

2023

BAYESIAN REGRESSION & META-ANALYSIS

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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?

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

Meta-analysis: a statistical approach for quantitative synthesis

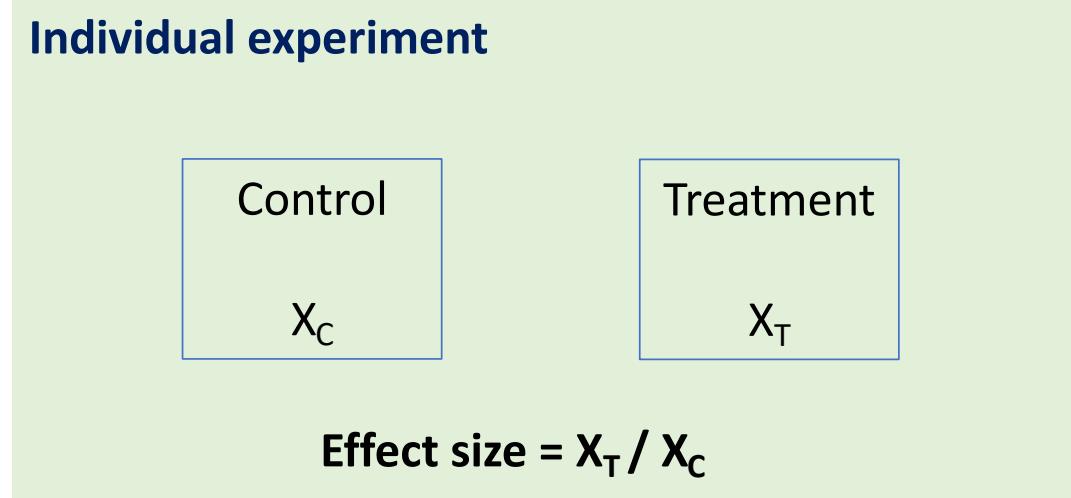
« The analysis of analyses »

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

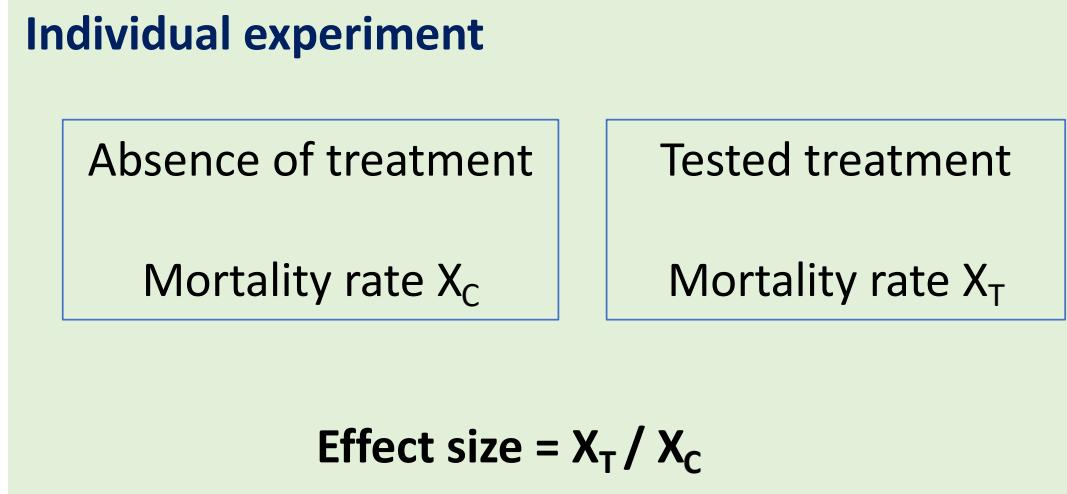
« Systematic review + statistical analysis »

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

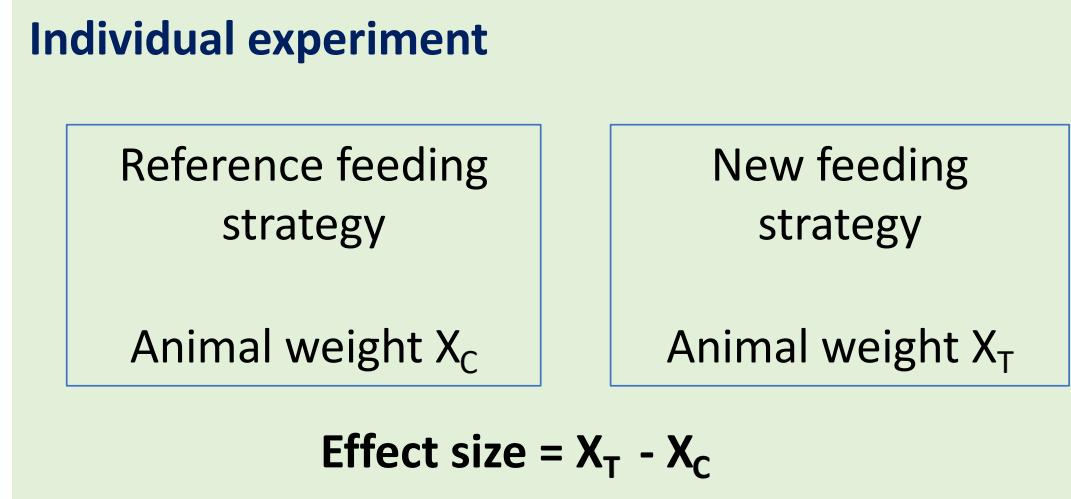
Meta-analysis main objective: estimating a mean effect size from a set of individual experiments



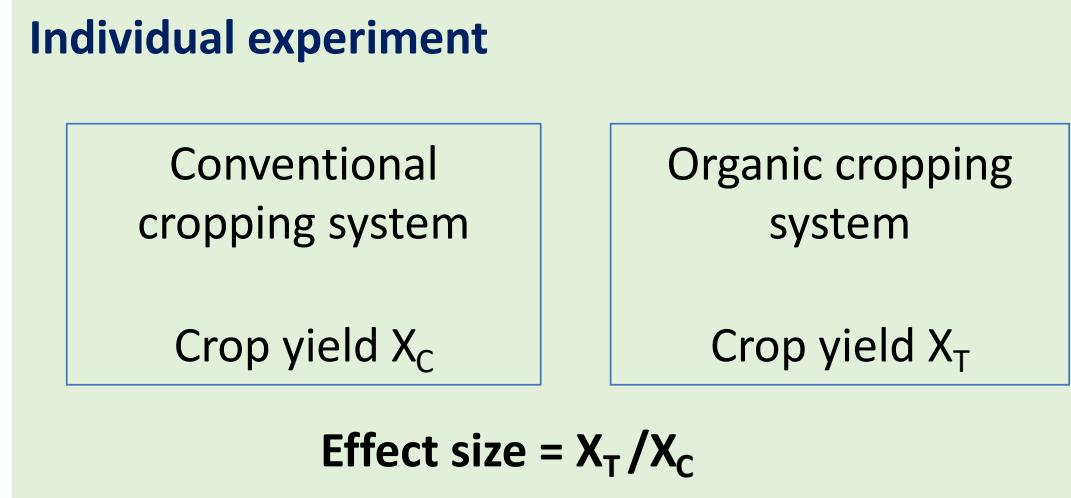
Meta-analysis main objective: estimating a mean effect size from a set of individual experiments



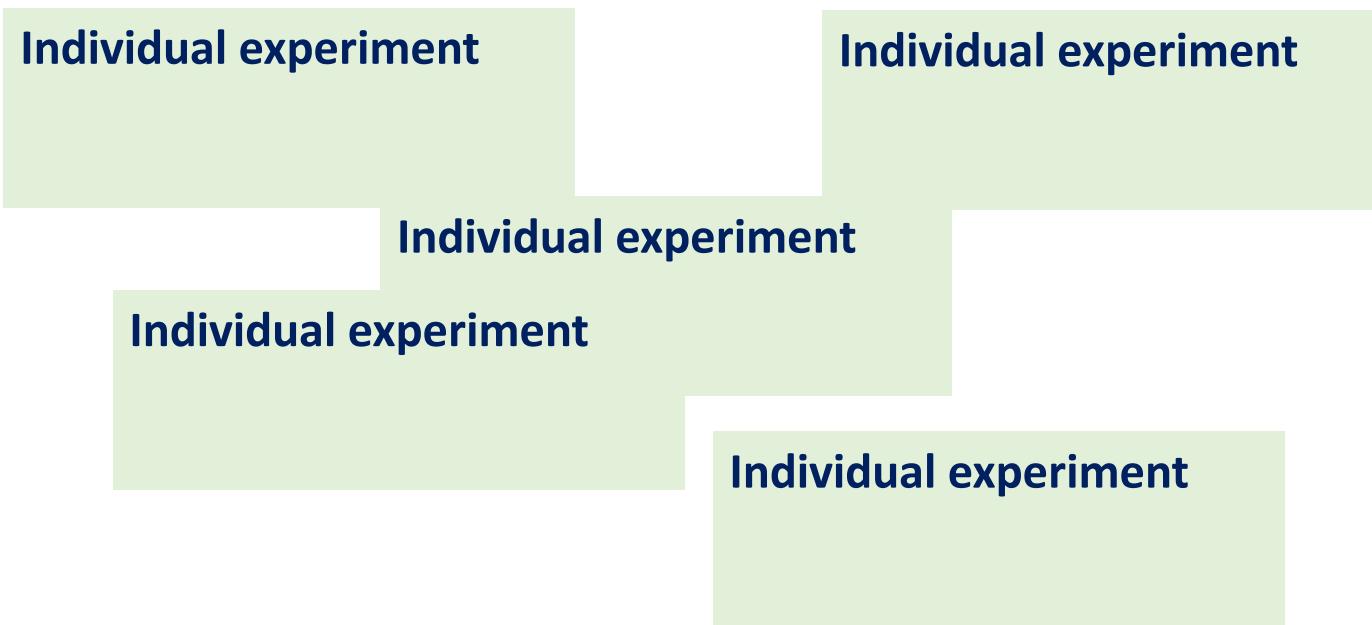
Meta-analysis main objective: estimating a mean effect size from a set of individual experiments



