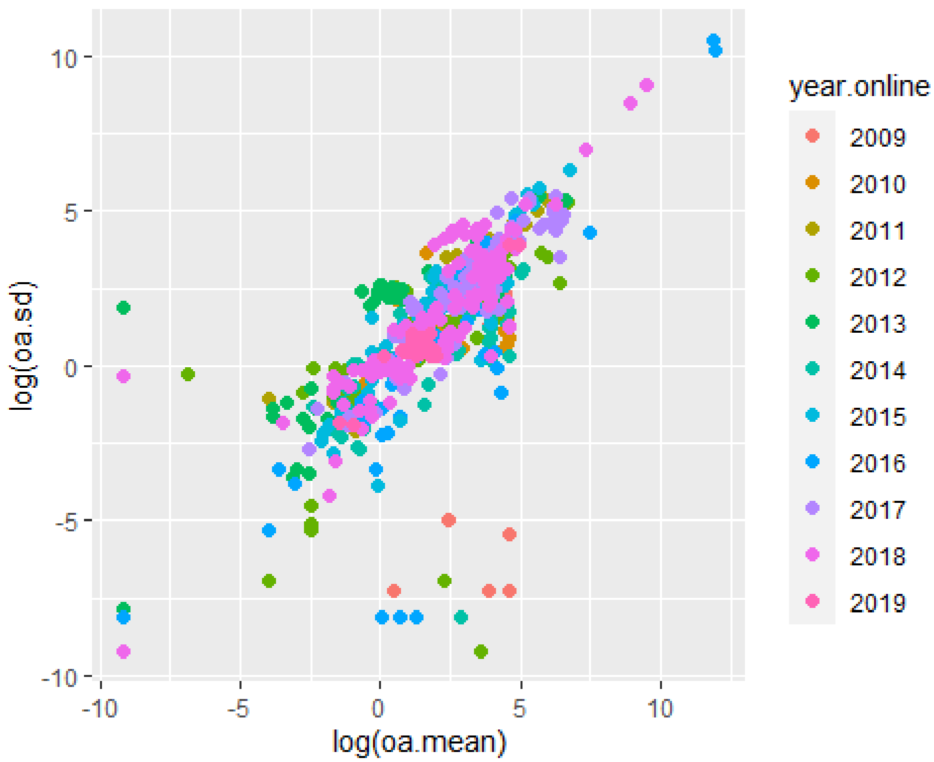
```
lnRR2018clean<-na.omit(lnRR2018)
lnRR2019clean<-na.omit(lnRR2019)
```

##view mean-variance relationship

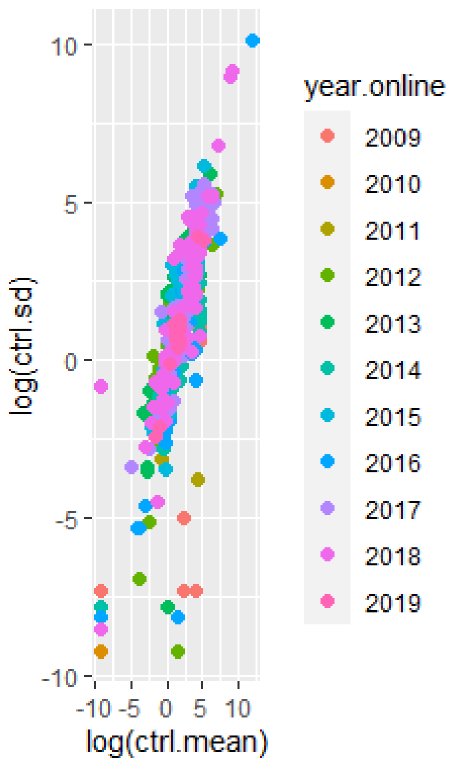
```
pp1<-ggplot(decline,aes(x=log(ctrl.mean),y=log(ctrl.sd),col=year.online))+
geom_point(size=2,na.rm = TRUE)
pp2<-ggplot(decline,aes(x=log(oa.mean),y=log(oa.sd),col=year.online))+
geom_point(size=2,na.rm = TRUE)
pp1 #Note added

## Warning in log(ctrl.mean): NaNs produced

## Warning in log(ctrl.mean): NaNs produced
```

