STATISTICAL MODELS FOR QUANTITATIVE SYNTHESIS OF CLIMATE CHANGE IMPACT STUDIES

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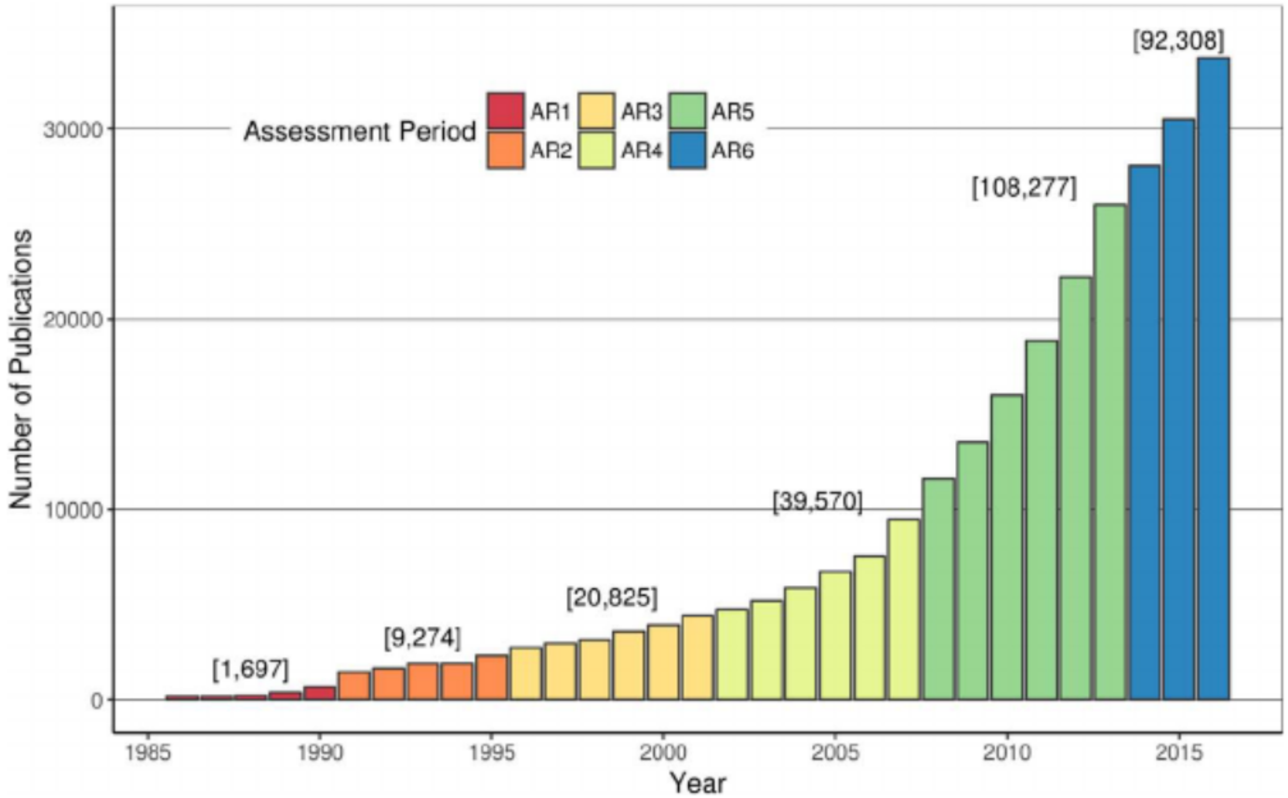
The ‘data synthesis challenge’

As more and more data become available, how to conduct rigorous and comprehensive assessments on climate change?

The Intergovernmental Panel on Climate Change

The Intergovernmental Panel on Climate Change (IPCC) is the United Nations body for assessing the science related to climate change.

The growth of the literature on climate change was much faster than the growth in other areas of research (16% vs. 4%)



Minx J.C., Callaghan M., Lamb W.F., Garard J., Edenhofer O. 2017. Learning about climate change solutions in the IPCC and beyond. Environmental Science and Policy 77, 252-259

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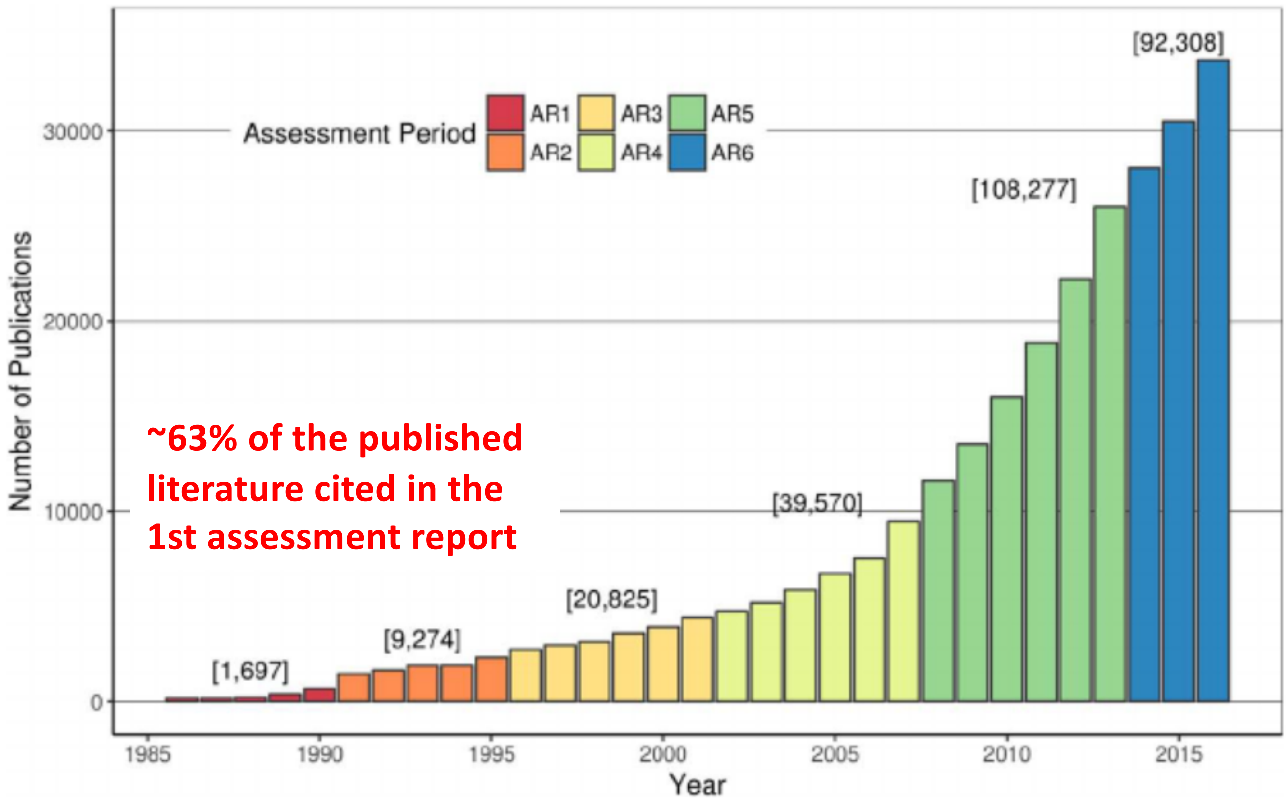

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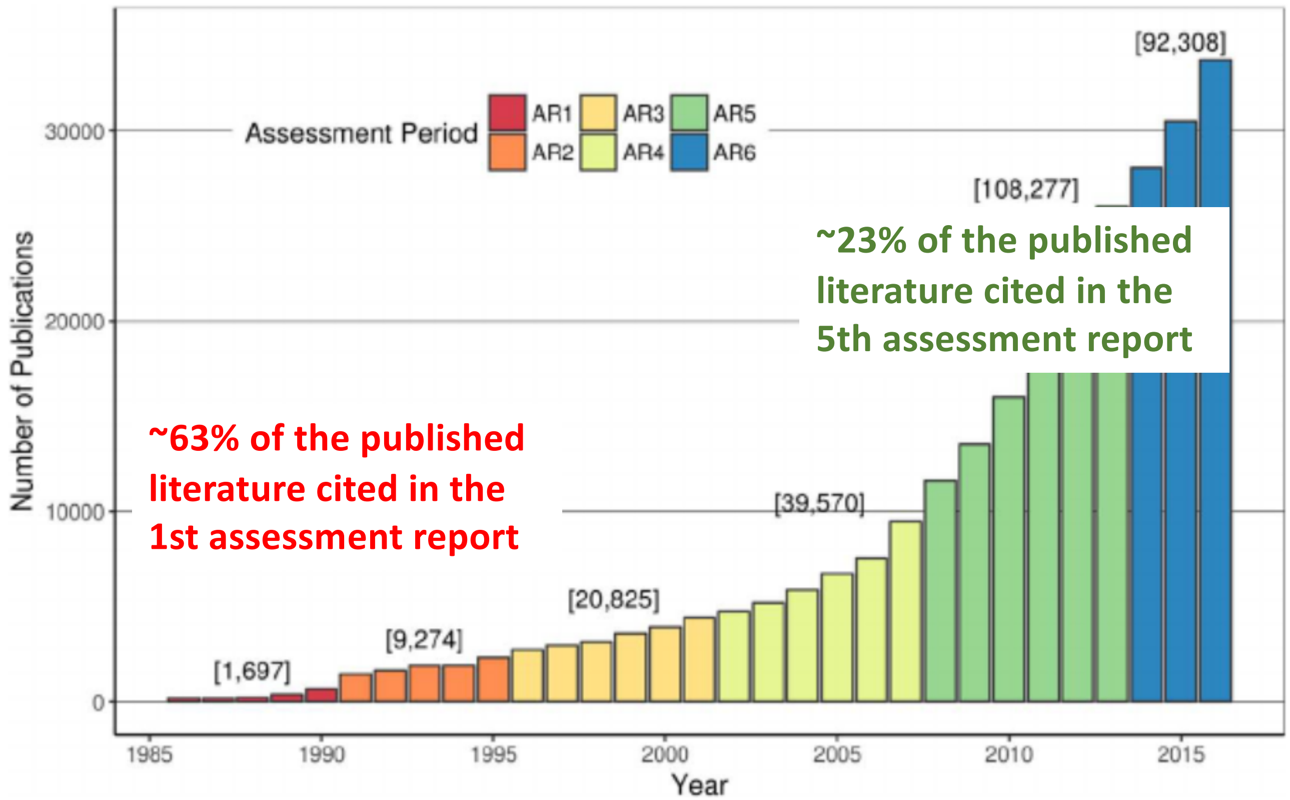


Minx J.C., Callaghan M., Lamb W.F., Garard J., Edenhofer O. 2017. Learning about climate change solutions in the IPCC and beyond. Environmental Science and Policy 77, 252-259

Formal methods are needed to help researchers to conduct rigorous and comprehensive literature synthesis

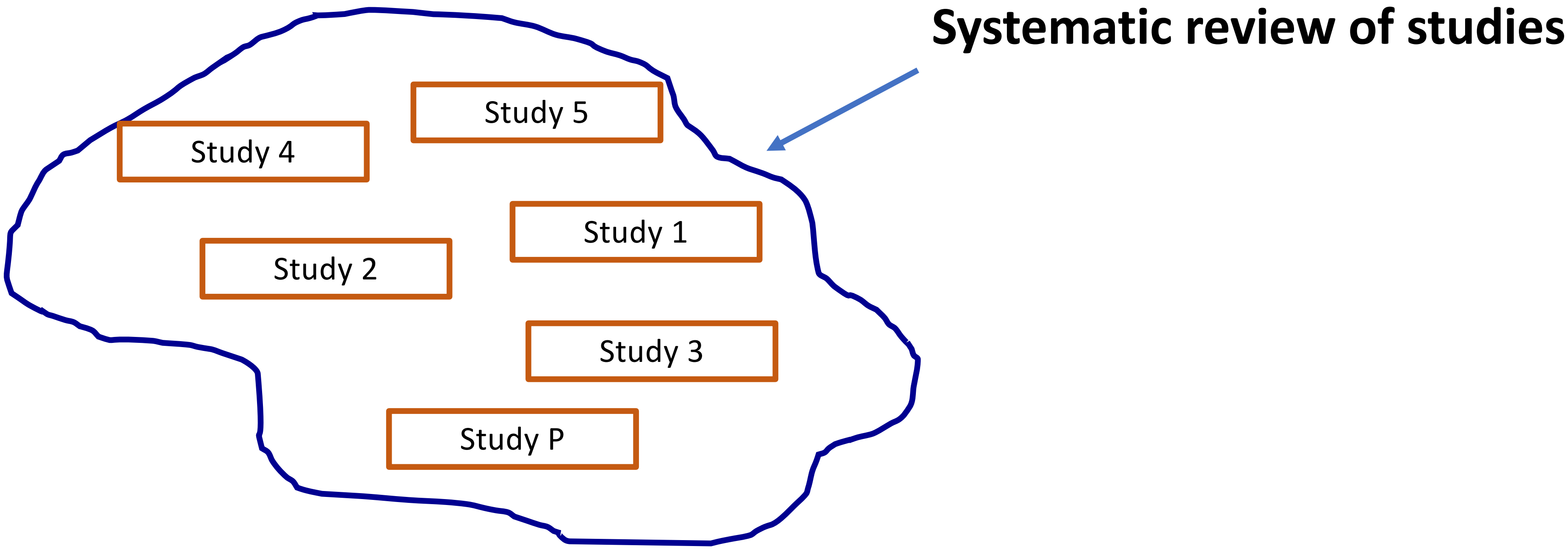
Meta-analysis: a statistical approach for quantitative synthesis