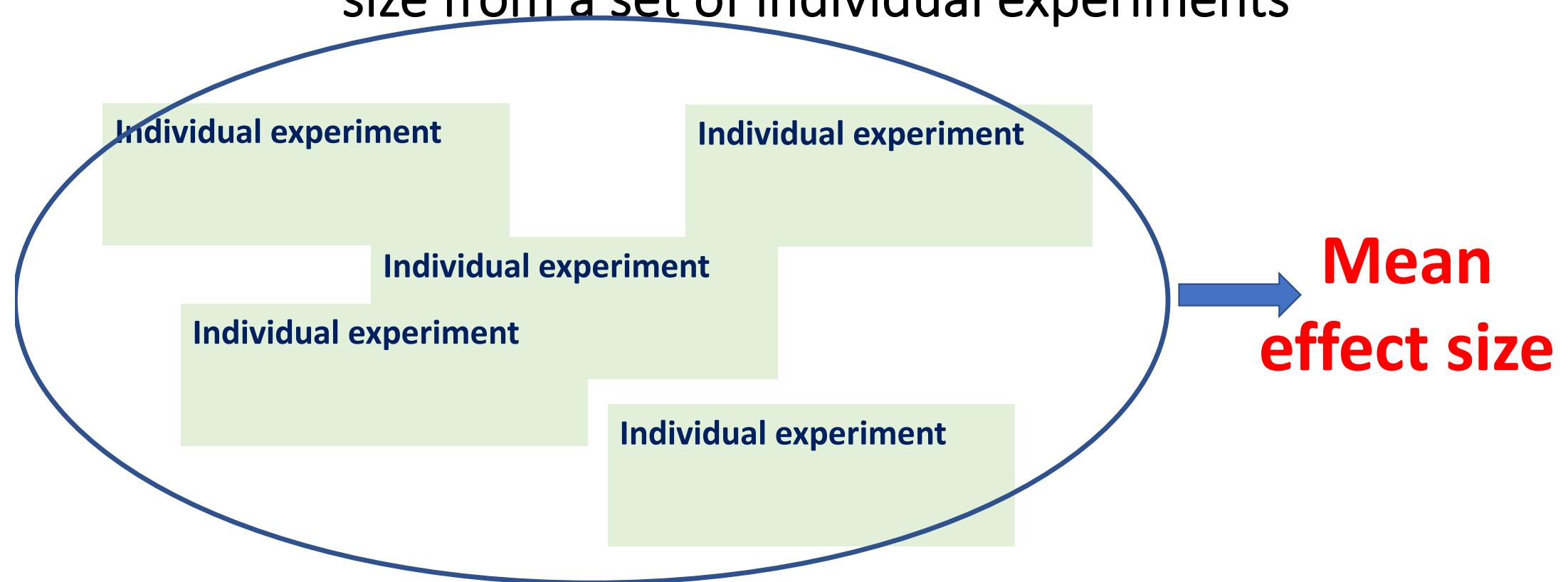
Meta-analysis main objective: estimating a mean effect size from a set of individual experiments



Meta-analysis main objective: estimating a mean effect size from a set of individual experiments



Meta-analysis main objective: estimating a mean effect size from a set of individual experiments



Main steps of a meta-analysis

Scoping

Literature search

Paper selection

Data extraction

Statistical analysis

Bias and uncertainty

Main steps of a meta-analysis

Scoping

A few hours

Literature search

One day

Paper selection

One day, up to a
few days

Data extraction

Two papers per day

Statistical analysis

One to two days

Bias and uncertainty

One to a
couple of
hours

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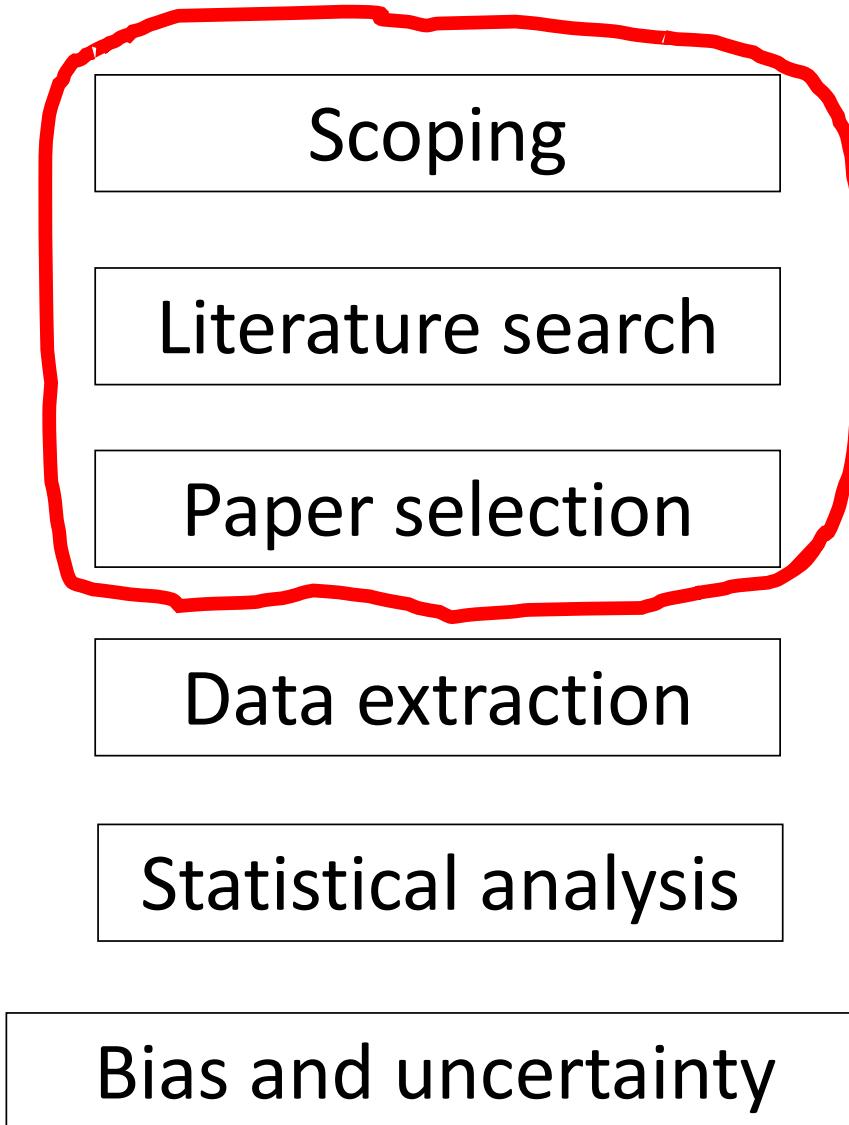
Bias and uncertainty

One to a couple of hours

Because of the steps « Paper selection » and « Data extraction », a meta-analysis often require several months of work.