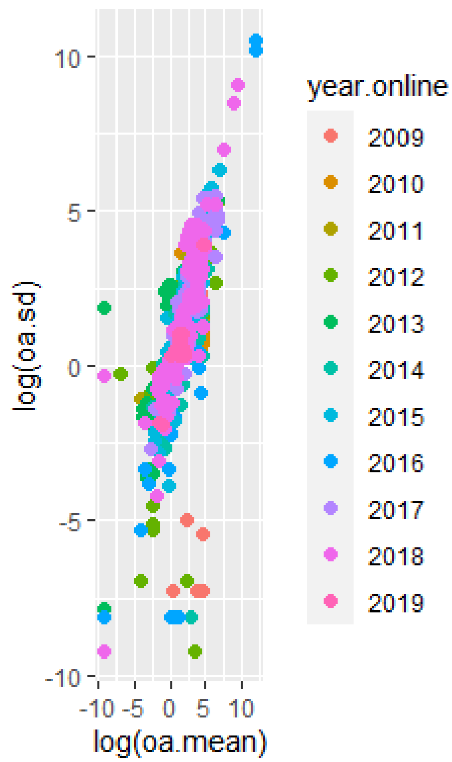



```
pp2 #Note added

## Warning in log(oa.mean): NaNs produced

## Warning in log(oa.mean): NaNs produced
```




```
grid.arrange(pp1,pp2, nrow =1)

## Warning in log(ctrl.mean): NaNs produced

## Warning in log(ctrl.mean): NaNs produced

## Warning in log(oa.mean): NaNs produced

## Warning in log(oa.mean): NaNs produced
```






```
#Note there are a number of NAs created due the the log of a negative being
not computible
```