« The analysis of analyses »

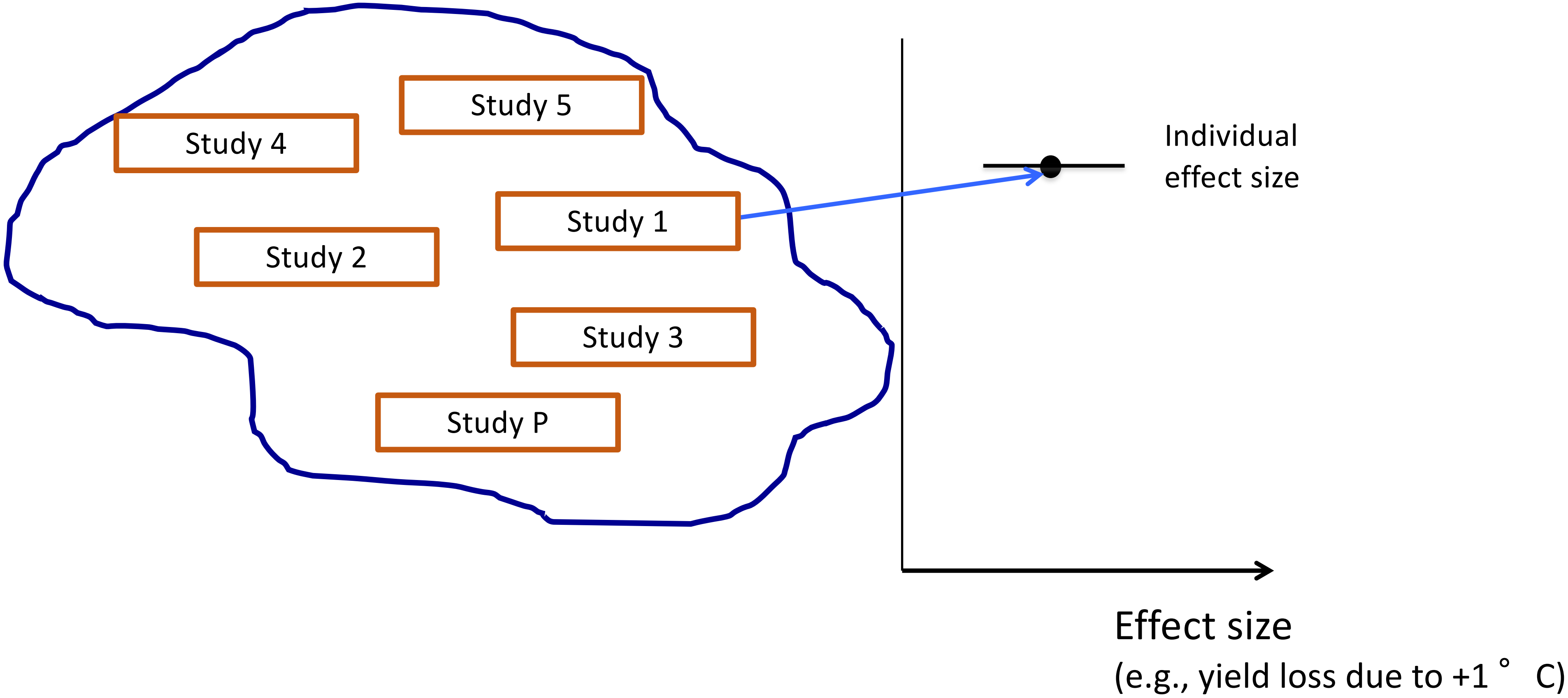
« The statistical analysis of a large collection of results from individual studies for the purpose of integrating the findings »

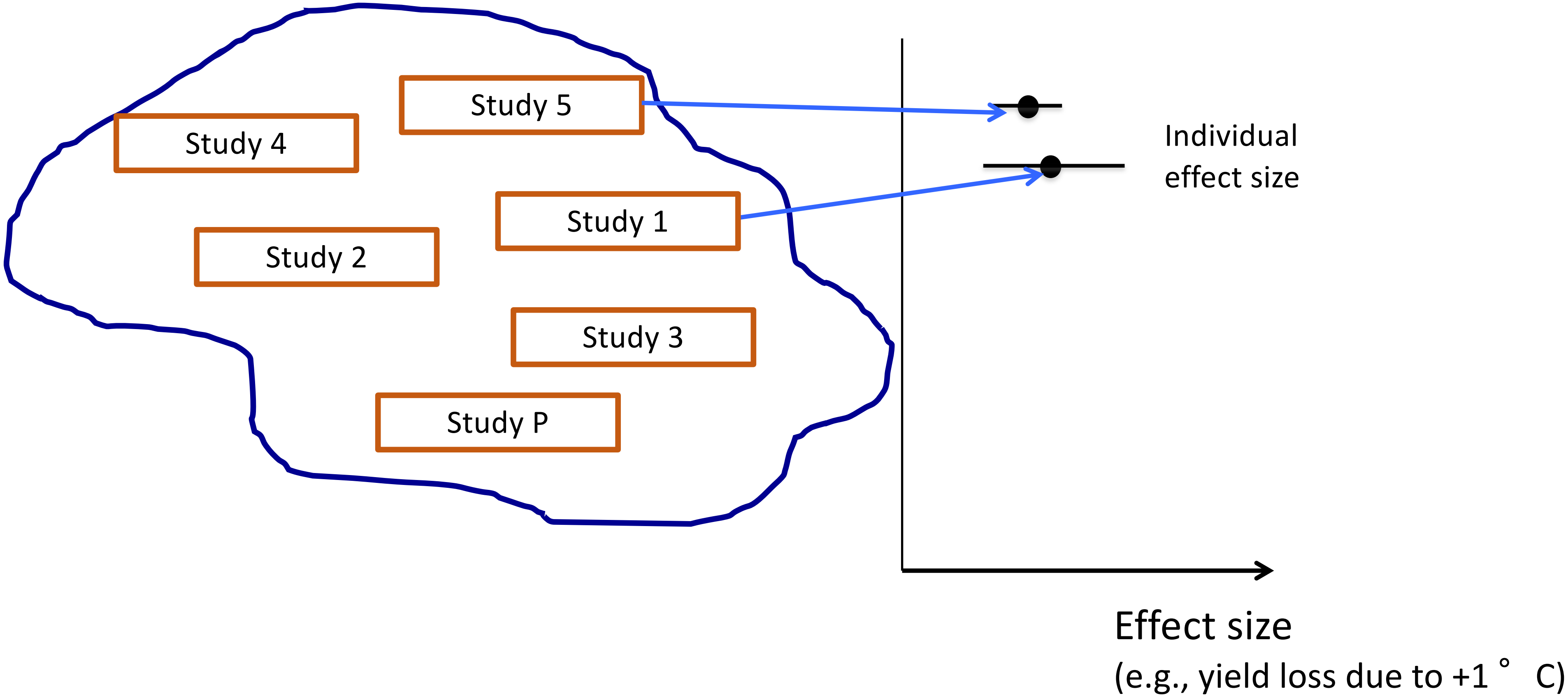
« Systematic review + statistical analysis »

Dictionary of epidemiology, 2001; Chalmers et al., 2002; Glass, 1976; Koricheva et al., 2013



Set of studies dealing with a specific topic
(e.g., %yield loss due to +1°C)