Main steps of a meta-analysis

Systematic review



Main steps of a meta-analysis

Systematic review

Quantitative estimation

Scoping

Literature search

Paper selection

Data extraction

Statistical analysis

Bias and uncertainty

Main steps of a meta-analysis

Meta-analysis
=

Systematic review +
Quantitative estimation
=

Quantitative systematic review

Scoping

Literature search

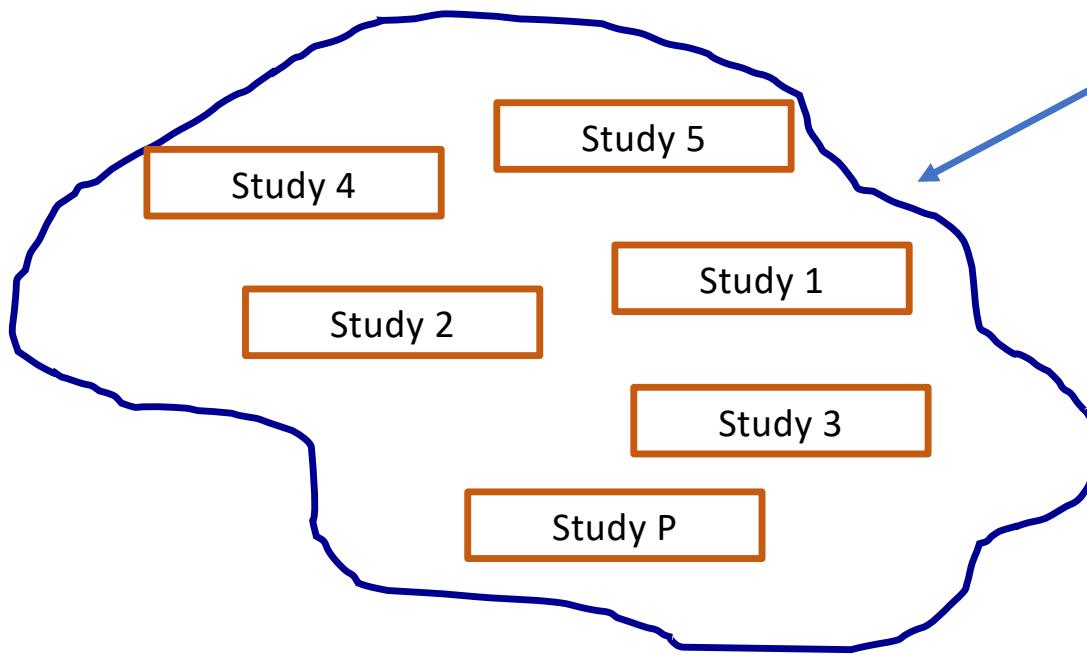
Paper selection

Data extraction

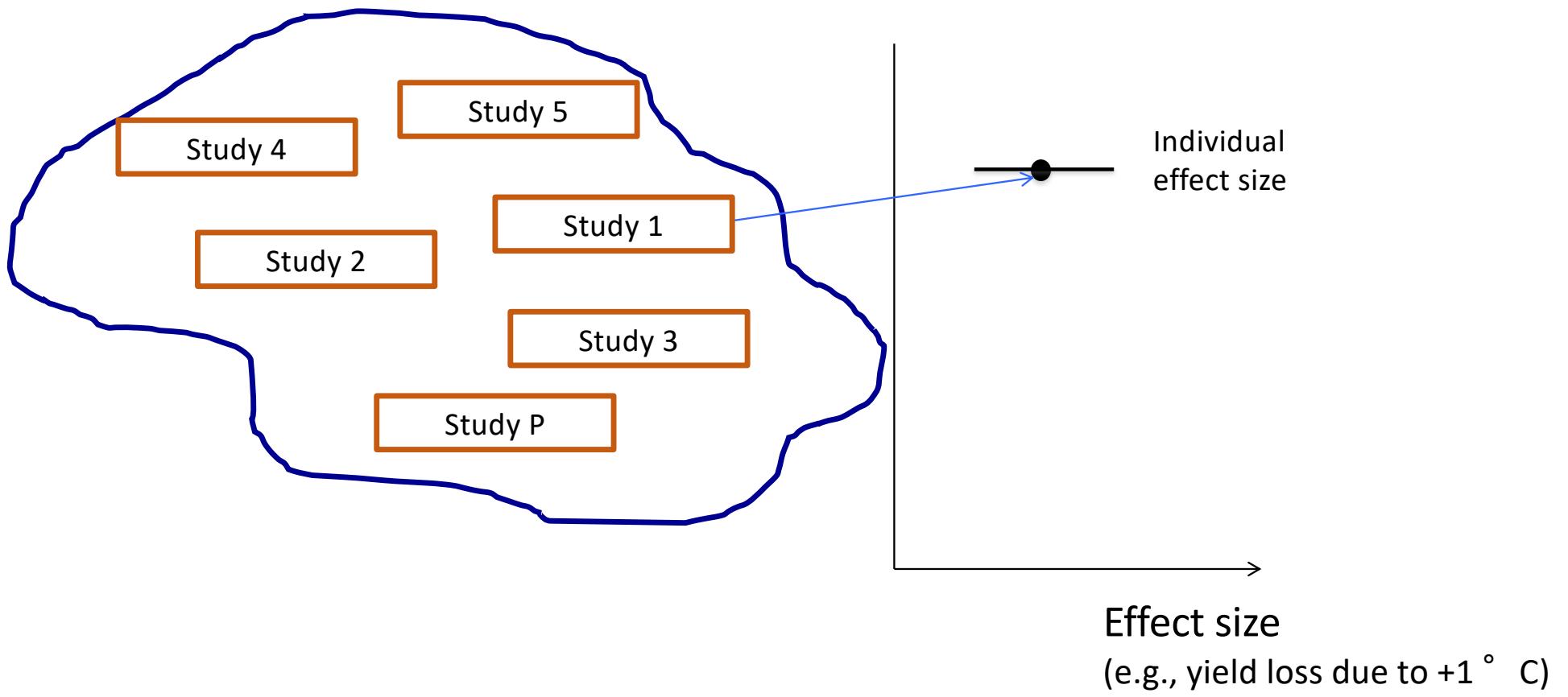
Statistical analysis

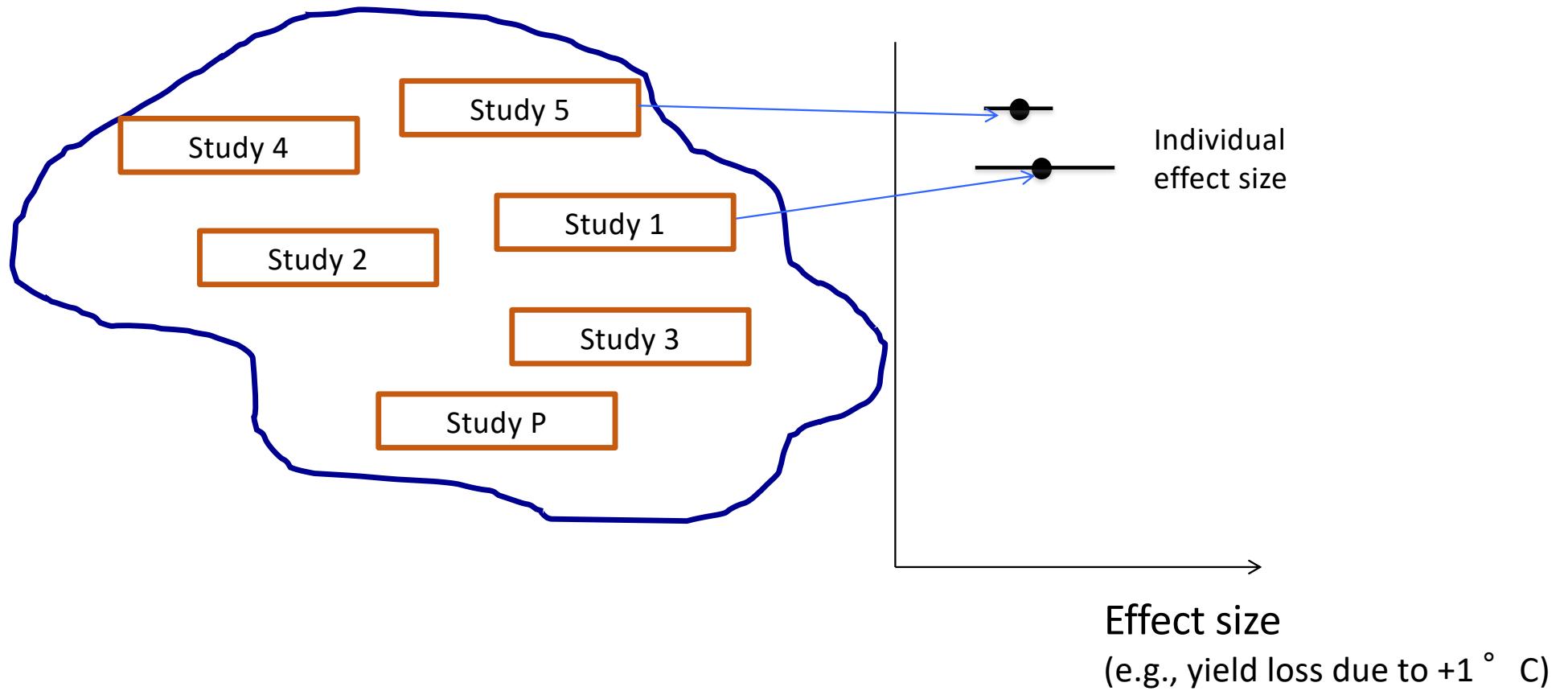
Bias and uncertainty

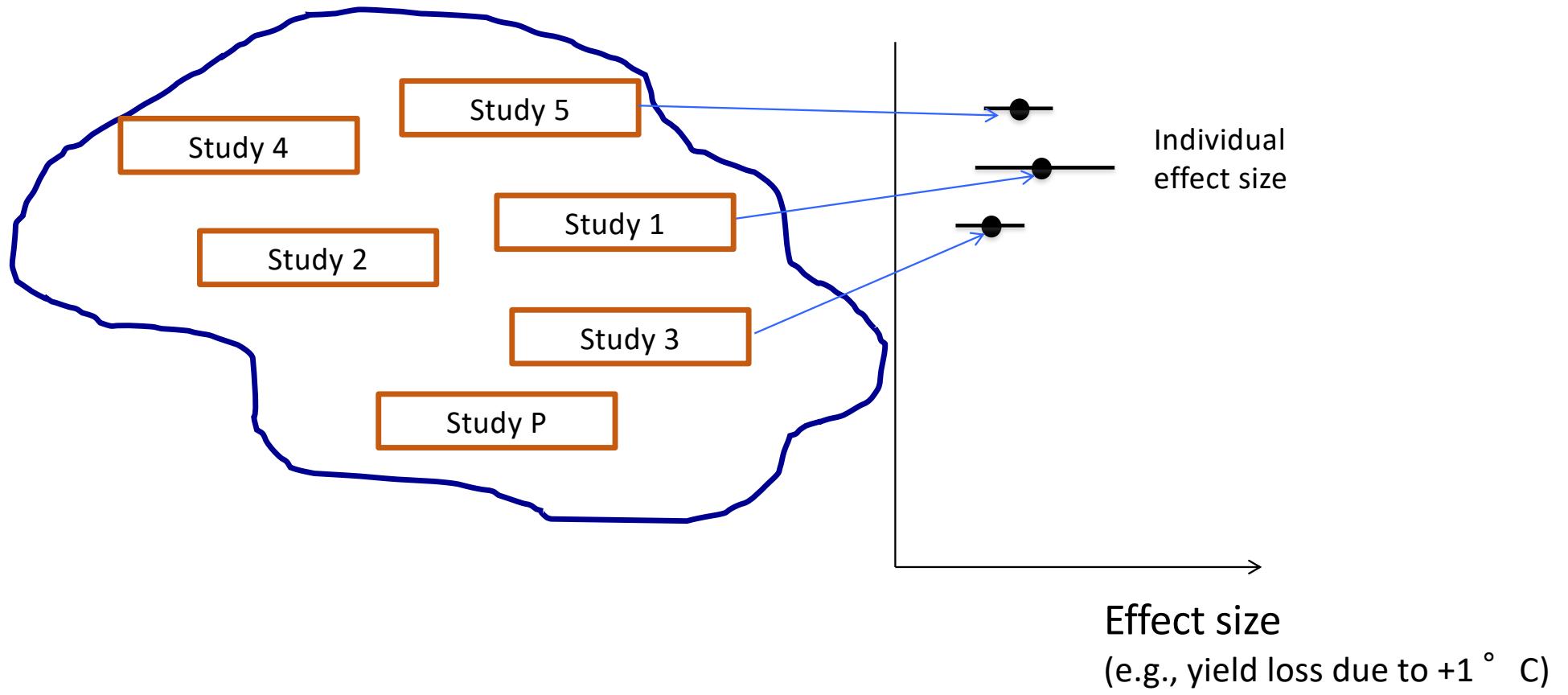
Systematic review of studies

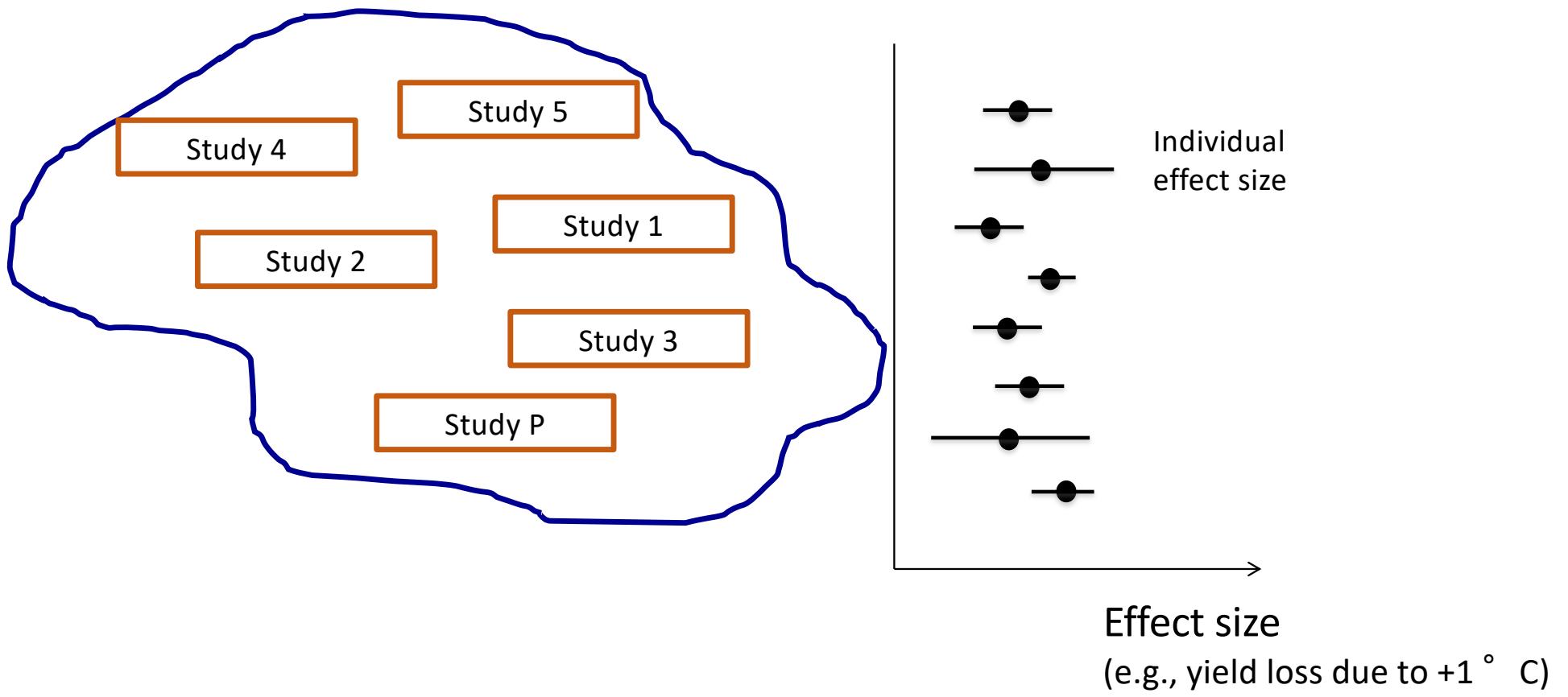


**Set of studies dealing with a specific topic
(e.g., %yield loss due to +1°C in China)**

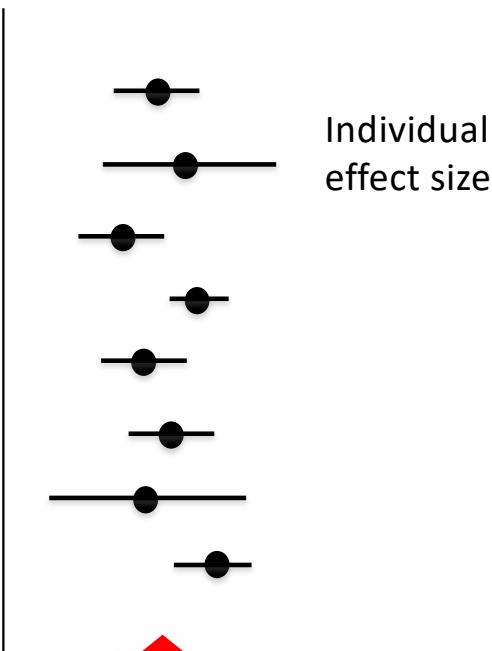




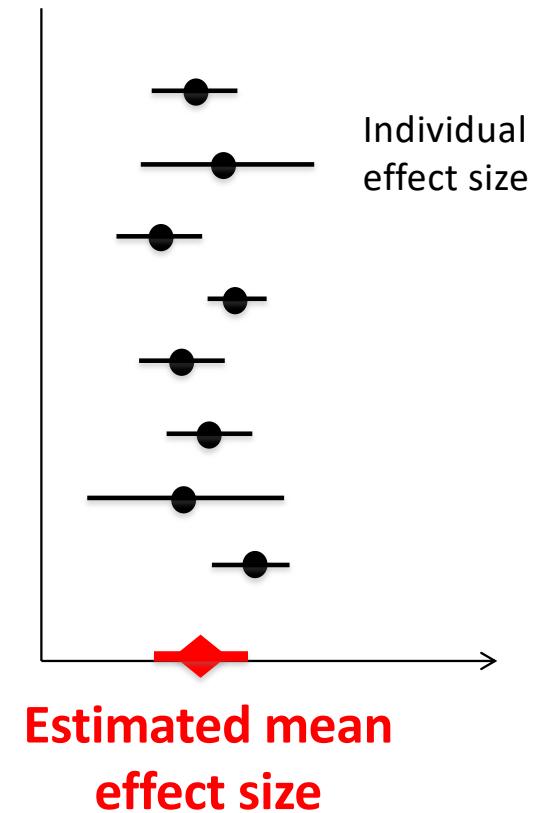
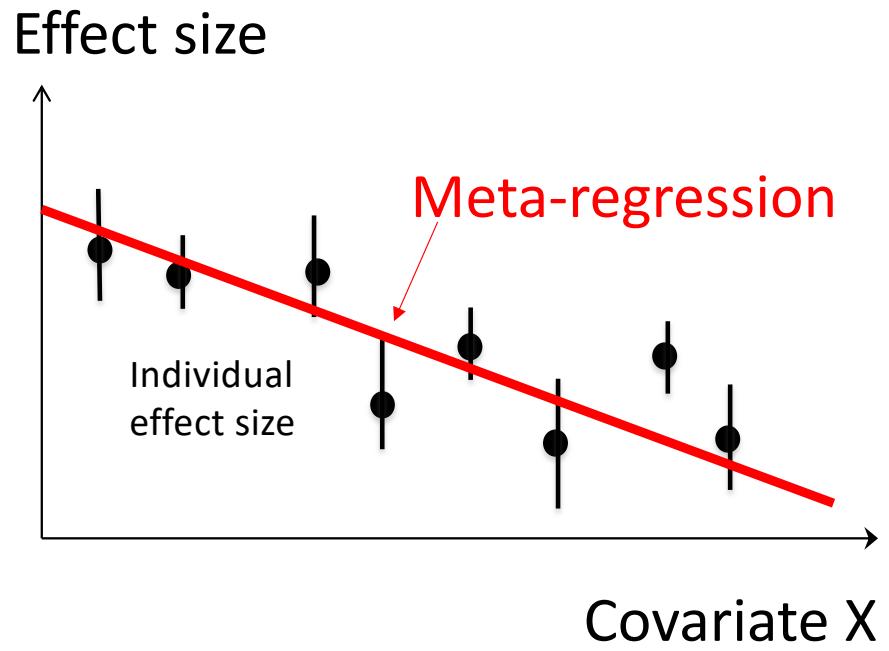




Use of simple hierarchical models to estimate the mean effect size from the individual effect sizes



**Estimated mean
effect size**



Meta-analysis often used to deal with controversial topics in human health...

Review

Exposure to glyphosate-based herbicides and risk for non-Hodgkin lymphoma: A meta-analysis and supporting evidence

Luoping Zhang ^a✉, Iemaan Rana ^a, Rachel M. Shaffer ^b, Emanuela Taioli ^c, Lianne Sheppard ^{b, d}

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Systematic review