##look at lnRR by year

```
MLMA_2009_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2009)

## Warning: Ratio of largest to smallest sampling variance extremely large.
May not
## be able to obtain stable results.

summary(MLMA_2009_lnRR)

##
## Multivariate Meta-Analysis Model (k = 19; method: REML)
##
##    logLik  Deviance       AIC       BIC      AICc
## -56.5722  113.1444  117.1444  118.9251  117.9444
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed  factor
## sigma^2    30.6312  5.5345     19     no     obs
##
## Test for Heterogeneity:
## Q(df = 18) = 10724056.2936, p-val < .0001
##
## Model Results:
```

```
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   3.1705  1.2759  2.4849  0.0130  0.6698  5.6713  *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2010_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2010)
summary(MLMA_2010_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 48; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -143.4474   286.8948   290.8948   294.5951   291.1675
##
## Variance Components:
##
##               estim    sqrt  nlvls  fixed  factor
## sigma^2    25.9986  5.0989     48     no     obs
##
## Test for Heterogeneity:
## Q(df = 47) = 20986.5067, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   3.7009  0.7397  5.0033  <.0001  2.2511  5.1507  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2011_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2011)
```

```
## Warning: Rows with NAs omitted from model fitting.
```

```
summary(MLMA_2011_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 48; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -37.4820   74.9639   78.9639   82.6642   79.2367
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed  factor
## sigma^2    0.1496  0.3868     48     no     obs
##
## Test for Heterogeneity:
## Q(df = 47) = 228.8028, p-val < .0001
```

```
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0398  0.0716  -0.5553  0.5787  -0.1801  0.1006
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2012_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2012)
```

```
## Warning: Rows with NAs omitted from model fitting.

## Warning: Ratio of largest to smallest sampling variance extremely large.
May not
## be able to obtain stable results.
```

```
summary(MLMA_2012_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 88; method: REML)
##
##    logLik   Deviance        AIC         BIC       AICc
## -149.7127   299.4253   303.4253   308.3572   303.5682
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed  factor
## sigma^2    1.2064  1.0984     88     no     obs
##
## Test for Heterogeneity:
## Q(df = 87) = 29290.8615, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.1353  0.1308  1.0343  0.3010  -0.1211  0.3917
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2013_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2013)
```

```
## Warning: Rows with NAs omitted from model fitting.

## Warning: Ratio of largest to smallest sampling variance extremely large.
May not
## be able to obtain stable results.
```

```
summary(MLMA_2013_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 52; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -102.2558   204.5116   208.5116   212.3752   208.7616
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed  factor
## sigma^2    1.2182  1.1037     52     no     obs
##
## Test for Heterogeneity:
## Q(df = 51) = 321.2026, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.5545  0.1848  -3.0002  0.0027  -0.9168  -0.1923  **
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2014_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2014)
summary(MLMA_2014_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 83; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -226.5561   453.1122   457.1122   461.9256   457.2641
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed  factor
## sigma^2    13.8435  3.7207     83     no     obs
##
## Test for Heterogeneity:
## Q(df = 82) = 6974.5766, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0765  0.4110  -0.1860  0.8524  -0.8821  0.7292
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2015_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2015)
```

```
## Warning: Rows with NAs omitted from model fitting.
```

```
summary(MLMA_2015_lnRR)

##
## Multivariate Meta-Analysis Model (k = 105; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -77.7140  155.4281  159.4281  164.7169  159.5469
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed  factor
## sigma^2    0.0887  0.2979    105     no     obs
##
## Test for Heterogeneity:
## Q(df = 104) = 368.7121, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.0936  0.0410  -2.2807  0.0226  -0.1740  -0.0132  *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

MLMA_2016_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2016)

## Warning: Ratio of largest to smallest sampling variance extremely large.
May not
## be able to obtain stable results.

summary(MLMA_2016_lnRR)

##
## Multivariate Meta-Analysis Model (k = 57; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -44.9446   89.8892   93.8892   97.9399   94.1156
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed  factor
## sigma^2    0.2268  0.4762     57     no     obs
##
## Test for Heterogeneity:
## Q(df = 56) = 70885.9993, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0193  0.0687  -0.2806  0.7790  -0.1539  0.1154
##
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2017_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2017)
```

```
## Warning: Rows with NAs omitted from model fitting.
```

```
summary(MLMA_2017_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 99; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
## -74.2817  148.5633  152.5633  157.7333  152.6897
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed  factor
## sigma^2    0.1508  0.3884     99     no     obs
##
## Test for Heterogeneity:
## Q(df = 98) = 2575.9384, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.0320  0.0460  0.6952  0.4869  -0.0582  0.1221
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2018_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2018)
```

```
## Warning: Ratio of largest to smallest sampling variance extremely large.
May not
## be able to obtain stable results.
```

```
summary(MLMA_2018_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 153; method: REML)
##
##    logLik   Deviance        AIC        BIC       AICc
## -257.9394   515.8788   519.8788   525.9266   519.9594
##
## Variance Components:
##
##             estim    sqrt  nlvls  fixed  factor
## sigma^2    0.2818  0.5309    153     no     obs
##
## Test for Heterogeneity:
## Q(df = 152) = 3035.7779, p-val < .0001
```

```
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.0129  0.0493  0.2613  0.7939  -0.0838  0.1095
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
MLMA_2019_lnRR <- rma.mv(yi ~ 1, V = vi, random=~1|obs, data=lnRR2019)
summary(MLMA_2019_lnRR)
```

```
##
## Multivariate Meta-Analysis Model (k = 43; method: REML)
##
##   logLik  Deviance       AIC       BIC      AICc
##  18.8145  -37.6289  -33.6289  -30.1536  -33.3212
##
## Variance Components:
##
##              estim    sqrt  nlvls  fixed  factor
## sigma^2     0.0097  0.0986     43     no     obs
##
## Test for Heterogeneity:
## Q(df = 42) = 100.4464, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb   ci.ub
##  -0.0207  0.0207  -1.0004  0.3171  -0.0612  0.0198
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

##set prior

```
prior <- list(R=list(V = 1, nu =0.002), G = list(G = list(V=1, nu = 0.002)))
```

##run bayesian MLMA models

```
model_magnitude_bayes_2009 <- MCMCglmm(yi ~ 1, mev = lnRR2009clean$vi, random
= ~obs, data = lnRR2009clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2010 <- MCMCglmm(yi ~ 1, mev = lnRR2010clean$vi, random
= ~obs, data = lnRR2010clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2011 <- MCMCglmm(yi ~ 1, mev = lnRR2011clean$vi, random
= ~obs, data = lnRR2011clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2012 <- MCMCglmm(yi ~ 1, mev = lnRR2012clean$vi, random
= ~obs, data = lnRR2012clean, prior = prior, burnin = 10000, nitt = 1000000,
```