Study 5
Study 4
Study 1
Study 2
Study 3
Study P
Individual
effect size
Effect size
(e.g., yield loss due to +1 ° C)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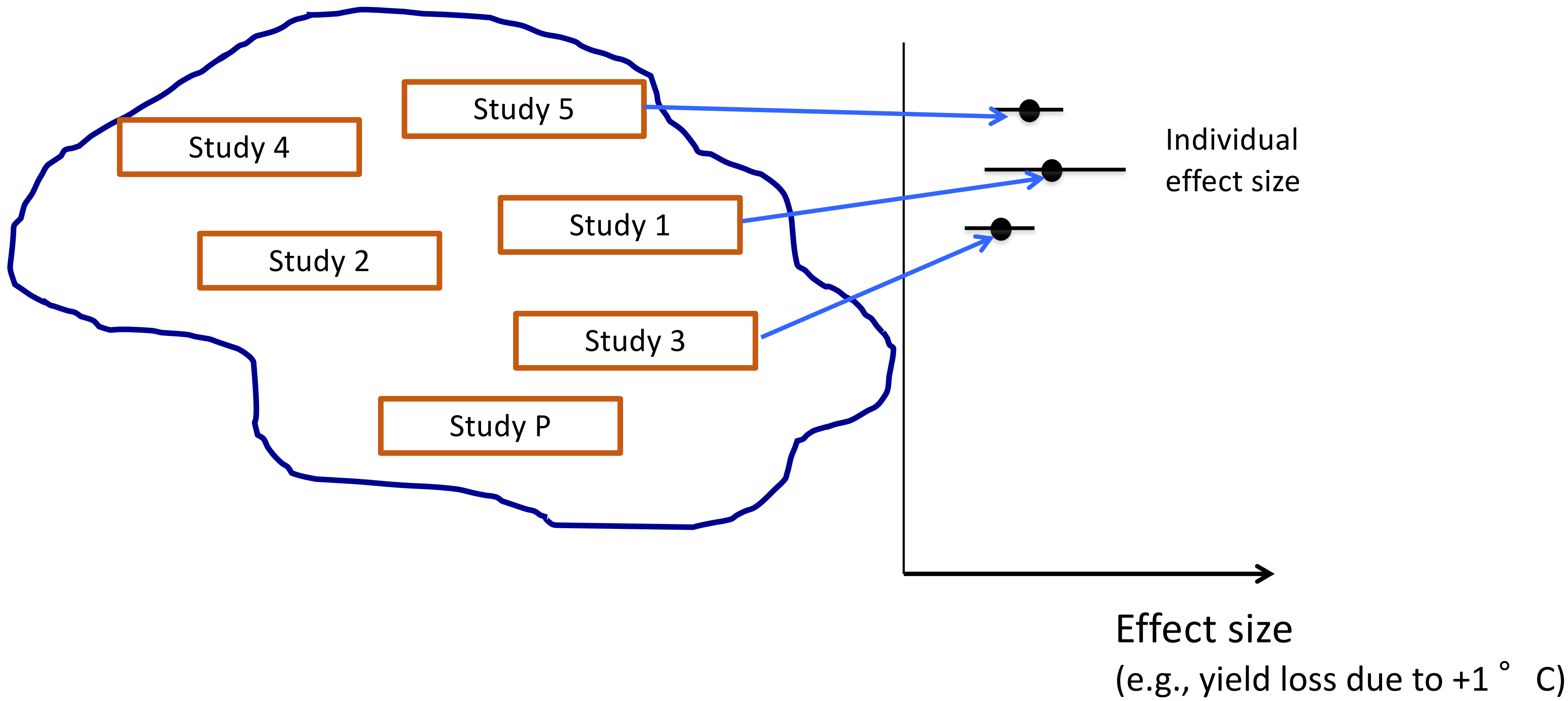
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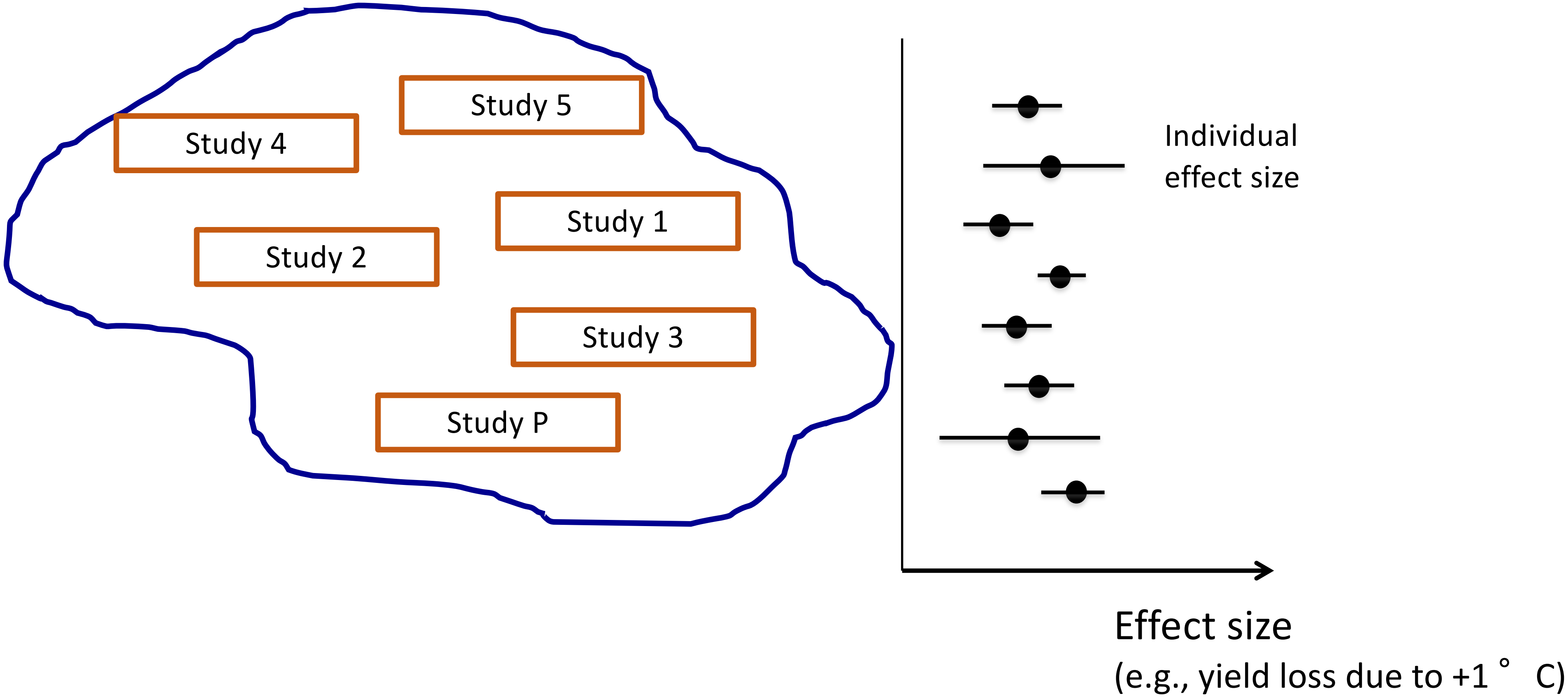
Study 5
Study 4
Study 1
Study 2
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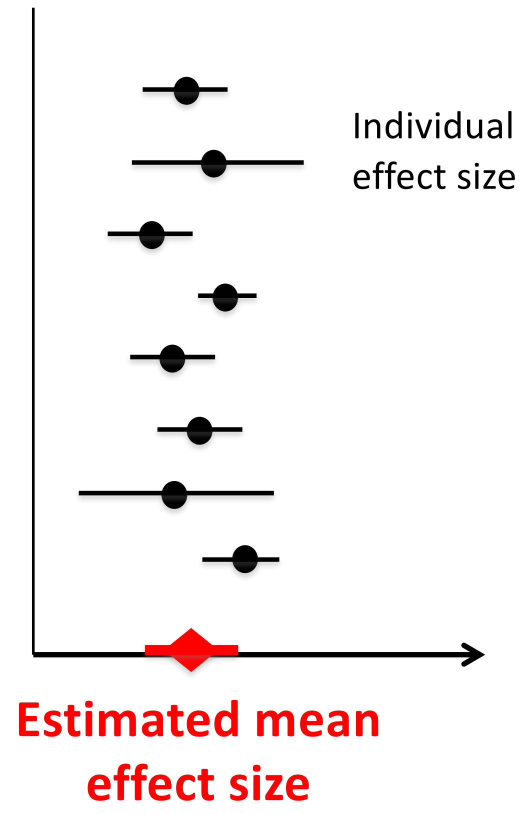
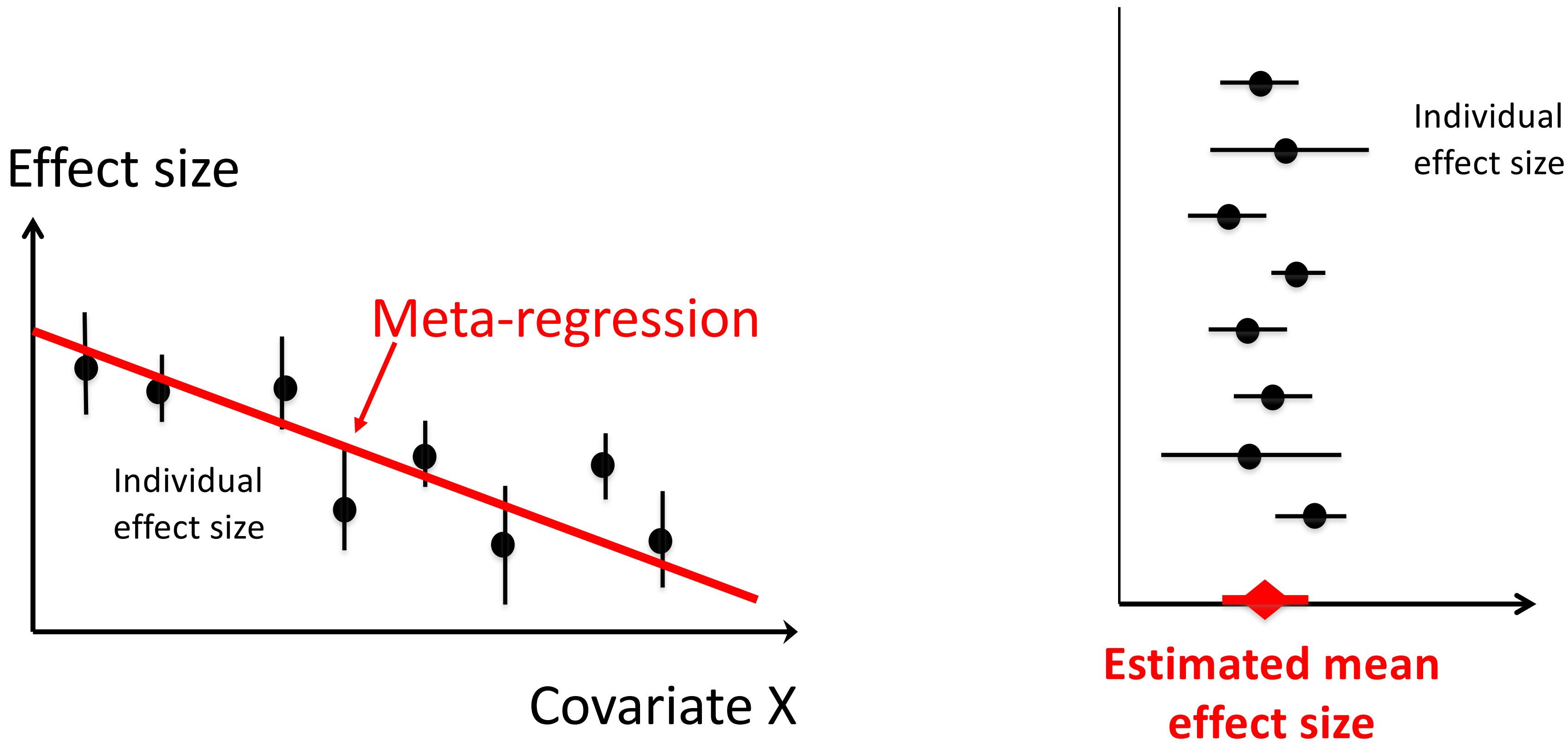
Study P
Individual
effect size
Effect size
(e.g., yield loss due to +1 ° C)


Individual
effect size
Estimated mean
effect size



Effect size
Meta-regression
Individual
effect size
Covariate X
Individual
effect size
Estimated mean
effect size

Example: Assessment of the impact of temperature increase on crop yield

Two sources of information:

- Experiments
- Crop model simulations

Example: Assessment of the impact of temperature increase on crop yield

Two sources of information:

- **Experiments**
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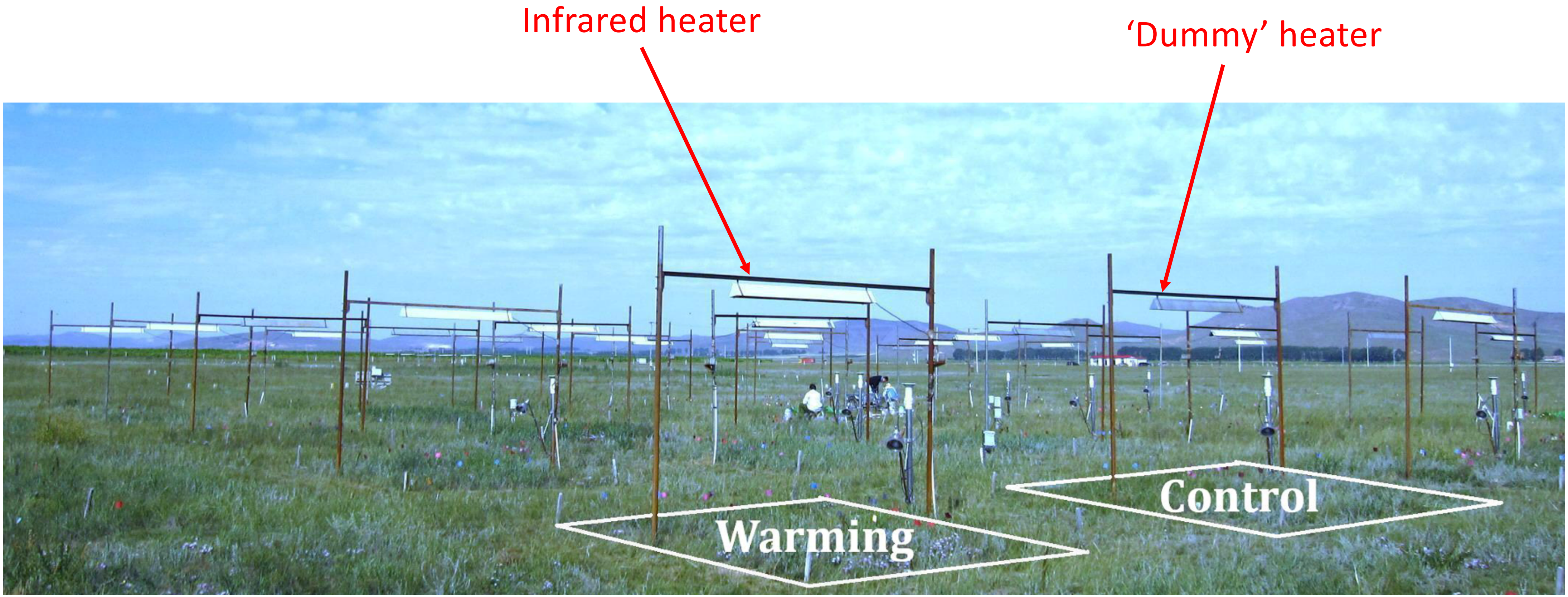
Field warming experiment



from Chi et al. 2013 doi.org/10.1371/journal.pone.0056482

$$\Delta Y = (Yield_{warm} \text{-} Yield_{control})/Yield_{control}$$

$$Sensitivity = Yield\ \%\ change\ per\ °\mathrm{C} = 100\frac{\Delta Y}{\Delta T}$$

nature plants

Letter | Published: 19 December 2016

Plausible rice yield losses under future climate warming

Chuang Zhao, Shilong Piao, Xuhui Wang, Yao Huang, Philippe Ciais, Joshua Elliott, Mengtian Huang, Ivan A. Janssens, Tao Li, Xu Lian, Yongwen Liu, Christoph Müller, Shushi Peng, Tao Wang, Zhenzhong Zeng & Josep Peñuelas