Effect of hydroxychloroquine with or without azithromycin on the mortality of coronavirus disease 2019 (COVID-19) patients: a systematic review and meta-analysis

Thibault Fiolet ^{1, 2, *}, Anthony Guihur ³, Mathieu Edouard Rebeaud ³, Matthieu Mulot ⁴, Nathan Peiffer-Smadja ^{5, 6, 7}, Yahya Mahamat-Saleh ^{1, 2}

... and in agriculture as well

A Meta-Analysis of the Impacts of Genetically Modified Crops

Wilhelm Klümper, Matin Qaim*

... and in agriculture as well

A Meta-Analysis of the Impacts of Genetically Modified Crops

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A meta-analysis of experiments testing the effects of a neonicotinoid insecticide (imidacloprid) on honey bees

James E. Cresswell

... and in agriculture as well

A Meta-Analysis of the Impacts of Genetically Modified Crops

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A meta-analysis of experiments testing the effects of a neonicotinoid insecticide (imidacloprid) on honey bees

James E. Cresswell

A meta-analysis of crop yield under climate change and adaptation

A. J. Challinor , J. Watson, D. B. Lobell, S. M. Howden, D. R. Smith  & N. Chhetri

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

Two sources of information:

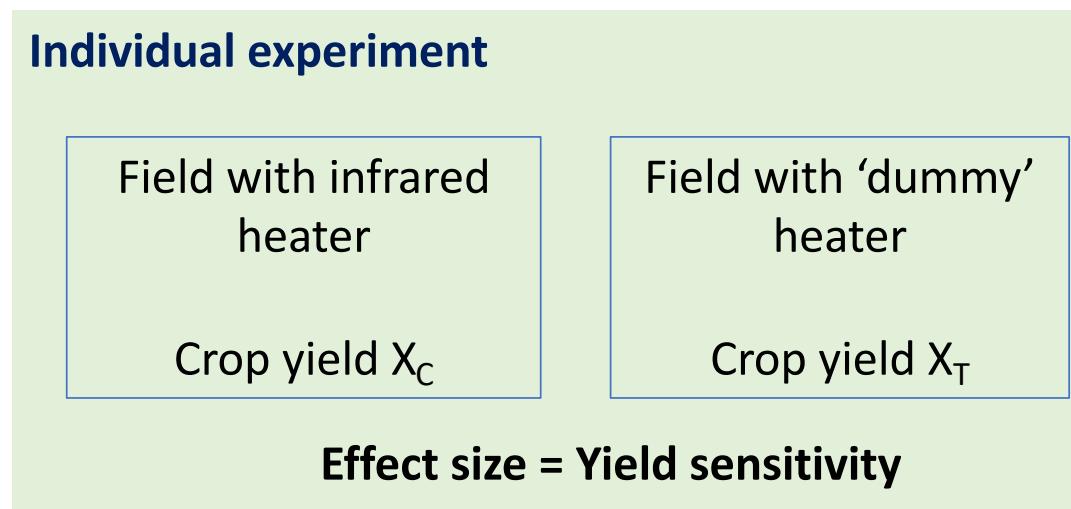
- Experiments
- Crop model simulations

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

Two sources of information:

- **Experiments**
- Crop model simulations

Field warming experiment



from Chi et al. 2013

doi.org/10.1371/journal.pone.0056482

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

$$Sensitivity = Yield \% change per {}^\circ\text{C} = 100 \frac{\Delta Y}{\Delta T}$$

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 CO₂

Objectives

- Estimate the mean yield sensitivity to +1°C
- Estimate the effect of the mean local temperature on the sensitivities
- Analyse uncertainties

Site_name	Lat	Long	Design	Temp_increase	Irrigation_mm	Nitrogen_kgha	TGS	PGS	DGS	Sensitivity	Ref
Nanjing	32.03	118.86	Infrared heaters	1.5	0	225	10.3	393	8	11.1	1
Nanjing	32.03	118.86	Infrared heaters	1.5	0	225	10.6	476	7.6	10.5	1
Nanjing	32.03	118.86	Infrared heaters	1.5	0	225	11.6	341	8.3	14.5	1
Nanjing	32.03	118.86	Infrared heaters	1.5	0	225	10.0	387	7.9	6.7	1
Nanjing	32.03	118.86	Infrared heaters	1.5	0	225	10.5	325	8.1	11.8	1
Tongwei County	35.22	105.23	Heating cable	1.4	0	NA	5.7	288	6.6	2.21	2
Tongwei County	35.22	105.23	Heating cable	2.2	0	NA	5.7	288	6.6	1.18	2
Lulu Mountain	35.29	105.26	Heating cable	0.6	0	NA	5.7	288	6.6	0.83	2
Lulu Mountain	35.29	105.26	Heating cable	1.4	0	NA	5.7	288	6.6	2.57	2
Lulu Mountain	35.29	105.26	Heating cable	2.2	0	NA	5.7	288	6.6	2.73	2
Guyuan	36.03	106.46	Greenhouse	0.5	0	NA	12.4	97	11.2	-9.33	3
Guyuan	36.03	106.46	Greenhouse	1.2	0	NA	12.4	97	11.2	-11.03	3
Guyuan	36.03	106.46	Greenhouse	2.0	0	NA	12.4	97	11.2	-7.4	3
Guyuan	36.03	106.46	Greenhouse	0.5	60	NA	12.4	97	11.2	-11.84	3
Guyuan	36.03	106.46	Greenhouse	1.2	60	NA	12.4	97	11.2	-10.65	3
Guyuan	36.03	106.46	Greenhouse	2.0	60	NA	12.4	97	11.2	-6.78	3
Dingxing	39.13	115.66	Infrared heaters	2.9	500	210	8.9	77	9.3	-3.1	4
Dingxing	39.13	115.66	Infrared heaters	2.9	500	210	6.4	113	8.2	8.25	4
Xidatan	38.80	106.30	Infrared heaters	0.5	NA	136	14.3	23	12.2	-1.0	5
Xidatan	38.80	106.30	Infrared heaters	1.0	NA	136	14.3	23	12.2	-0.8	5
Xidatan	38.80	106.30	Infrared heaters	1.5	NA	136	14.3	23	12.2	-3.33	5
Xidatan	38.80	106.30	Infrared heaters	2.0	NA	136	14.3	23	12.2	-8.25	5
Xidatan	38.80	106.30	Infrared heaters	2.5	NA	136	14.3	23	12.2	-7.4	5
Shanghai	31.21	121.13	Infrared heaters	1.5	NA	NA	11.0	433	6.1	3.46	6
Shanghai	31.21	121.13	Infrared heaters	1.5	NA	NA	11.4	343	6.6	3.33	6
Shanghai	31.21	121.13	Infrared heaters	1.5	NA	NA	10.2	476	5.7	3.45	6
Yucheng	36.83	116.57	Infrared heaters	1.3	150	285	8.6	118	10	1.23	7
Yucheng	36.83	116.57	Infrared heaters	1.3	150	285	8.6	118	10	-2.54	7
Yucheng	36.83	116.57	Infrared heaters	1.3	150	285	8.8	160	8.8	-1.15	7
Yucheng	36.83	116.57	Infrared heaters	1.3	150	285	8.8	160	8.8	-4.69	7
Lianyungang	34.55	119.39	Infrared heaters	2.2	0	0	7.9	372	7.3	12.92	8
Lianyungang	34.55	119.39	Infrared heaters	2.2	0	150	7.9	372	7.3	6.31	8
Lianyungang	34.55	119.39	Infrared heaters	2.2	0	225	7.9	372	7.3	2.95	8
Lianyungang	34.55	119.39	Infrared heaters	2.2	0	300	7.9	372	7.3	5.82	8
Luancheng	37.88	114.68	Infrared heaters	2.0	160	240	9.6	131	9.5	-13.0	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	240	8.9	65	9.8	-13.5	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	240	8.8	153	8.6	-6.0	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	0	9.6	131	9.5	-12.5	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	0	8.9	65	9.8	-3.5	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	0	8.8	153	8.6	-4.5	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	240	7.3	167	8.5	15.5	9
Luancheng	37.88	114.68	Infrared heaters	2.0	160	0	7.3	167	8.5	0.5	9
Dingxi	35.58	104.62	Infrared heaters	1.0	0	NA	13.6	171	8.6	-8.37	10
Dingxi	35.58	104.62	Infrared heaters	2.0	0	NA	13.6	171	8.6	-7.55	10
Dingxi	35.58	104.62	Infrared heaters	3.0	0	NA	13.6	171	8.6	-7.27	10