```
thin = 100, verbose = FALSE)
model_magnitude_bayes_2013 <- MCMCglmm(yi ~ 1, mev = lnRR2013clean$vi, random
= ~obs, data = lnRR2013clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2014 <- MCMCglmm(yi ~ 1, mev = lnRR2014clean$vi, random
= ~obs, data = lnRR2014clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2015 <- MCMCglmm(yi ~ 1, mev = lnRR2015clean$vi, random
= ~obs, data = lnRR2015clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2016 <- MCMCglmm(yi ~ 1, mev = lnRR2016clean$vi, random
= ~obs, data = lnRR2016clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2017 <- MCMCglmm(yi ~ 1, mev = lnRR2017clean$vi, random
= ~obs, data = lnRR2017clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2018 <- MCMCglmm(yi ~ 1, mev = lnRR2018clean$vi, random
= ~obs, data = lnRR2018clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
model_magnitude_bayes_2019 <- MCMCglmm(yi ~ 1, mev = lnRR2019clean$vi, random
= ~obs, data = lnRR2019clean, prior = prior, burnin = 10000, nitt = 1000000,
thin = 100, verbose = FALSE)
```

##get model summaries

```
summary(model_magnitude_bayes_2009)

##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: 46.16273
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs     17.35 0.0002051    49.73     2438
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units     17.39 0.0002823    49.29     2391
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp  pMCMC
## (Intercept)    3.1558   0.5123   5.9564    10249 0.0236 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(model_magnitude_bayes_2010)

##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: 108.8127
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs     13.46 0.0001863    33.46    865.2
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units     13.91 0.0001939    34.03    861.2
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp  pMCMC
## (Intercept)     3.697    2.216    5.167     9584 <1e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(model_magnitude_bayes_2011)

##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: -21.05161
##
##  G-structure:  ~obs
##
##     post.mean l-95% CI u-95% CI eff.samp
## obs   0.08085 0.000207   0.2081     4033
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units   0.08089 0.0002172   0.2087     4099
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)  -0.04049 -0.18989  0.10236     9900  0.57

summary(model_magnitude_bayes_2012)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: 63.1746
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs    0.6186 0.0001803    1.458      973
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units    0.6332 0.0001652    1.474    926.4
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)    0.1371  -0.1223   0.3958     9900 0.295
```

```
summary(model_magnitude_bayes_2013)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: 32.29096
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs    0.6546 0.0001715    1.712     1692
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units    0.6393 0.0001818    1.706     1697
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp   pMCMC
## (Intercept)   -0.5566  -0.9429  -0.1827     9900 0.00263 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(model_magnitude_bayes_2014)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: 155.1452
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs      7.21 0.0001178    16.91    527.1
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units     7.005 0.0002317    16.68    547.1
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)  -0.08333 -0.92816  0.72264     9900 0.843
```

```
summary(model_magnitude_bayes_2015)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: -82.93562
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs   0.04754 0.0001931    0.112     3378
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units   0.04511 0.0002274   0.1105     2531
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp  pMCMC
## (Intercept)  -0.09305 -0.17506 -0.01287     9900 0.0275 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(model_magnitude_bayes_2016)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: -17.68007
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs    0.1193 0.0002338   0.2842     2485
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units    0.1187 0.0002407    0.288     2584
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)  -0.01813 -0.16100  0.11992     9900 0.783
```

```
summary(model_magnitude_bayes_2017)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: -48.80205
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs   0.07871 0.0001776   0.1835     1858
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units   0.07764 0.0001581   0.1835     1866
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)   0.03190 -0.05685  0.12726     9900 0.499
```

```
summary(model_magnitude_bayes_2018)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
```

```
##  Sample size  = 9900
##
##  DIC: -20.8453
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs    0.1549 0.0002214   0.3959     1082
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units    0.1575 0.0001902    0.399     1094
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)   0.01220 -0.09014  0.11642     9900 0.814
```

```
summary(model_magnitude_bayes_2019)
```

```
##
##  Iterations = 10001:999901
##  Thinning interval  = 100
##  Sample size  = 9900
##
##  DIC: -97.31065
##
##  G-structure:  ~obs
##
##     post.mean  l-95% CI u-95% CI eff.samp
## obs  0.005837 0.0002286   0.0149     9477
##
##  R-structure:  ~units
##
##       post.mean l-95% CI u-95% CI eff.samp
## units  0.005793 0.000182  0.01459     9606
##
##  Location effects: yi ~ 1
##
##             post.mean l-95% CI u-95% CI eff.samp pMCMC
## (Intercept)  -0.02201 -0.06463  0.02346     9900 0.322
```

##extract posteriors

```
sol2009 <- model_magnitude_bayes_2009$Sol
VCV2009 <- model_magnitude_bayes_2009$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2009$VCV))]
sol2010 <- model_magnitude_bayes_2010$Sol
VCV2010 <- model_magnitude_bayes_2010$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2010$VCV))]
```