Compilation of results of 83 field warming experiments located in 14 sites in the world

Field experiment
Ambient CO_2

83 values of yield sensitivity (% yield loss per°C) in 14 sites

Country	Site name	Latitude	Longtitude	Research time (year)	Nitrogen (kg ha^{-1})	Warming design	Warming type	Temperature change (ΔK)	Growing season temperature (K)	$S^{obs}_{Y,T}$ (% K^{-1})
Philippines	Los Banos	14.22	121.25	1994	110	Open top camber	Passive	4.0	299.7	-6.4
Philippines	Los Banos	14.22	121.25	1995	220	Open top camber	Passive	4.0	299.1	-4.1
Nepal	Khumaltar	27.65	85.33	2001	N.A.	Open top camber	Passive	6.8	296.8	1.1
Nepal	Khumaltar	27.65	85.33	2002	N.A.	Open top camber	Passive	4.4	296.2	2.3
Nepal	Khumaltar	27.65	85.33	2003	N.A.	Open top camber	Passive	5.8	296.7	6.6
Nepal	Khumaltar	27.65	85.33	2004	N.A.	Open top camber	Passive	7.3	296.4	2.1

…

from Zhao et al., 2016

83 values of yield sensitivity in 14 sites

Country	Site name	Latitude	Longtitude	Research time (year)	Nitrogen (kg ha^{-1})	Warming design	Warming type	Temperature change (ΔK)	Growing season temperature (K)	$S^{obs}_{Y,T}$ (% K^{-1})
Philippines	Los Banos	[illegible]	[illegible]	1994	110	Open top camber	Passive	4.0	299.7	-6.4
Philippines	Los Banos	**Study 1**	[illegible]	1995	220	Open top camber	Passive	4.0	299.1	-4.1
Nepal	Khumaltar	[illegible]	[illegible]	2001	N.A.	Open top camber	Passive	6.8	296.8	1.1
Nepal	Khumaltar	[illegible]	[illegible]	2002	N.A.	Open top camber	Passive	4.4	296.2	2.3
Nepal	Khumaltar	**Study 2**	[illegible]	2003	N.A.	Open top camber	Passive	5.8	296.7	6.6
Nepal	Khumaltar	[illegible]	[illegible]	2004	N.A.	Open top camber	Passive	7.3	296.4	2.1

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from Zhao et al., 2016

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...

from Zhao et al., 2016

Two levels of variability:
- Within study
- Between studies

Country	Site name	Latitude	Longtitude	Research time (year)	Nitrogen (kg ha^{-1})	Warming design	Warming type	Temperature change (ΔK)	Growing season temperature (K)	$S^{obs}_{Y,T}$ (% K^{-1})
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…

from Zhao et al., 2016

Hierarchical statistical model
« Random-effect model »

Overall mean

Effect of study i

Within-study level: $S_{ij} = \mu + b_i + \varepsilon_{ij}$ $\qquad \varepsilon_{ij} \sim N\left(0, \sigma_{\varepsilon i}^2\right)$

Yield sensitivity in study i, replicate j

Residual for jth data in study i

Hierarchical statistical model
« Random-effect model (1) »

Overall mean

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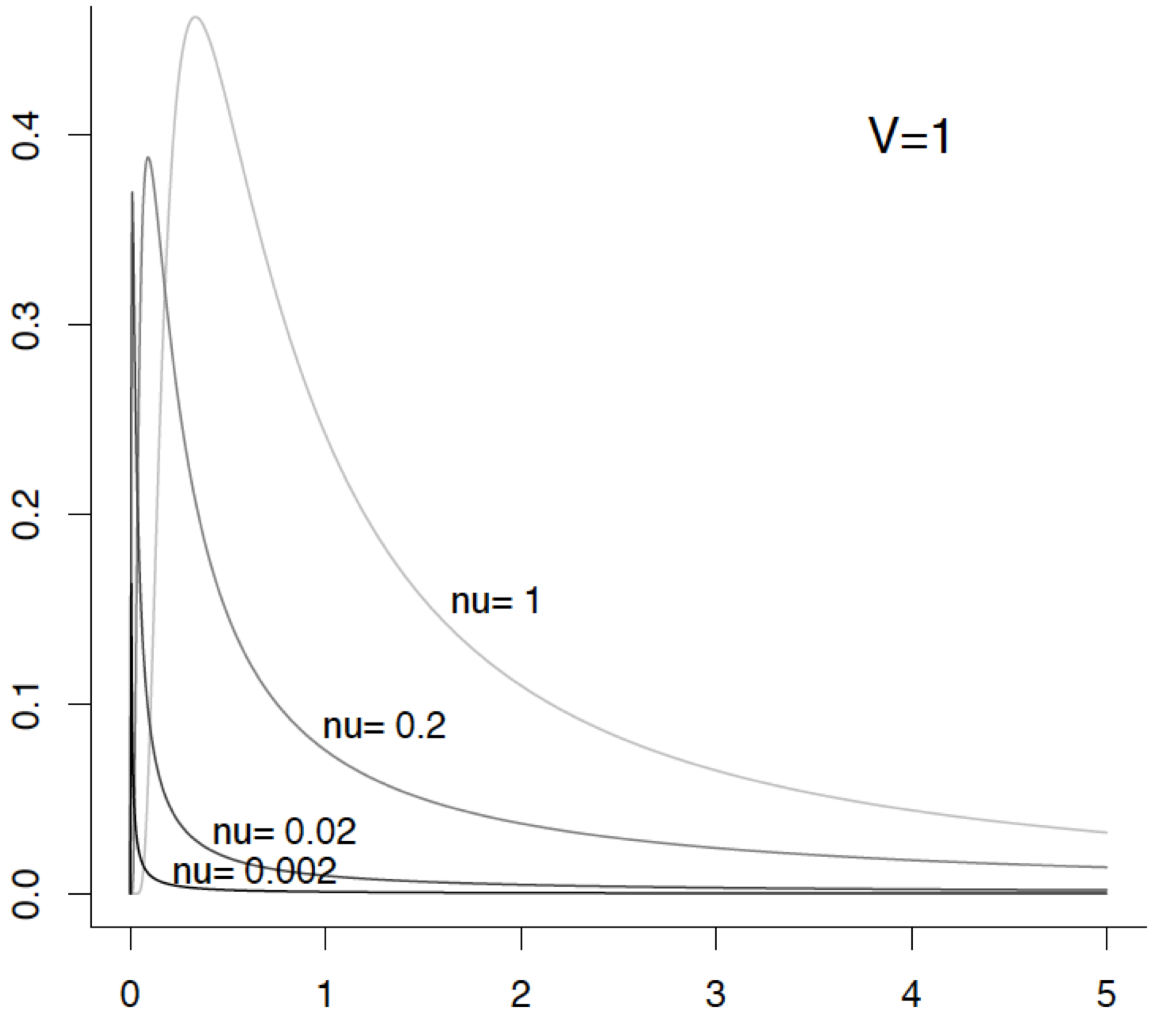
Yield sensitivity in study i, replicate j

Residual for jth data in study i

Between-study level: $b_i \sim N\left(0, \sigma_b^2\right)$

Prior: Gaussian and InvGamma

$$\begin{cases} \mu \sim N(mu, V) \\ \sigma_{\varepsilon i}^2 \sim InvGamma(scaleR, shapeR) \\ \sigma_b^2 \sim InvGamma(scaleB, shapeB) \end{cases}$$