Steps

- Explore the dataset
- Define and fit Bayesian models
- Conclude

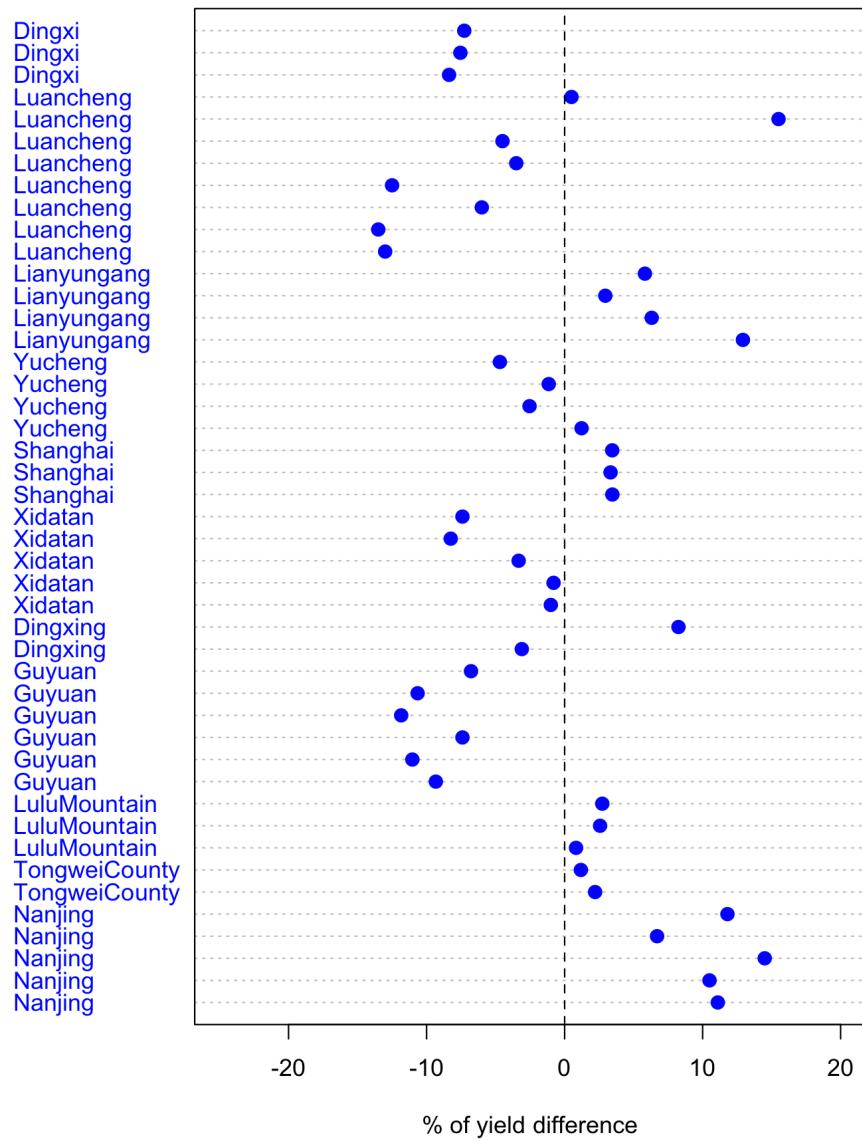
Steps

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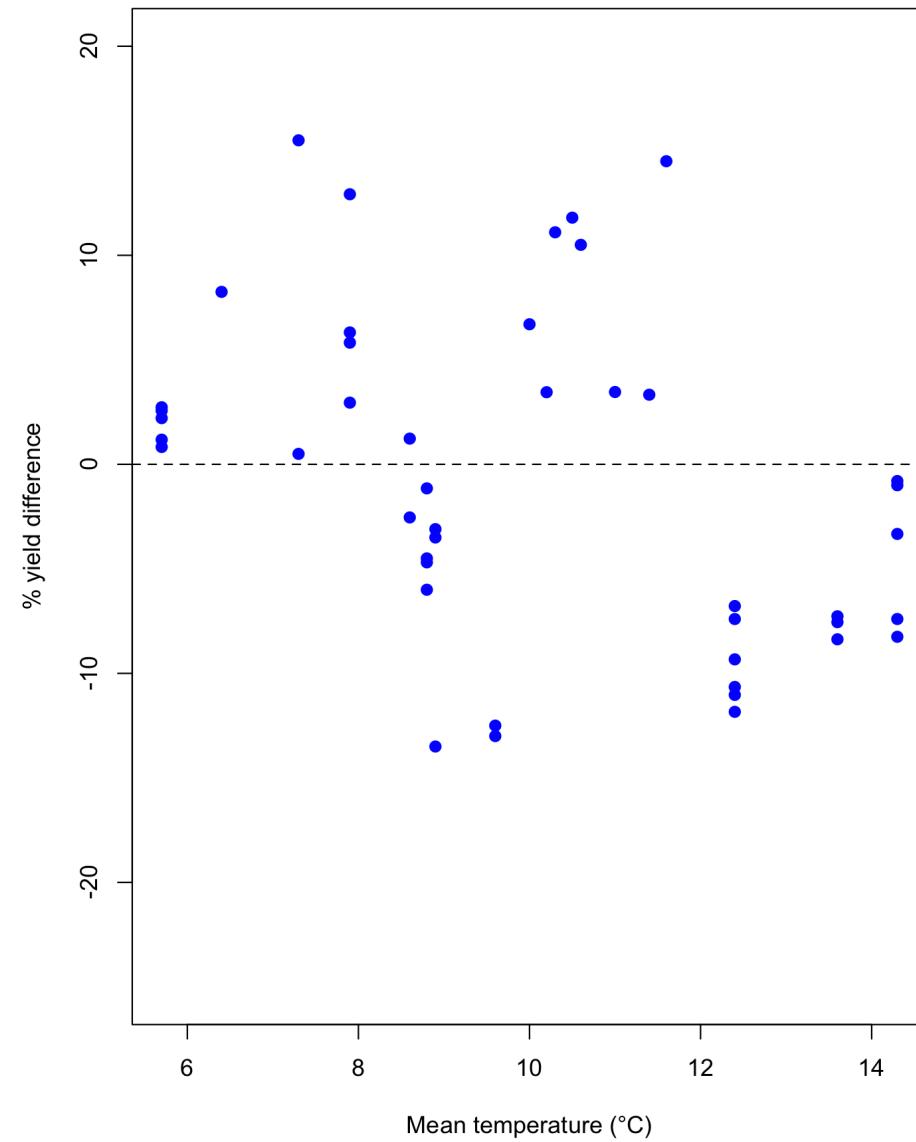
Open and run BayesianRegression_1.R

Wheat_type	Site_name	Lat	Long	Design	Temp_increase	Irrigation_mm	Nitrogen_kgha	TGS	PGS
Springwheat:14	Luancheng : 8	Min. :31.21	Min. :104.6	Greenhouse : 6	Min. :0.5	Min. : 0.0	Min. : 0.0	Min. : 5.70	Min. : 23
Winterwheat:31	Guyuan : 6	1st Qu.:34.55	1st Qu.:106.3	Heatingcable : 5	1st Qu.:1.3	1st Qu.: 0.0	1st Qu.:136.0	1st Qu.: 7.90	1st Qu.: 97
	Nanjing : 5	Median :36.03	Median :114.7	Infraredheaters:34	Median :1.5	Median : 0.0	Median :225.0	Median : 9.60	Median :160
	Xidatan : 5	Mean :35.86	Mean :112.5		Mean :1.7	Mean : 82.7	Mean :178.6	Mean :10.04	Mean :202
	Lianyungang: 4	3rd Qu.:37.88	3rd Qu.:118.9		3rd Qu.:2.0	3rd Qu.:160.0	3rd Qu.:240.0	3rd Qu.:12.40	3rd Qu.:325
	Yucheng : 4	Max. :39.13	Max. :121.1		Max. :3.0	Max. :500.0	Max. :300.0	Max. :14.30	Max. :476
	(Other) :13					NA's :8	NA's :17		
DGS	Sensitivity	Ref							
Min. : 5.700	Min. :-13.5000	Min. : 1.000							
1st Qu.: 7.300	1st Qu.: -7.4000	1st Qu.: 3.000							
Median : 8.600	Median : -1.0000	Median : 5.000							
Mean : 8.942	Mean : -0.8364	Mean : 5.467							
3rd Qu.:10.000	3rd Qu.: 3.4500	3rd Qu.: 8.000							
Max. :12.200	Max. : 15.5000	Max. :10.000							

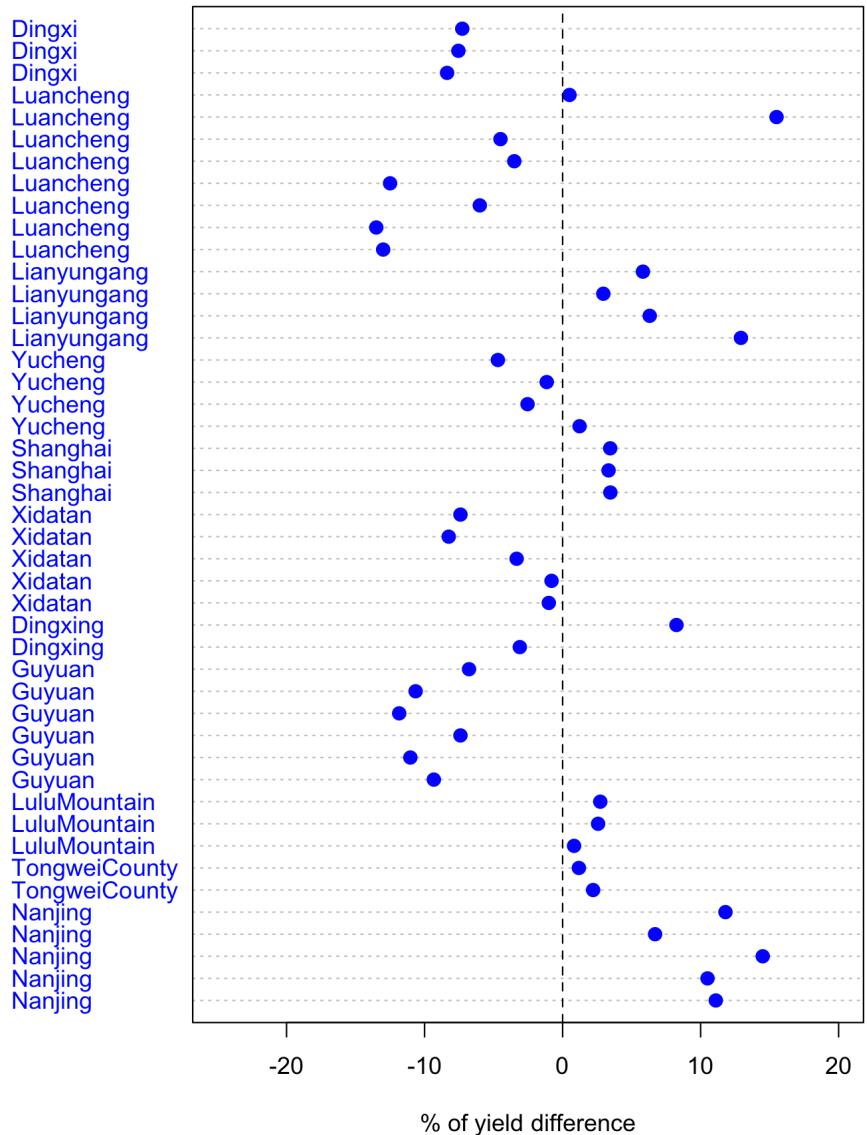
Individual yield sensitivity values, by site



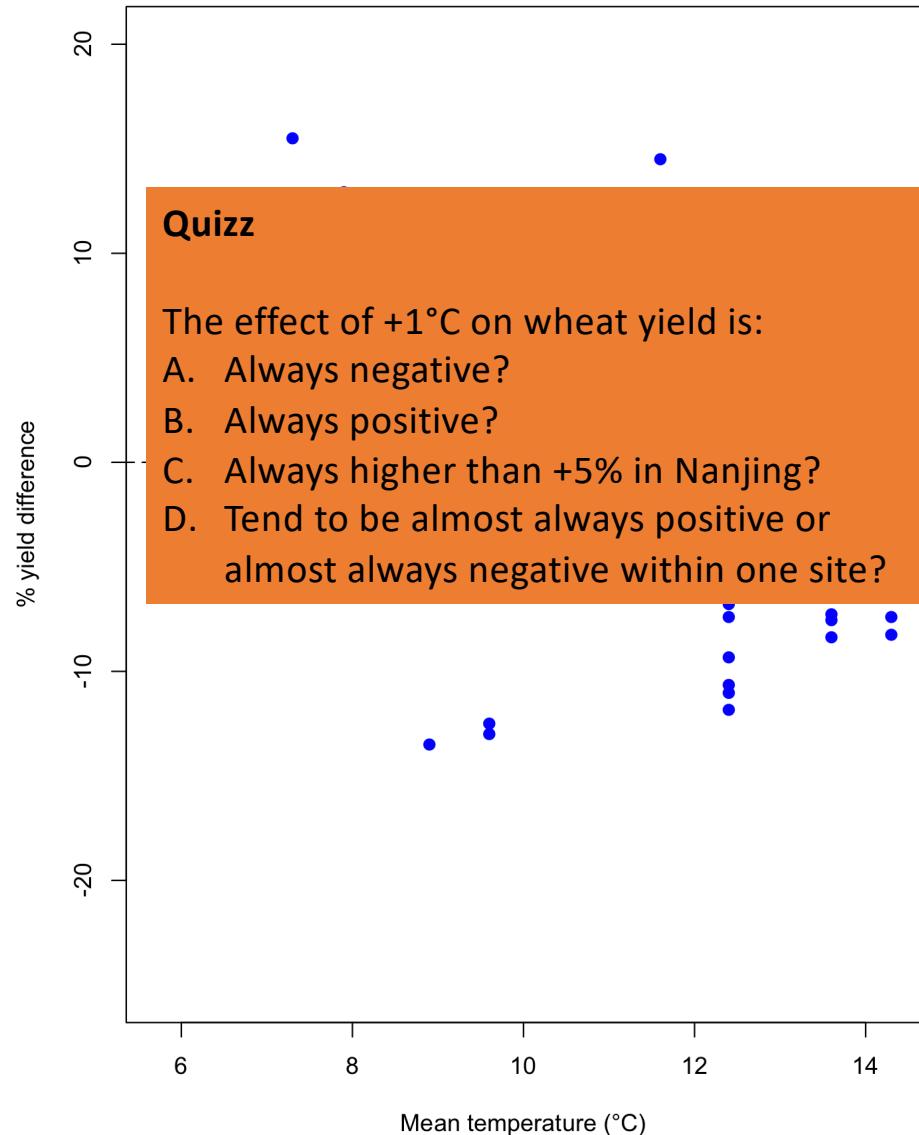
Individual yield sensitivity values vs. Site average temperature