```
sol2011 <- model_magnitude_bayes_2011$Sol
VCV2011 <- model_magnitude_bayes_2011$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2011$VCV))]
sol2012 <- model_magnitude_bayes_2012$Sol
VCV2012 <- model_magnitude_bayes_2012$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2012$VCV))]
sol2013 <- model_magnitude_bayes_2013$Sol
VCV2013 <- model_magnitude_bayes_2013$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2013$VCV))]
sol2014 <- model_magnitude_bayes_2014$Sol
VCV2014 <- model_magnitude_bayes_2014$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2014$VCV))]
sol2015 <- model_magnitude_bayes_2015$Sol
VCV2015 <- model_magnitude_bayes_2015$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2015$VCV))]
sol2016 <- model_magnitude_bayes_2016$Sol
VCV2016 <- model_magnitude_bayes_2016$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2016$VCV))]
sol2017 <- model_magnitude_bayes_2017$Sol
VCV2017 <- model_magnitude_bayes_2017$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2017$VCV))]
sol2018 <- model_magnitude_bayes_2018$Sol
VCV2018 <- model_magnitude_bayes_2018$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2018$VCV))]
sol2019 <- model_magnitude_bayes_2019$Sol
VCV2019 <- model_magnitude_bayes_2019$VCV[,-match("sqrt(mev):sqrt(mev).meta",
colnames(model_magnitude_bayes_2019$VCV))]
```

##get folded normal function

```
mu.fnorm <- function(mu, sigma){dnorm(mu, 0, sigma)*2*sigma^2 +
mu*(2*pnorm(mu, 0, sigma) -1)}
```

##get magnitude means + variance

```
magnitude_mean_2009 <- mu.fnorm(sol2009[,1], sqrt(rowSums(VCV2009)))
magnitude_2009_mean <- data.frame(mean_mag = mean(magnitude_mean_2009), L_CI
= HPDinterval(magnitude_mean_2009)[1], U_CI =
HPDinterval(magnitude_mean_2009)[2])
magnitude_mean_2010 <- mu.fnorm(sol2010[,1], sqrt(rowSums(VCV2010)))
magnitude_2010_mean <- data.frame(mean_mag = mean(magnitude_mean_2010), L_CI
= HPDinterval(magnitude_mean_2010)[1], U_CI =
HPDinterval(magnitude_mean_2010)[2])
magnitude_mean_2011 <- mu.fnorm(sol2011[,1], sqrt(rowSums(VCV2011)))
magnitude_2011_mean <- data.frame(mean_mag = mean(magnitude_mean_2011), L_CI
= HPDinterval(magnitude_mean_2011)[1], U_CI =
HPDinterval(magnitude_mean_2011)[2])
magnitude_mean_2012 <- mu.fnorm(sol2012[,1], sqrt(rowSums(VCV2012)))
magnitude_2012_mean <- data.frame(mean_mag = mean(magnitude_mean_2012), L_CI
= HPDinterval(magnitude_mean_2012)[1], U_CI =
HPDinterval(magnitude_mean_2012)[2])
```

```
magnitude_mean_2013 <- mu.fnorm(sol2013[,1], sqrt(rowSums(VCV2013)))
magnitude_2013_mean <- data.frame(mean_mag = mean(magnitude_mean_2013), L_CI
= HPDinterval(magnitude_mean_2013)[1], U_CI =
HPDinterval(magnitude_mean_2013)[2])
magnitude_mean_2014 <- mu.fnorm(sol2014[,1], sqrt(rowSums(VCV2014)))
magnitude_2014_mean <- data.frame(mean_mag = mean(magnitude_mean_2014), L_CI
= HPDinterval(magnitude_mean_2014)[1], U_CI =
HPDinterval(magnitude_mean_2014)[2])
magnitude_mean_2015 <- mu.fnorm(sol2015[,1], sqrt(rowSums(VCV2015)))
magnitude_2015_mean <- data.frame(mean_mag = mean(magnitude_mean_2015), L_CI
= HPDinterval(magnitude_mean_2015)[1], U_CI =
HPDinterval(magnitude_mean_2015)[2])
magnitude_mean_2016 <- mu.fnorm(sol2016[,1], sqrt(rowSums(VCV2016)))
magnitude_2016_mean <- data.frame(mean_mag = mean(magnitude_mean_2016), L_CI
= HPDinterval(magnitude_mean_2016)[1], U_CI =
HPDinterval(magnitude_mean_2016)[2])
magnitude_mean_2017 <- mu.fnorm(sol2017[,1], sqrt(rowSums(VCV2017)))
magnitude_2017_mean <- data.frame(mean_mag = mean(magnitude_mean_2017), L_CI
= HPDinterval(magnitude_mean_2017)[1], U_CI =
HPDinterval(magnitude_mean_2017)[2])
magnitude_mean_2018 <- mu.fnorm(sol2018[,1], sqrt(rowSums(VCV2018)))
magnitude_2018_mean <- data.frame(mean_mag = mean(magnitude_mean_2018), L_CI
= HPDinterval(magnitude_mean_2018)[1], U_CI =
HPDinterval(magnitude_mean_2018)[2])
magnitude_mean_2019 <- mu.fnorm(sol2019[,1], sqrt(rowSums(VCV2019)))
magnitude_2019_mean <- data.frame(mean_mag = mean(magnitude_mean_2019), L_CI
= HPDinterval(magnitude_mean_2019)[1], U_CI =
HPDinterval(magnitude_mean_2019)[2])
```

##view ES magnitudes and uncertainty