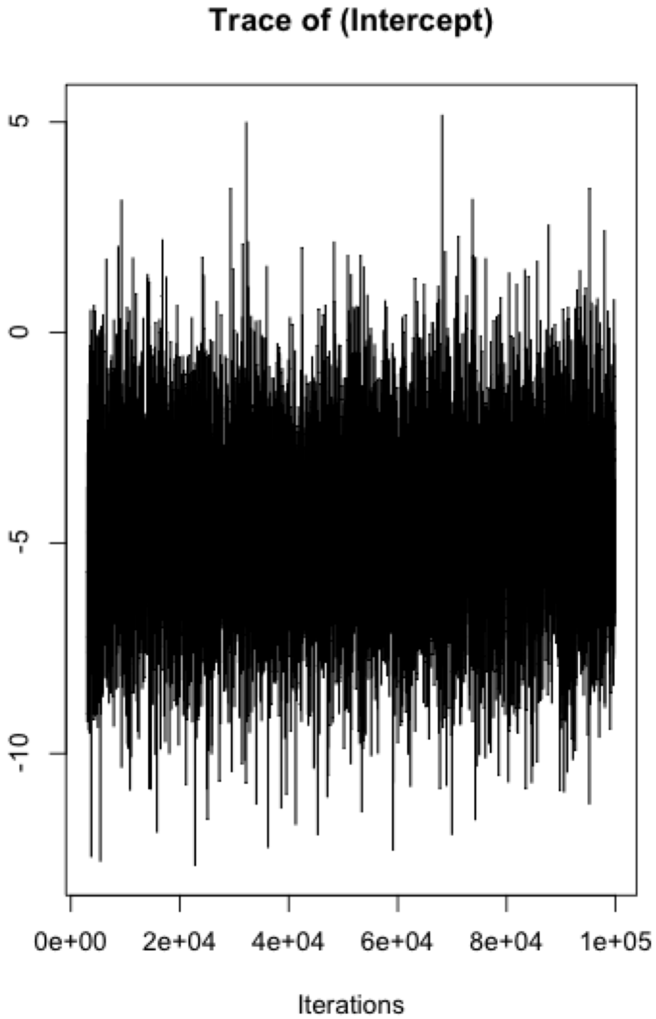


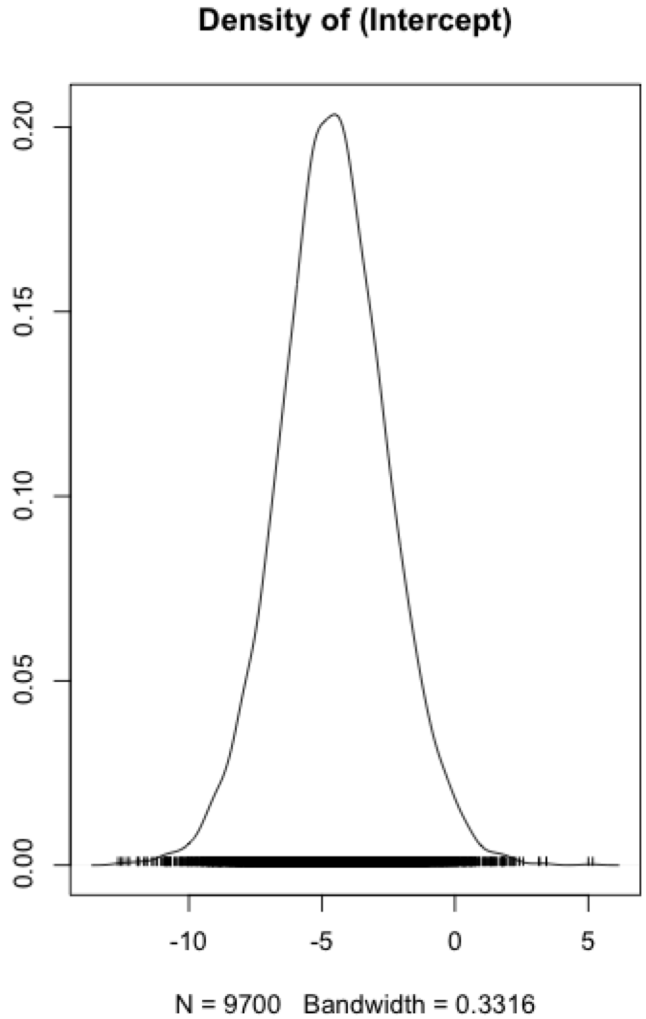
scale = nu/2

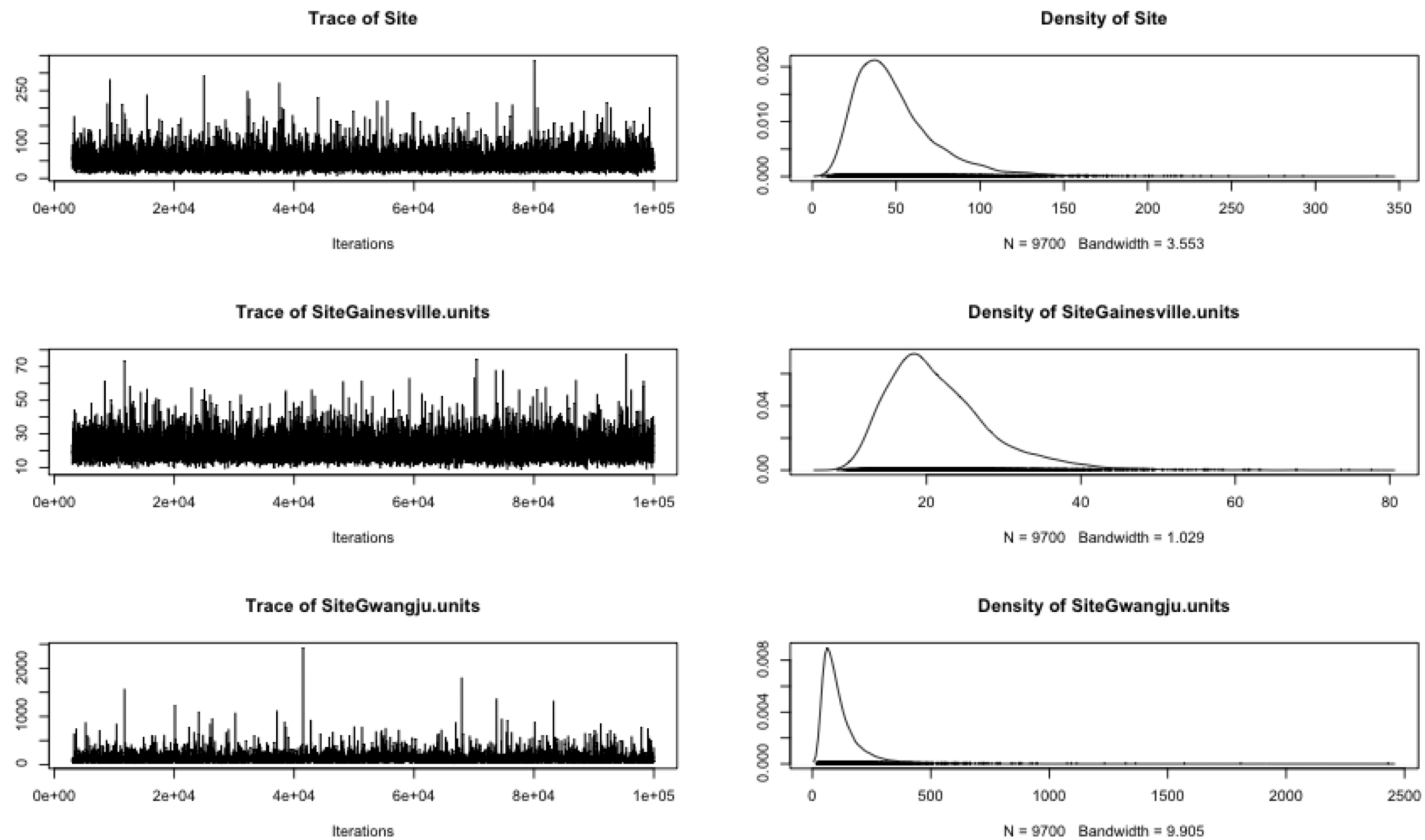
shape=V*nu/2

R package MCMCglmm

```
prior_rand_het<- list(
B=list(mu=0,V=10^6),
R=list(V=diag(1,length(unique(TAB$Site)), length(unique(TAB$Site))),nu=1),
G=list(G1=list(V=1,nu=1))
)

Mod_mcmc_rand_het<-MCMCglmm(
Sobs_perc~1,
random=~Site,
rcov=~idh(Site):units,
data=TAB, verbose=F, nitt=100000, burnin=3000, thin=10,
prior=prior_rand_het, pr=T
)
```


Trace of (Intercept)
5
0
-5
-10
0e+00
2e+04
4e+04
6e+04
8e+04
1e+05
Iterations


Density of (Intercept)
0.20
0.15
0.10
0.05
0.00
-10
-5
0
5
N = 9700   Bandwidth = 0.3316