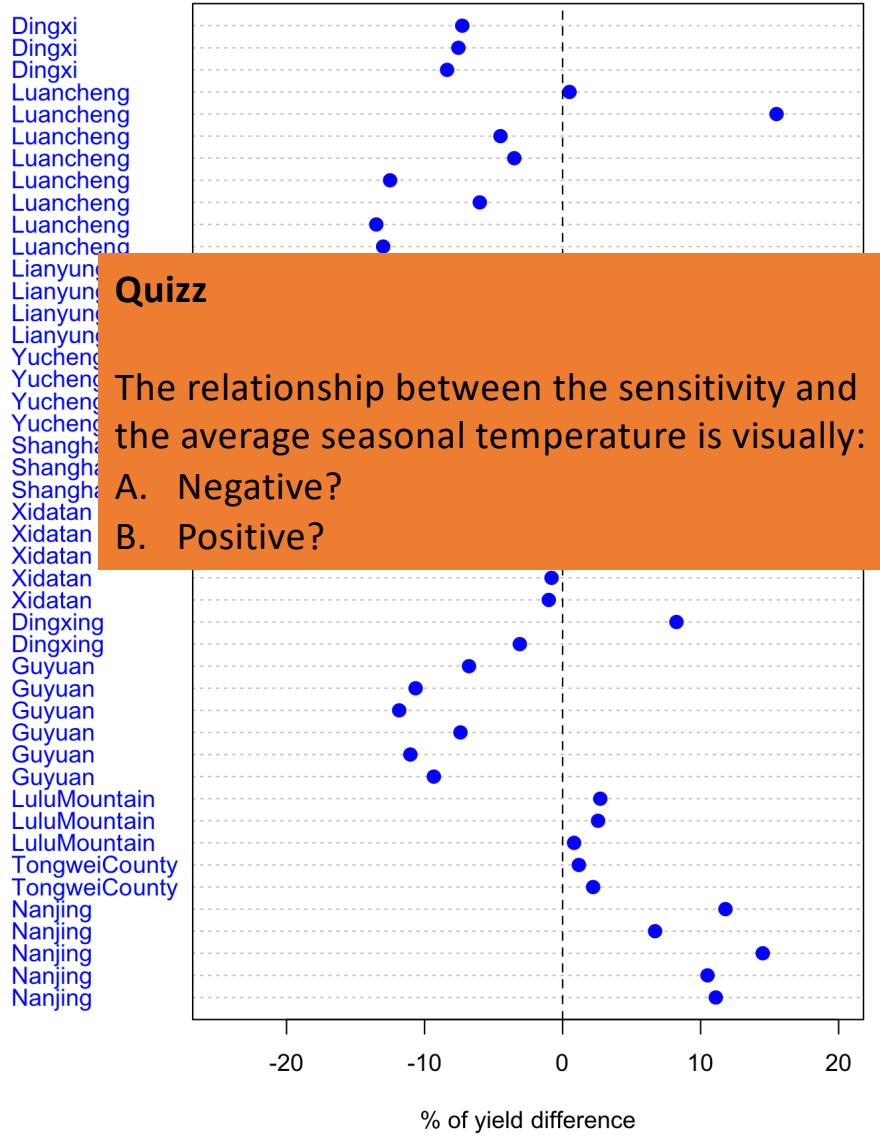
Individual yield sensitivity values, by site



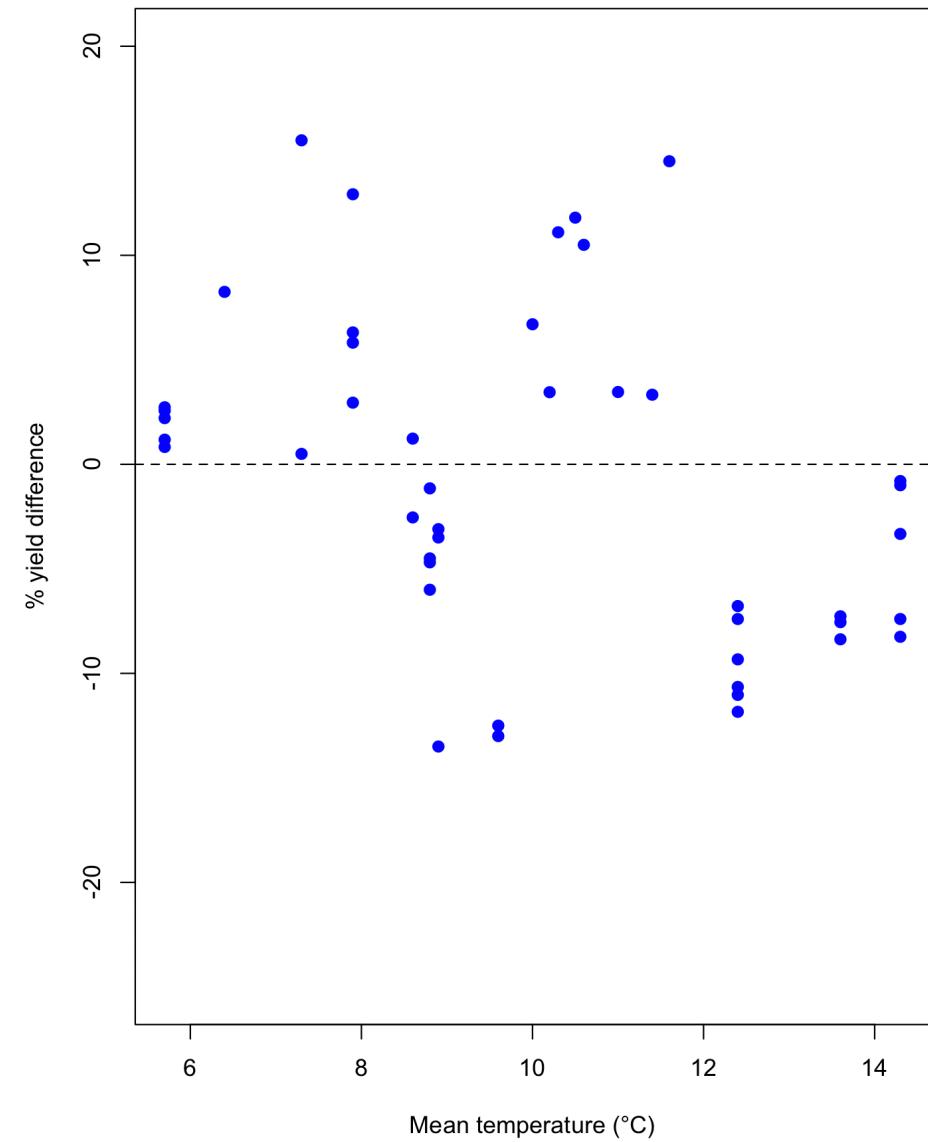
Individual yield sensitivity values vs. Site average temperature



Individual yield sensitivity values, by site

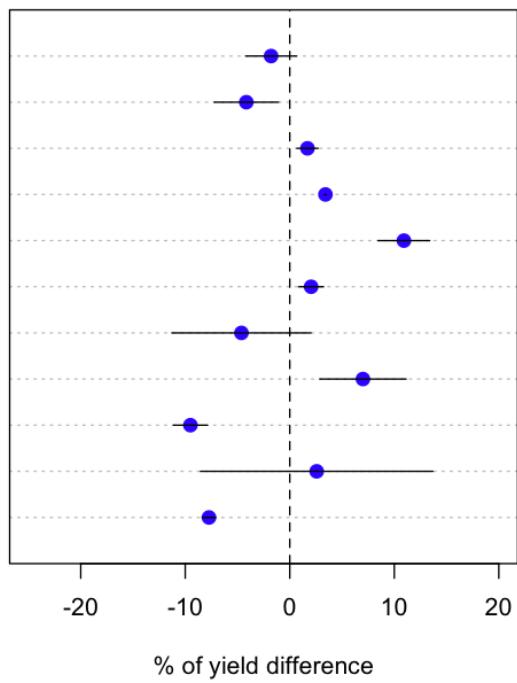


Individual yield sensitivity values vs. Site average temperature

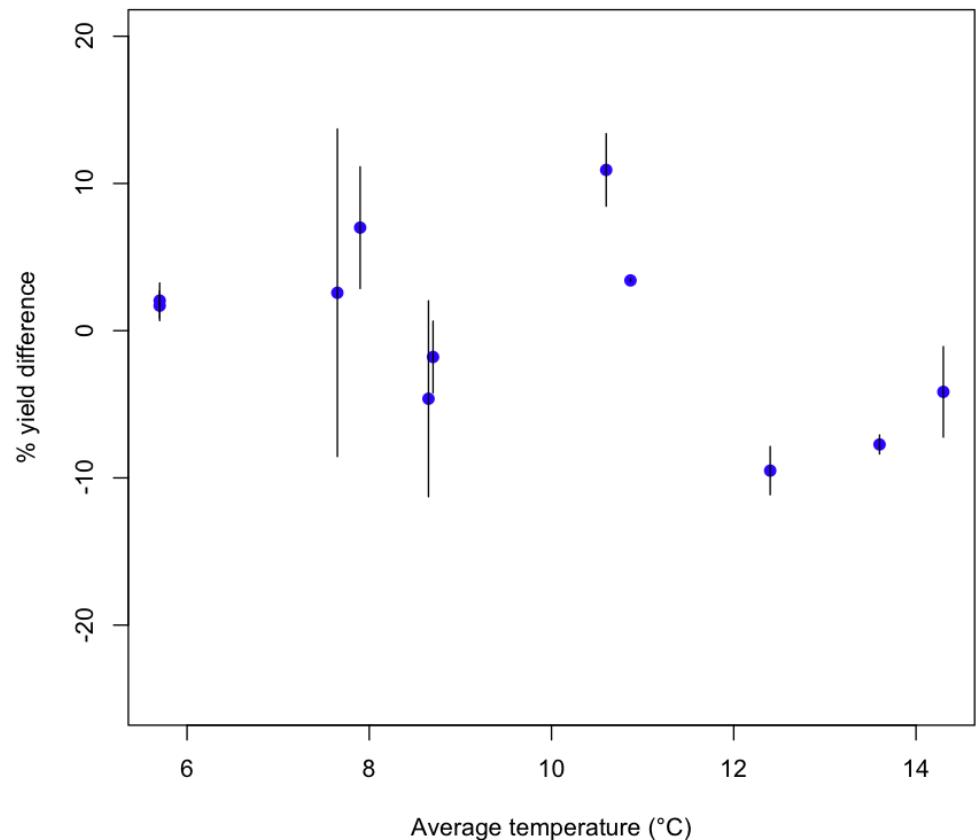


Yield sensitivities to +1°C by site

Yucheng (n=4)
Xidatan (n=5)
TongweiCounty (n=2)
Shanghai (n=3)
Nanjing (n=5)
LuluMountain (n=3)
Luancheng (n=8)
Lianyungang (n=4)
Guyuan (n=6)
Dingxing (n=2)
Dingxi (n=3)