```
magnitude_2009_mean

##   mean_mag     L_CI     U_CI
## 1 5.416246 3.758106 7.365909

magnitude_2010_mean

##   mean_mag     L_CI     U_CI
## 1 5.199176 4.196557 6.226312

magnitude_2011_mean

##    mean_mag      L_CI      U_CI
## 1 0.3239374 0.2247471 0.4237778

magnitude_2012_mean

##    mean_mag      L_CI     U_CI
## 1 0.9020142 0.7537249 1.073976

magnitude_2013_mean
```

```
##   mean_mag      L_CI     U_CI
## 1 1.015485 0.7084387 1.334864
```

```
magnitude_2014_mean
```

```
##   mean_mag     L_CI     U_CI
## 1 3.016854 2.519681 3.494669
```

```
magnitude_2015_mean
```

```
##    mean_mag      L_CI      U_CI
## 1 0.2544772 0.1972141 0.3211297
```

```
magnitude_2016_mean
```

```
##   mean_mag      L_CI      U_CI
## 1 0.390854 0.3068355 0.4855179
```

```
magnitude_2017_mean
```

```
##    mean_mag      L_CI      U_CI
## 1 0.3169368 0.2492119 0.3829632
```

```
magnitude_2018_mean
```

```
##   mean_mag      L_CI      U_CI
## 1 0.443245 0.3278022 0.5776087
```

```
magnitude_2019_mean
```

```
##     mean_mag       L_CI      U_CI
## 1 0.08770257 0.05318047 0.1262964
```

#Note Code below not in original. Made to allow a data frame to be constructed and plotted from.

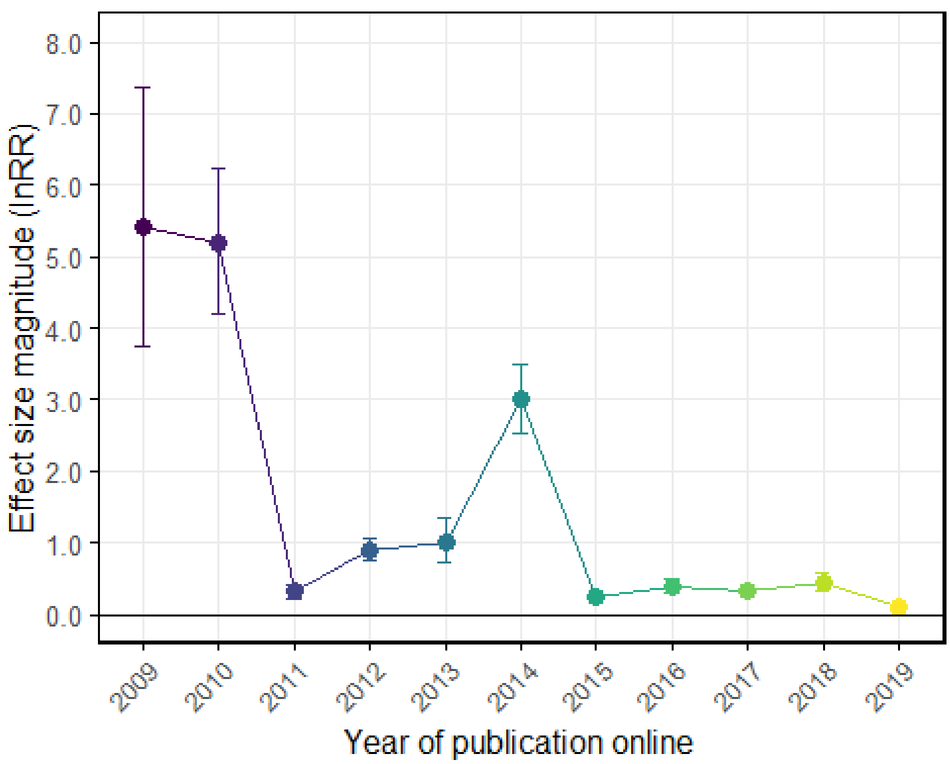
```
magnitudedata = rbind(magnitude_2009_mean, magnitude_2010_mean,
magnitude_2011_mean, magnitude_2012_mean, magnitude_2013_mean,
magnitude_2014_mean, magnitude_2015_mean, magnitude_2016_mean,
magnitude_2017_mean, magnitude_2018_mean, magnitude_2019_mean)