Trace of Site
0
100
250
0e+00
2e+04
4e+04
6e+04
8e+04
1e+05
Iterations
Density of Site
0.000
0.010
0.020
0
50
100
150
200
250
300
350
N = 9700 Bandwidth = 3.553
Trace of SiteGainesville.units
10
30
50
70
0e+00
2e+04
4e+04
6e+04
8e+04
1e+05
Iterations
Density of SiteGainesville.units
0.00
0.04
20
40
60
80
N = 9700 Bandwidth = 1.029
Trace of SiteGwangju.units
0
1000
2000
0e+00
2e+04
4e+04
6e+04
8e+04
1e+05
Iterations
Density of SiteGwangju.units
0.000
0.004
0.008
0
500
1000
1500
2000
2500
N = 9700 Bandwidth = 9.905

```
> head(Mod_mcmc_rand_het$Sol)
Markov Chain Monte Carlo (MCMC) output:
Start = 3001
End = 3061
Thinning interval = 10
     (Intercept) Site.Gainesville Site.Gwangju Site.Harbin Site.Jingzhou Site.Khumaltar Site.Laguna Site.LosBanos Site.Nanjing
[1,]   -3.663948        -9.157550    -8.182304    2.999596      7.696671       6.673977    6.577363   -0.14991159     2.458215
[2,]   -9.244114        -4.648341    -5.329561    8.464304     16.556600      13.991736   21.329155    5.26497470     8.522610
[3,]   -5.666136        -7.809612   -10.049718    7.102704      8.156297       8.233011   15.531659    1.72312768     2.069199
[4,]   -7.234126        -5.314662     1.658556    7.812815     17.397032       9.892770   16.337398    1.70098491     3.139434
[5,]   -9.076909        -4.778029    -7.885294   10.156391     13.435594      11.661039   16.953006    6.96367095     6.483576
[6,]   -2.861152       -10.925759    -9.286733    4.900929      3.875830       5.173759   12.838584    0.08522136     1.850122
[7,]   -4.724550        -8.209242    -7.749548    7.181760      7.392024       7.760264   15.142195    0.76559783     2.265024
     Site.NewDelhi Site.Okayama Site.Shanghai Site.TagusValley Site.TamilNadu Site.Wuhan
[1,]    -0.9380497   -1.2550962    -1.0652936        -9.147840     -1.2479499 -2.8408047
[2,]     3.7578353   -2.1402207     0.4982818        -3.379576      1.6338075 -2.4510295
[3,]     0.5780709    0.3309400    -3.3073448        -7.079364     -0.2821260 -3.3148406
[4,]     2.2999544    0.8296647    -6.7727841        -6.169214      1.2937221 -3.7325176
[5,]     4.0486649   -0.7128306     4.1200904        -3.821261      1.5488394 -0.8060147
[6,]    -2.8009391   -1.3550735    -6.3660256       -10.542310     -0.9232138 -5.5950056
[7,]    -0.3758061    0.5343792    -0.3340314        -8.510043     -1.0897470 -4.8249317
```

```
> summary(Mod_mcmc_rand_het)

 Iterations = 3001:99991
 Thinning interval  = 10
 Sample size  = 9700 

 DIC: 504.075 

 G-structure:  ~Site

     post.mean l-95% CI u-95% CI eff.samp
Site     49.53    13.13    100.4     9700

 R-structure:  ~idh(Site):units

                      post.mean l-95% CI u-95% CI eff.samp
SiteGainesville.units   21.6625 11.07280   35.994     9700
SiteGwangju.units      118.9091 20.61947  288.022    10046
SiteHarbin.units        17.2666  0.37466   59.503     9097
SiteJingzhou.units      89.7704  0.06955  192.922     9700
SiteKhumaltar.units      9.8583  1.02483   28.196     8539
SiteLaguna.units       113.6920  1.17723  424.701     9700
SiteLosBanos.units      17.2615  2.67768   44.524     9700
SiteNanjing.units       11.2997  1.75014   29.473     9264
SiteNewDelhi.units       0.4789  0.04440    1.324     9700
SiteOkayama.units       91.5031 26.12201  192.130     9700
SiteShanghai.units      84.0607  3.03350  279.681     9700
SiteTagusValley.units    4.4826  0.06152   11.982     8957
SiteTamilNadu.units      3.6675  0.08342   12.266     9700
SiteWuhan.units        135.2099 53.83306  249.980     9700

 Location effects: Sobs_perc ~ 1 

            post.mean l-95% CI u-95% CI eff.samp  pMCMC  
(Intercept)   -4.5672  -8.4410  -0.2943     9700 0.0297 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

A simpler model (frequently inappropriate): « Fixed-effect model »

Within-study level: $S_{ij} = \mu + \varepsilon_{ij}$ $\qquad \varepsilon_{ij} \sim N\left(0, \sigma_{\varepsilon i}^2\right)$

Yield sensitivity in
study i, replicate j

Prior: Gaussian and InvGamma

nature plants

Letter | Published: 19 December 2016

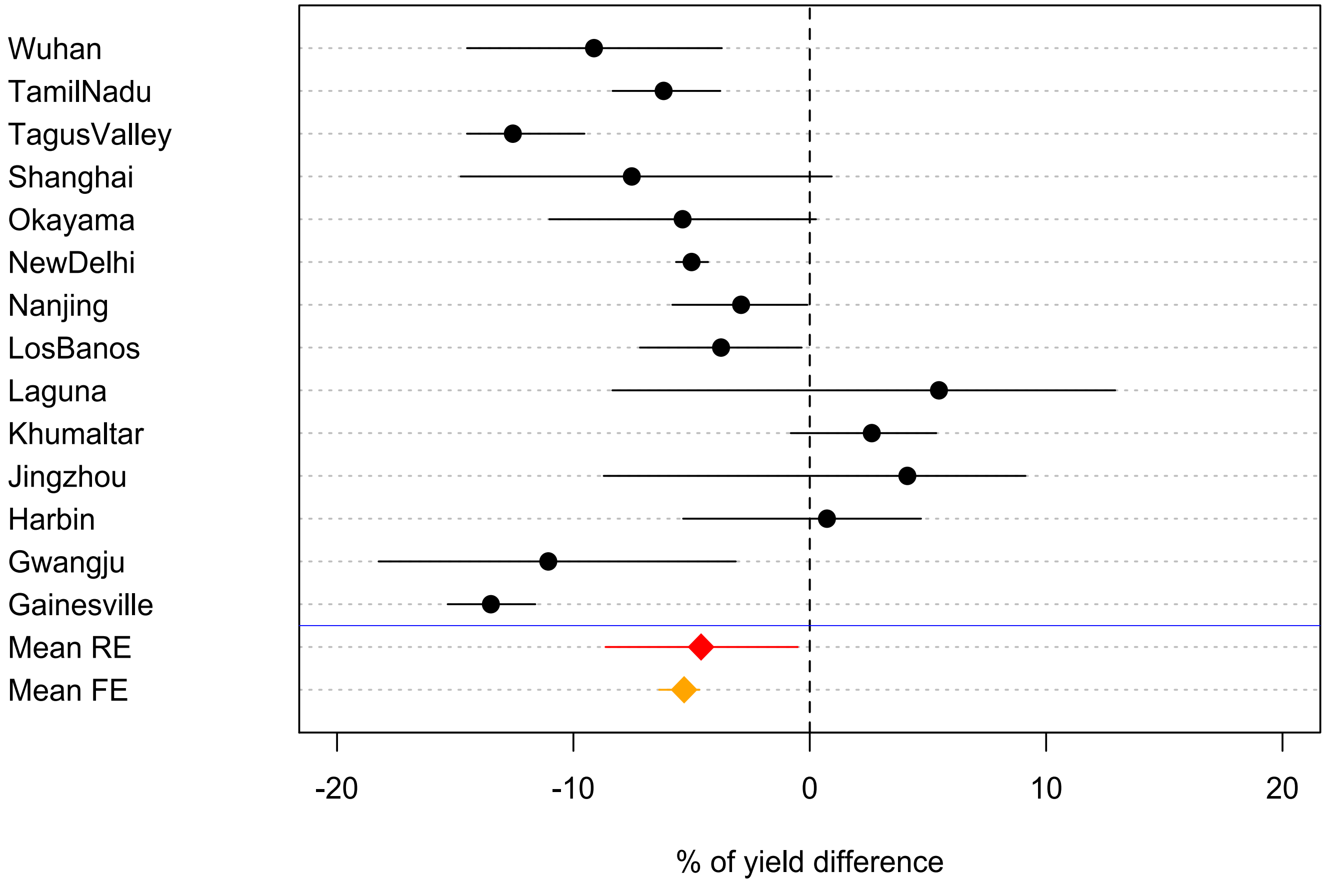
Plausible rice yield losses under future climate warming

Chuang Zhao, Shilong Piao, Xuhui Wang, Yao Huang, Philippe Ciais, Joshua Elliott, Mengtian Huang, Ivan A. Janssens, Tao Li, Xu Lian, Yongwen Liu, Christoph Müller, Shushi Peng, Tao Wang, Zhenzhong Zeng & Josep Peñuelas

Compilation of results of 83 field warming experiments located in 14 sites in the world

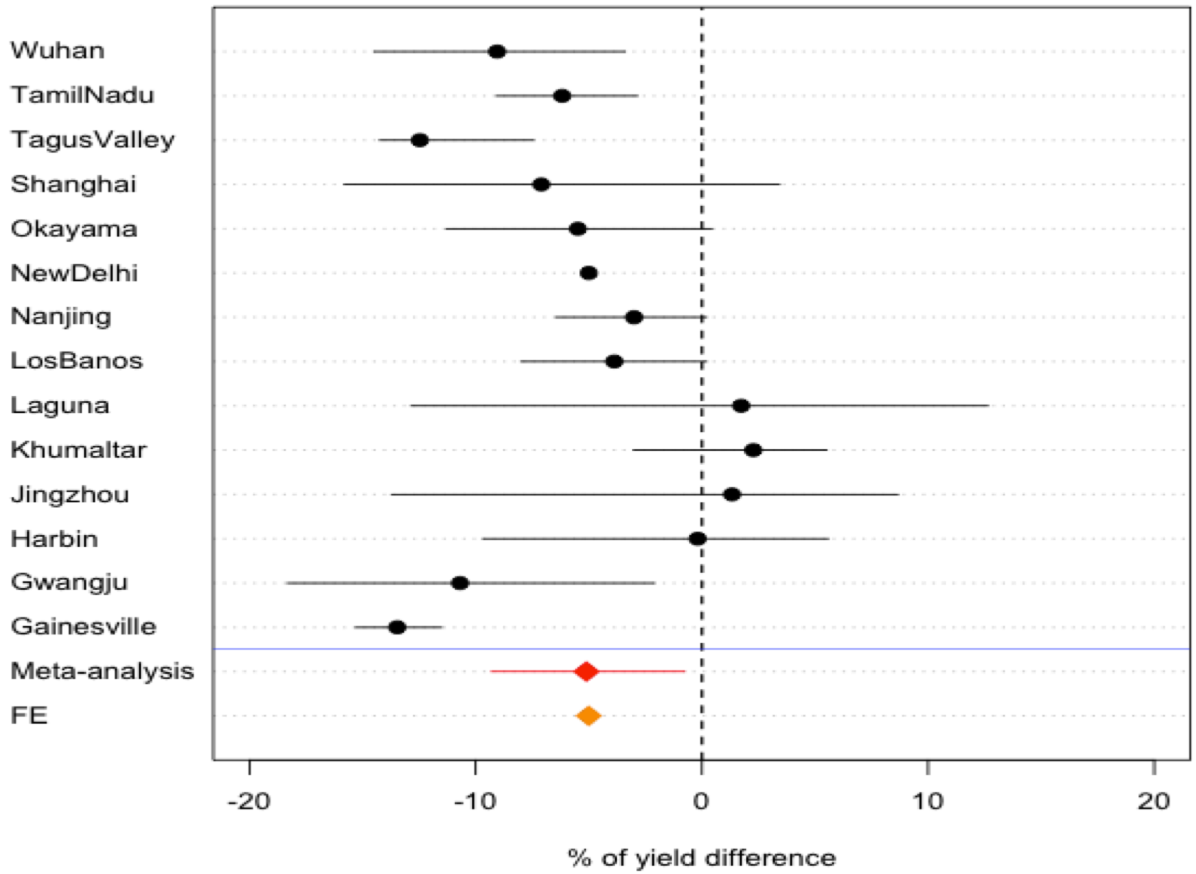
Field experiment Ambient CO_2

Meta-analysis of field warming experiments: Rice yield sensitivity to +1°C (ambient $[CO_2]$)

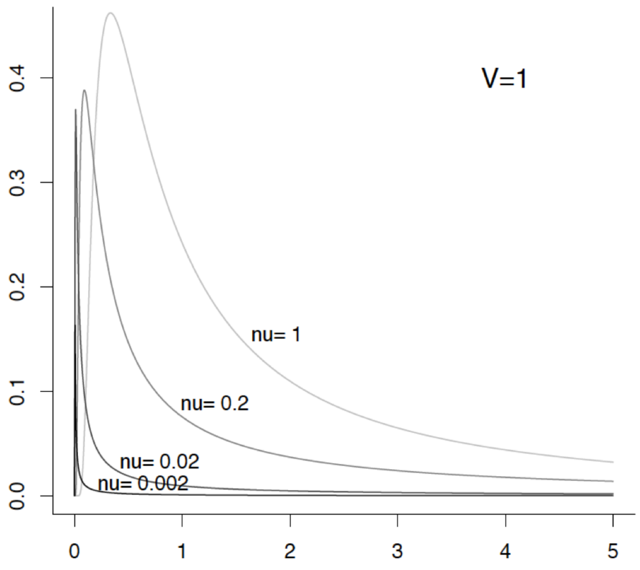


nu=1

Meta-analysis of field warming experiments: Rice yield sensitivity to +1°C (ambient [CO_2])



nu=0.002



nu	Mean	Q2.5	Q97.5
1	-4.57	-8.44	-0.29
0.2	-5.02	-9.02	-0.66
0.02	-5.10	-9.26	-0.88
0.002	-5.09	-9.87	-0.64

nature COMMUNICATIONS

Article | OPEN | Published: 17 November 2016

Field warming experiments shed light on the wheat yield response to temperature in China

Chuang Zhao, Shilong Piao, Yao Huang, Xuhui Wang, Philippe Ciais, Mengtian Huang, Zhenzhong Zeng & Shushi Peng

Compilation of 46 results of field warming experiments located in 11 sites in China

Field experiment Ambient CO_2

Hierarchical statistical model
« Random-effect model (1) »

Overall mean

Effect of study i

Within-study level: $$S_{ij} = \mu + b_i + \varepsilon_{ij} \qquad \varepsilon_{ij} \sim N\left(0, \sigma_{\varepsilon i}^2\right)$$

Yield sensitivity in study i, replicate j

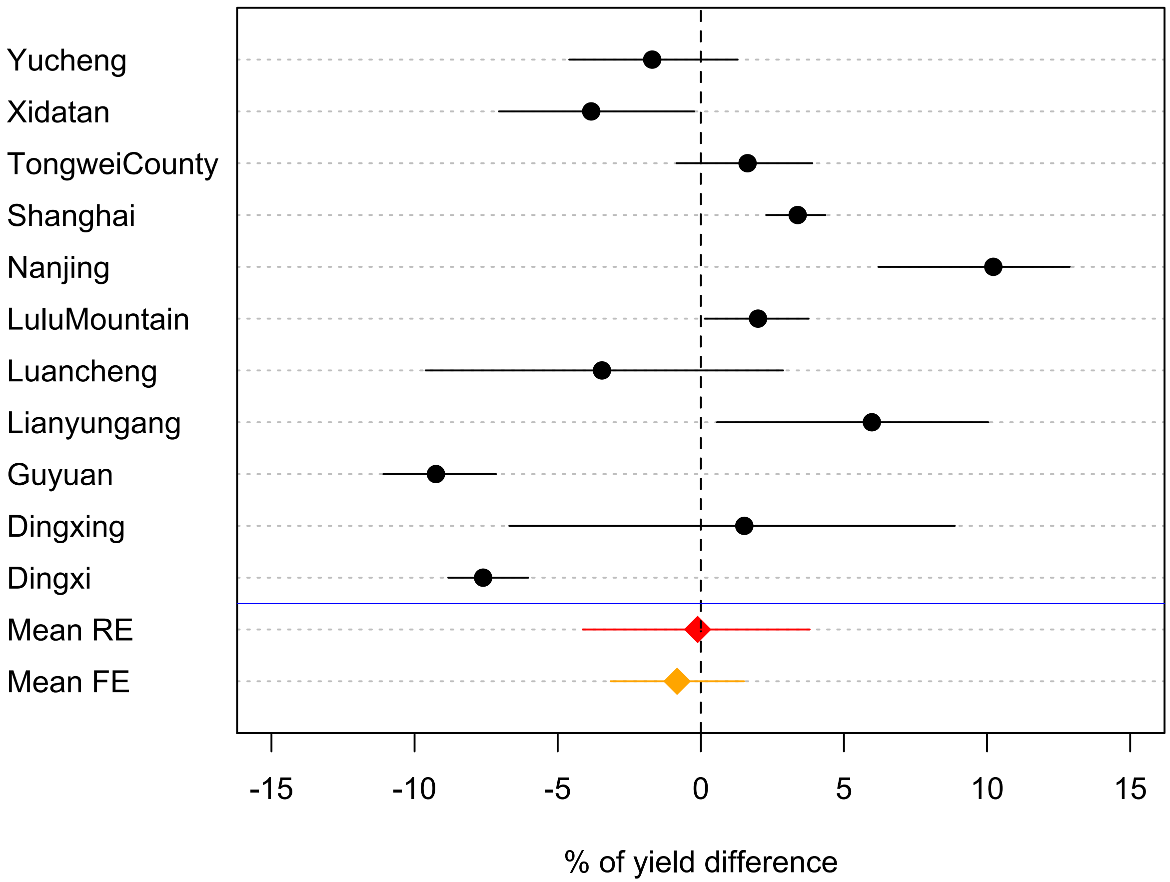
Residual for jth data in study i

Between-study level: $$b_i \sim N\left(0, \sigma_b^2\right)$$

Prior: Gaussian and InvGamma

$$\begin{cases} \mu \sim N(mu, V) \\ \sigma_{\varepsilon i}^2 \sim InvGamma(scaleR, shapeR) \\ \sigma_b^2 \sim InvGamma(scaleB, shapeB) \end{cases}$$

Meta-analysis of field warming experiments: Wheat yield sensitivity to +1°C (ambient [CO_2])



Hierarchical statistical model (with covariate) « Random-effect model (2)»

Covariate value for study i replicate j

Within-study level: $S_{ij} = \mu + \alpha X_{ij} + b_i + \varepsilon_{ij}$ $\qquad \varepsilon_{ij} \sim N\left(0, \sigma_{\varepsilon i}^2\right)$

Yield sensitivity in study i, replicate j

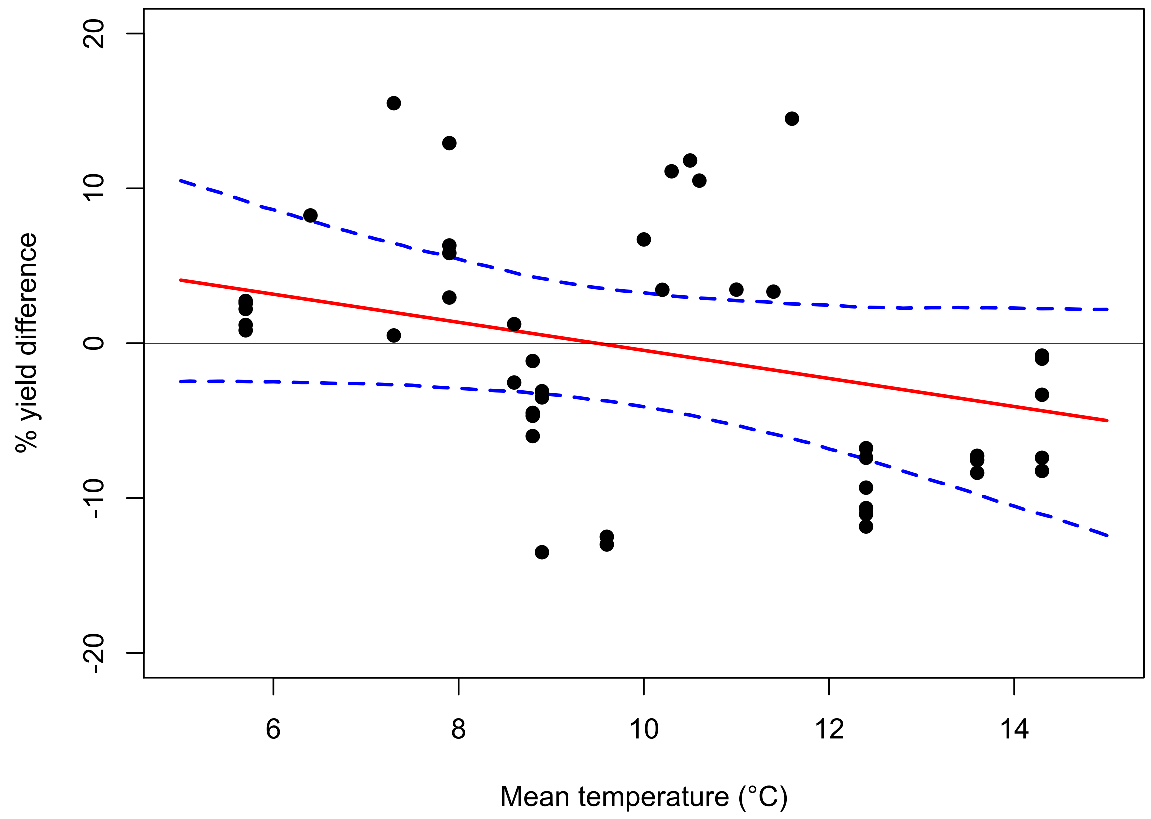
Between-study level: $b_i \sim N\left(0, \sigma_b^2\right)$

Prior: Gaussian and InvGamma