yearlabel = c("2009", "2010", "2011", "2012", "2013", "2014", "2015", "2016",
"2017", "2018", "2019")

magnitudedata = cbind(yearlabel, magnitudedata )
magnitudedata
```

```
##    yearlabel   mean_mag       L_CI      U_CI
## 1       2009 5.41624642 3.75810645 7.3659088
## 2       2010 5.19917624 4.19655742 6.2263116
## 3       2011 0.32393741 0.22474713 0.4237778
## 4       2012 0.90201423 0.75372493 1.0739760
## 5       2013 1.01548493 0.70843872 1.3348644
## 6       2014 3.01685434 2.51968134 3.4946689
```

```
## 7        2015 0.25447716 0.19721412 0.3211297
## 8        2016 0.39085404 0.30683550 0.4855179
## 9        2017 0.31693676 0.24921188 0.3829632
## 10       2018 0.44324502 0.32780217 0.5776087
## 11       2019 0.08770257 0.05318047 0.1262964
```

#Note Plot from above model was not included in the original code. This has been built from scratch. Should be the same as Fig 1B

```
Decline_magnitude<-ggplot(magnitudedata,aes(x=yearlabel, y=mean_mag,
colour=yearlabel))  + geom_line(aes(group=1)) +
scale_color_viridis(discrete=TRUE)+ geom_point(size=3) +  geom_errorbar(aes
(ymin = L_CI, ymax = U_CI), width=0.2) +  scale_y_continuous(breaks = seq(0,
15, by = 1), minor_breaks = NULL, limits=c(0,8),labels =
scales::number_format(accuracy = 0.1)) +  theme(legend.position = "none") +
xlab("Year of publication online") + ylab("Effect size magnitude (lnRR)")  +
theme_minimal(12) + theme(panel.border = element_rect(colour = "black",
fill=NA, size=1)) + theme(legend.position = "none") +
theme(axis.ticks=element_line()) + theme(axis.text.x = element_text(angle =
45, hjust=1))+ geom_hline(yintercept = 0)

Decline_magnitude
```




```
ggsave(Decline_magnitude, filename = 'Decline magnitude original model
lnRR.png', device=png,  width = 4.2, height = 4.6, units = "in", res = 800)
```

CREATE SCATTERPLOT FIGURE TO VISUALIZE MEAN EFFECT SIZE MAGNITUDE FOR EACH OBSERVATION OVER TIME (FIG 1A)

##attach dataset

```
decline_allobs<-read.csv(file.choose()) ##use dataset "S10 Data"
attach(decline_allobs)
```

```
## The following objects are masked from decline:
##
##     ctrl.n, study, year.online, year.print
```

```
summary(decline_allobs)
```

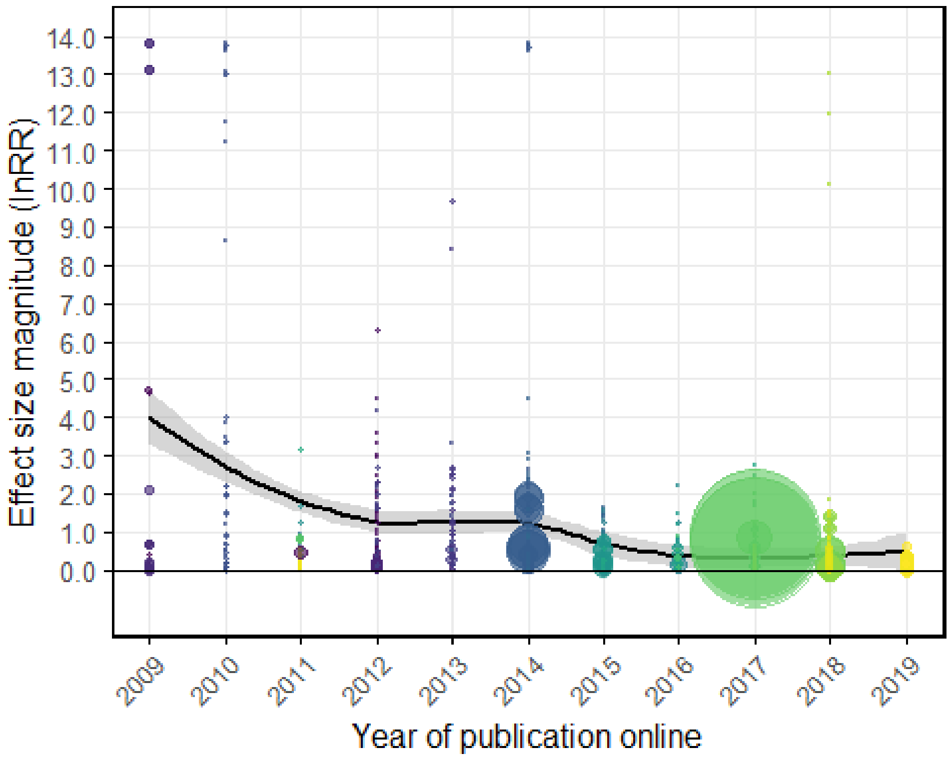
```
##      ï..obs          study             year.print    year.online
##  Min.   :  1.0   Length:795         Min.   :2009   Min.   :2009
##  1st Qu.:211.5   Class :character   1st Qu.:2013   1st Qu.:2012
##  Median :419.0   Mode  :character   Median :2015   Median :2015
##  Mean   :414.8                      Mean   :2015   Mean   :2015
##  3rd Qu.:619.5                      3rd Qu.:2018   3rd Qu.:2017
##  Max.   :818.0                      Max.   :2019   Max.   :2019
##      ctrl.n          lnrr.mag
##  Min.   :  4.00   Min.   : 0.00000
##  1st Qu.: 10.00   1st Qu.: 0.09394
##  Median : 18.00   Median : 0.26889
##  Mean   : 29.36   Mean   : 0.96125
##  3rd Qu.: 30.00   3rd Qu.: 0.75979
##  Max.   :752.00   Max.   :13.81551
```

##Create plot

#Note I had to fix the specifications of the scale continuous both x and y Original below not working: scale_x_continuous(breaks = round(seq(min(study*Year*), *max*(*study*Year), by = 1),1)) + scale_y_continuous(breaks = round(seq(min(study$lnrr), 15, by = 1),1)) #Note Code given did not produce a graph that looked exactly the same as in the figures of the paper. Changes to aesthetics were add to make it look the same as the published version.

```
Decline_studies_loess<-ggplot(decline_allobs,aes(x=year.online, y=lnrr.mag,
color=study)) + geom_smooth(method="loess", se=TRUE, fullrange=TRUE,
level=0.95,color="black") + geom_point(size=ctrl.n*0.03,alpha=0.6) +
scale_size(range = c(1, 2), name="Sample size")+
scale_color_viridis(discrete=TRUE)+ xlab("Year of publication
online")+ylab("Effect size magnitude (lnRR)") + scale_x_continuous(breaks =
round(seq(min(2009), max(2019), by = 1),1)) + scale_y_continuous(breaks =
seq(0, 14, by = 1), minor_breaks = NULL, limits=c(-1,14),labels =
scales::number_format(accuracy = 0.1)) + theme_minimal(12) +
theme(legend.position = "none") + theme(panel.grid.minor = element_blank())
+ theme(panel.border = element_rect(colour = "black", fill=NA, size=1)) +
theme(legend.position = "none")+ theme(axis.ticks=element_line()) +
theme(axis.text.x = element_text(angle = 45, hjust=1))+ geom_hline(yintercept
= 0)
```

```
Decline_studies_loess

## `geom_smooth()` using formula 'y ~ x'
```




```
ggsave(Decline_studies_loess, filename = 'Decline magnitude original
lnRR.png', device=png,  width = 4.2, height = 4.6, units = "in", res = 800)

## `geom_smooth()` using formula 'y ~ x'
```