```
prior1<- list(
B=list(mu=c(0,0),
V=diag(c(10^6,10^6))), R=list(V=diag(1,length(unique(TAB$Site_name)),
length(unique(TAB$Site_name))),nu=1),
G=list(G1=list(V=1,nu=1)))

Mod_mcmc_1<-MCMCglmm(Sensitivity~TGS,random=~Site_name,
rcov=~idh(Site_name):units, data=TAB, verbose=F, nitt=100000,
prior=prior1)
```

```
 Iterations = 3001:99991
 Thinning interval  = 10
 Sample size  = 9700

 DIC: 233.703

 G-structure:  ~Site_name

          post.mean l-95% CI u-95% CI eff.samp
Site_name     33.04    6.271    71.14     9312

 R-structure:  ~idh(Site_name):units

                             post.mean l-95% CI u-95% CI eff.samp
Site_nameDingxi.units            1.548  0.07759    4.752     9700
Site_nameDingxing.units         69.754  0.51302  195.425     9700
Site_nameGuyuan.units            5.604  0.97320   14.000     9700
Site_nameLianyungang.units      26.811  2.55963   74.126     9700
Site_nameLuancheng.units        92.167 21.48002  199.591    10073
Site_nameLuluMountain.units      2.963  0.17641    9.129     9700
Site_nameNanjing.units          22.344  1.50927   71.173     9700
Site_nameShanghai.units          1.742  0.07010    5.231     9700
Site_nameTongweiCounty.units     5.302  0.08926   12.584     9700
Site_nameXidatan.units          16.304  2.18605   43.444     9700
Site_nameYucheng.units           8.707  0.99998   25.566     9700

 Location effects: Sensitivity ~ TGS

            post.mean l-95% CI u-95% CI eff.samp pMCMC
(Intercept)    8.6881  -2.9256  20.7279     9700 0.127
TGS           -0.9096  -2.0424   0.2655     9700 0.103
```

Meta-regression:
Wheat yield sensitivity vs. Mean temperature

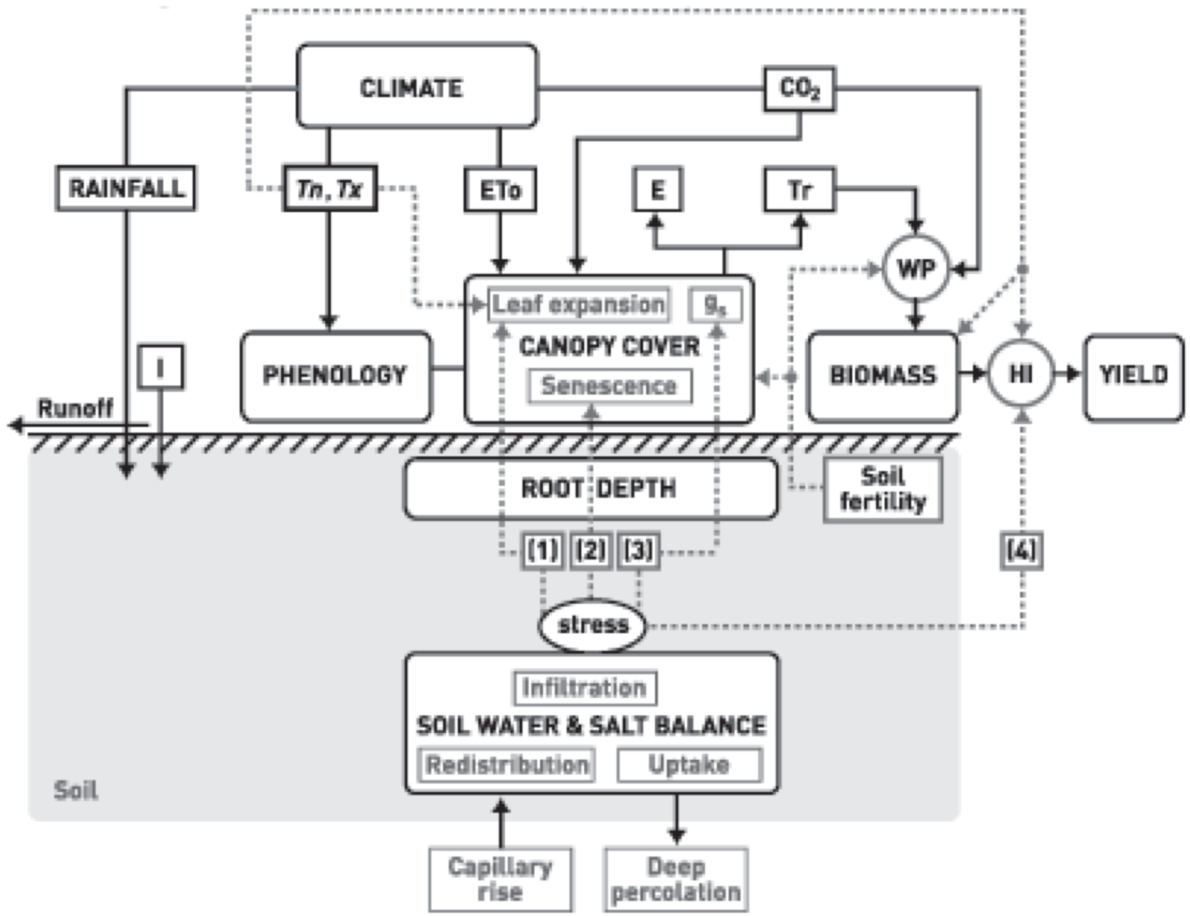


Example: Assessment of the impact of temperature increase on crop yield

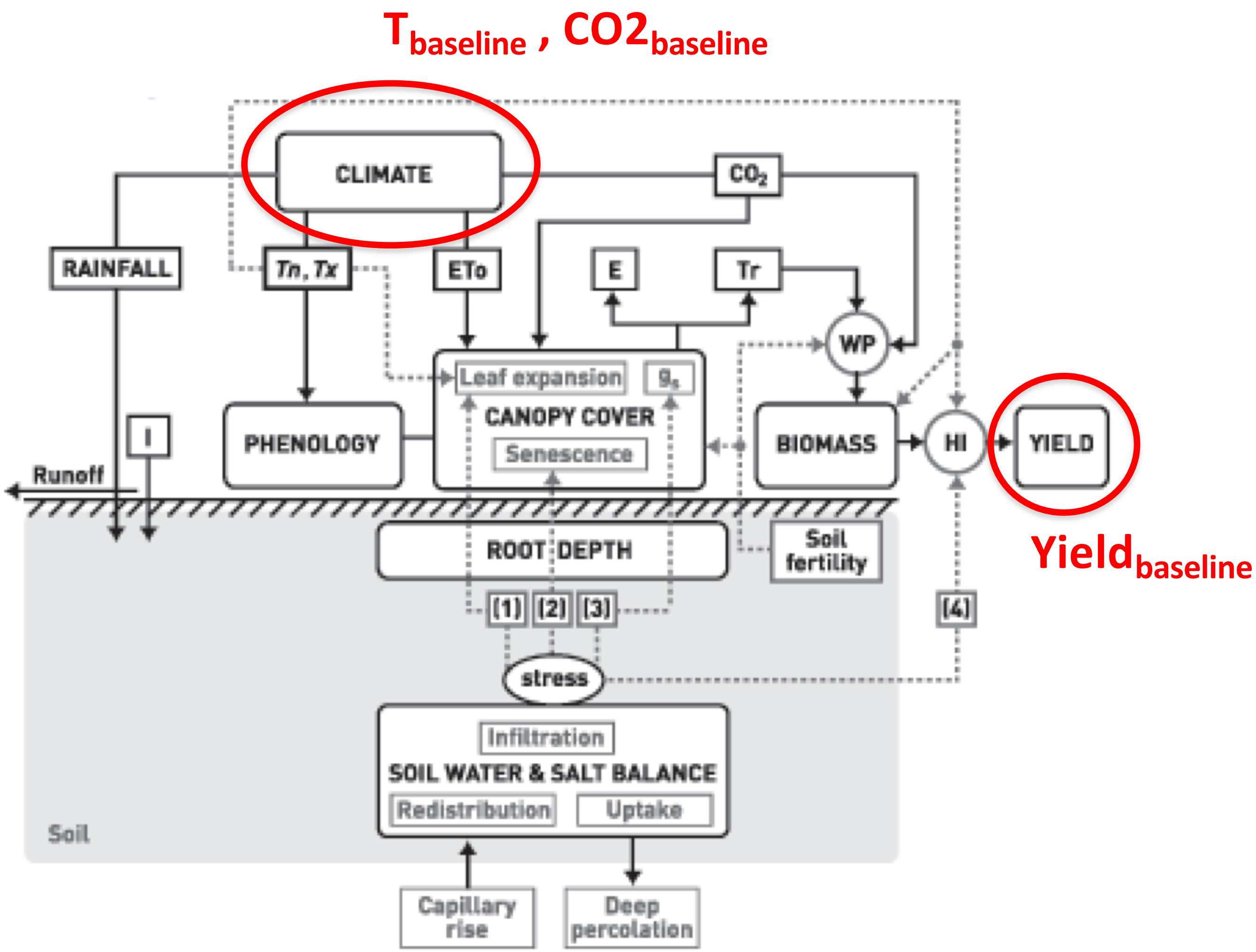
Two sources of information:

- Experiments
- **Crop model simulations**

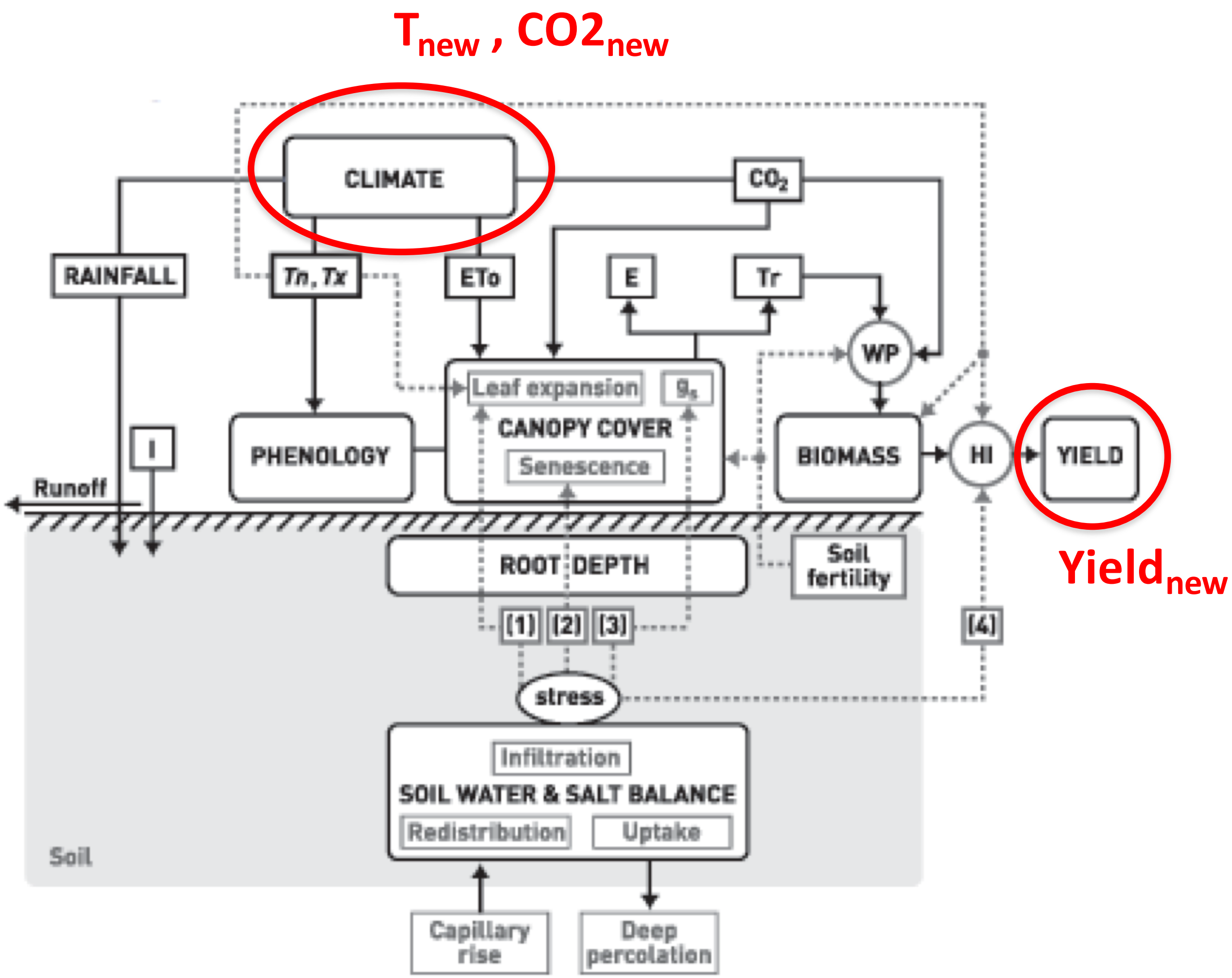
AquaCrop model (FAO)



AquaCrop model (FAO)



AquaCrop model (FAO)



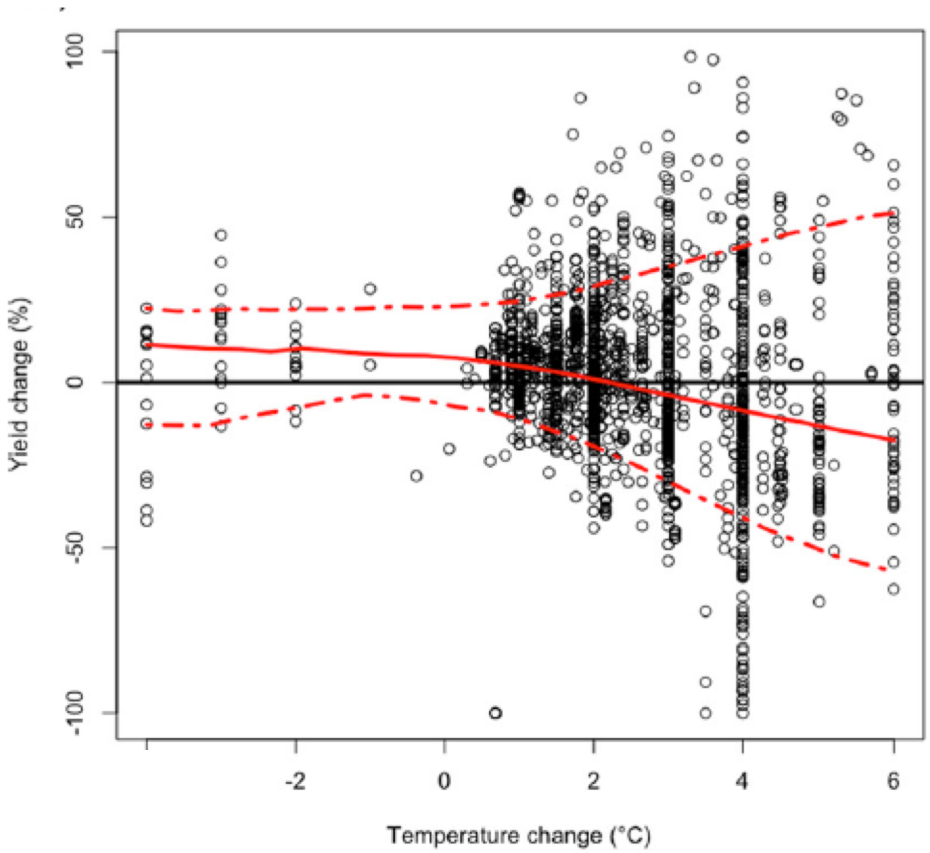
$$\Delta Y = f(\Delta T, \Delta CO_2)$$

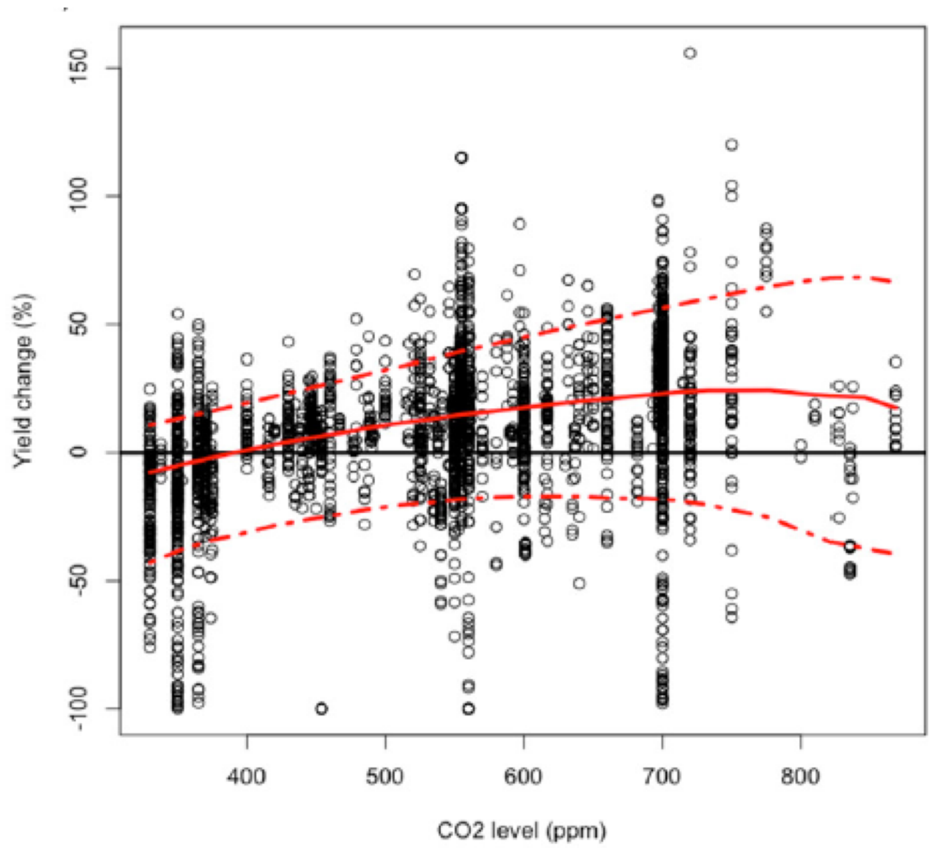
Relative yield change

Temperature change

$[CO_2]$ change

Simulated wheat yields from different crop models in several sites for various ‘Temperature change * [CO_2] scenarios’





Hierarchical statistical model (with covariate)
« Random-effect model (4) »

Temperature change for study i treatment j

[CO2] change for study i treatment j

Within-study level: $Y_{ij} = \mu + \alpha_{Ti}T_{ij} + \alpha_{Ci}C_{ij} + b_i + \varepsilon_{ij}$

Relative yield change in study i, treatment j

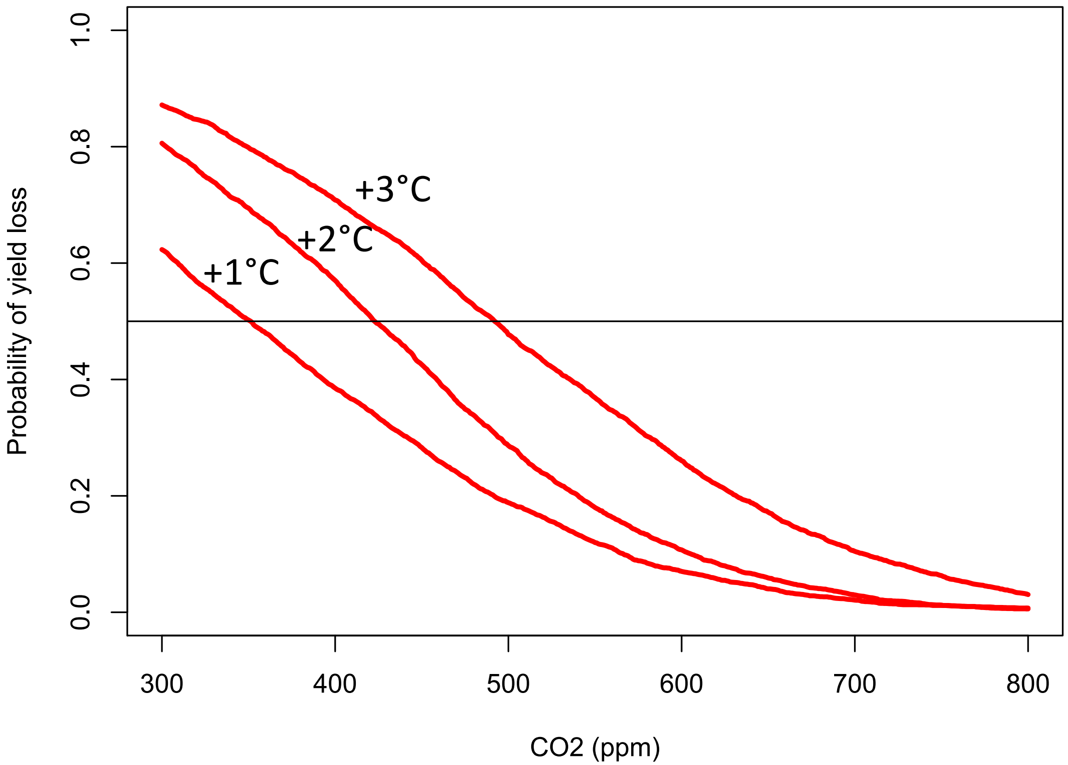
$\varepsilon_{ij} \sim N\left(0, \sigma^2_{\varepsilon i}\right)$

Between-study level: $b_i \sim N\left(0, \sigma^2_b\right)$ $\alpha_{Ti} \sim N(\mu_{T\alpha}, \sigma^2_{T\alpha})$

$\alpha_{Ci} \sim N(\mu_{C\alpha}, \sigma^2_{C\alpha})$

Prior: Gaussian and InvGamma

Probability of yield loss for +1, +2, +3°C computed from a meta-analysis of 927 crop model simulations



High chance of yield loss with +3°C

Conclusion

- Meta-analysis is a powerful tool

- It can be used to synthetize
  - ➢ Experimental data
  - ➢ Simulated data

- Its implementation requires special care
  - ➢ Comprehensive systematic review
  - ➢ Rigorous statistical analysis