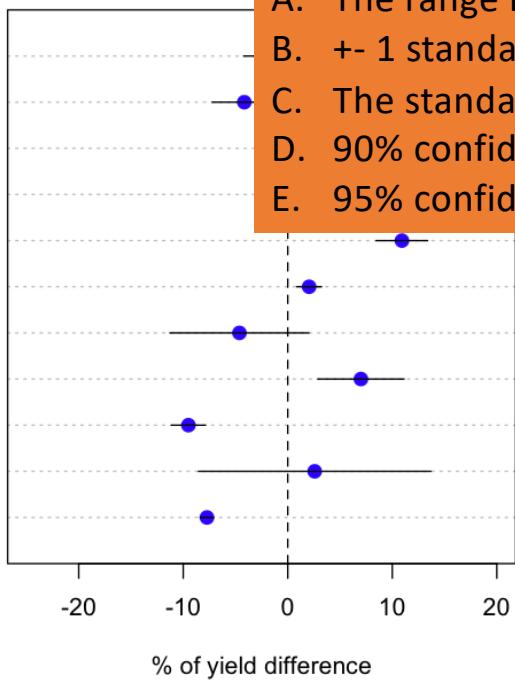
Yield sensitivities to +1°C vs. Average temperature



Quizz

Yield sensivities to +1°C by

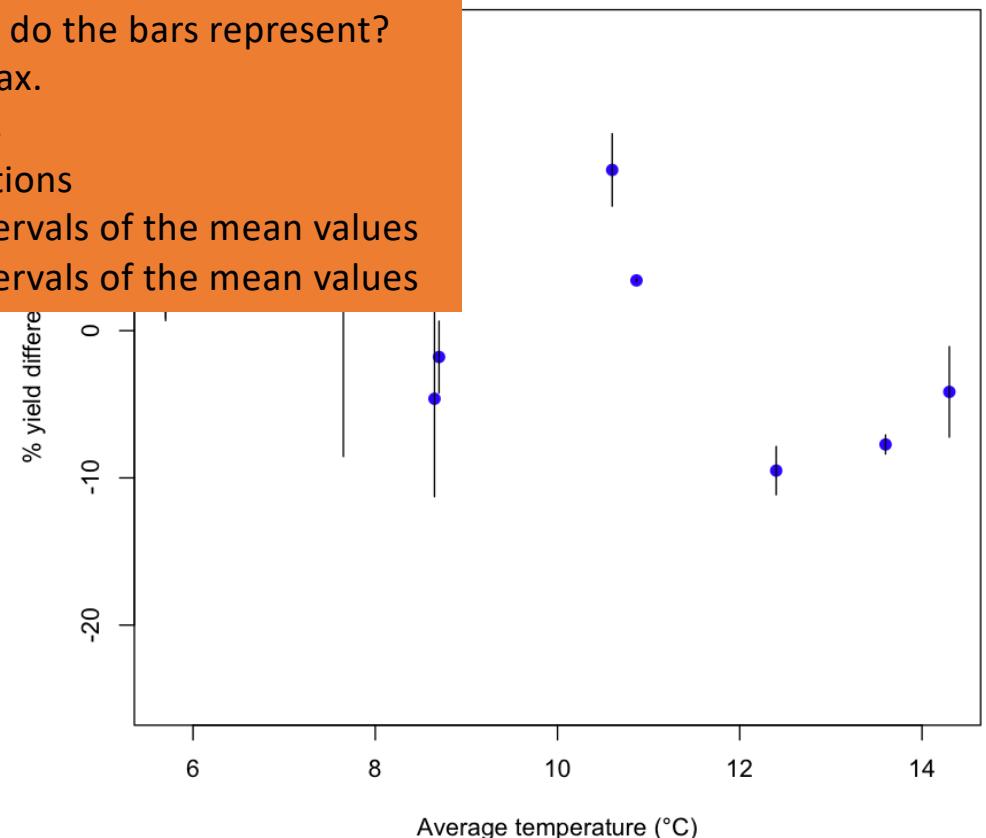
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Luancheng (n=8)
Lianyungang (n=4)
Guyuan (n=6)
Dingxing (n=2)
Dingxi (n=3)



Look at the code. What do the bars represent?

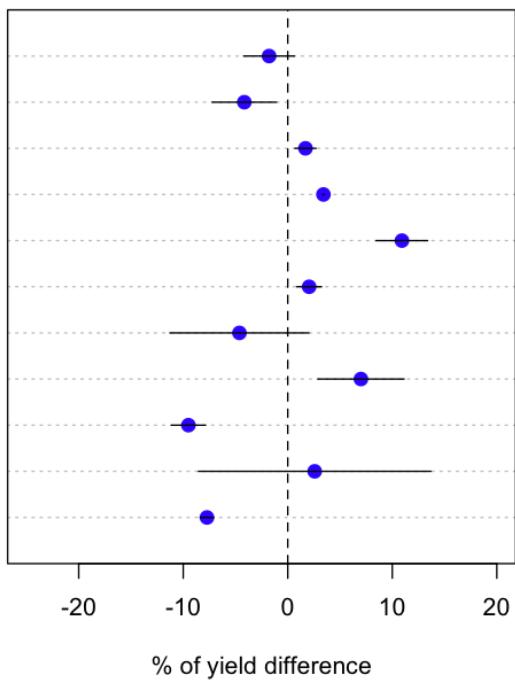
- A. The range min. – max.
- B. +- 1 standard errors
- C. The standard deviations
- D. 90% confidence intervals of the mean values
- E. 95% confidence intervals of the mean values

to +1°C vs. Average temperature

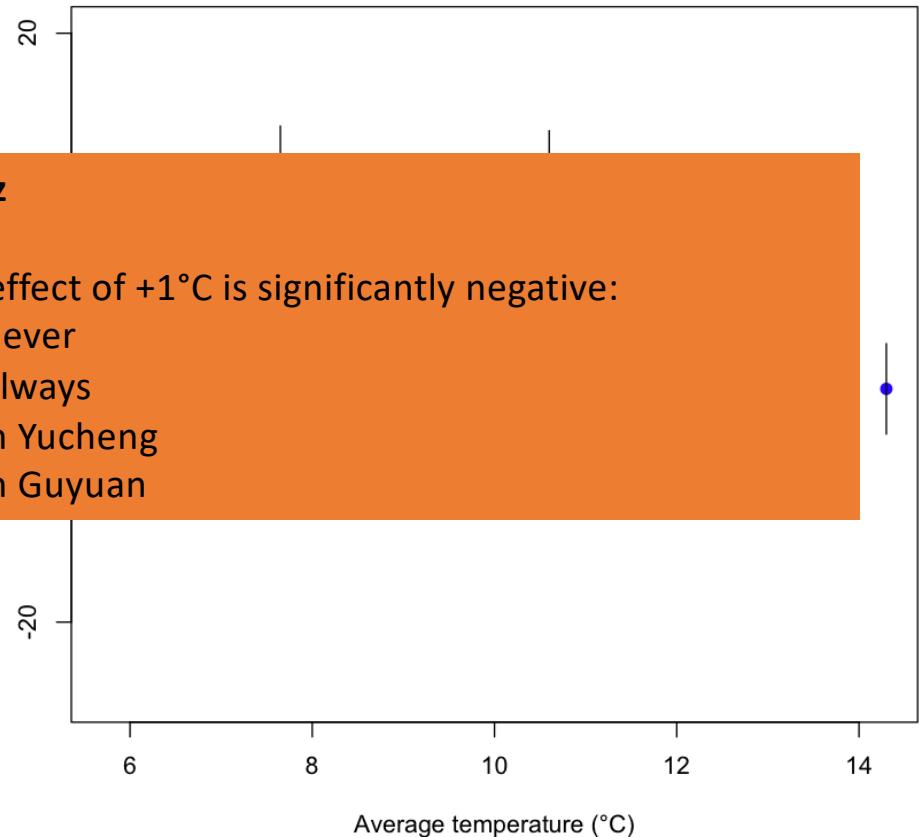


Yield sensitivities to +1°C by site

Yucheng (n=4)
Xidatan (n=5)
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Yield sensitivities to +1°C vs. Average temperature



Yucheng (n=4)

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TongweiCounty (n=2)

Shanghai (n=3)

Nanjing (n=5)

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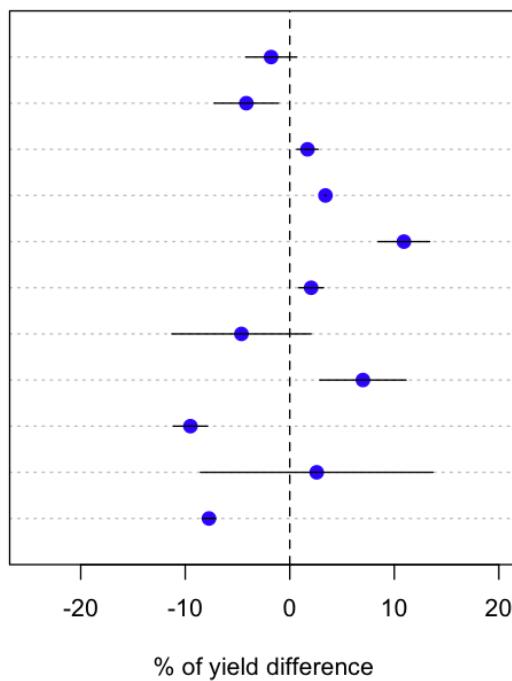
Lianyungang (n=4)

Guyuan (n=6)

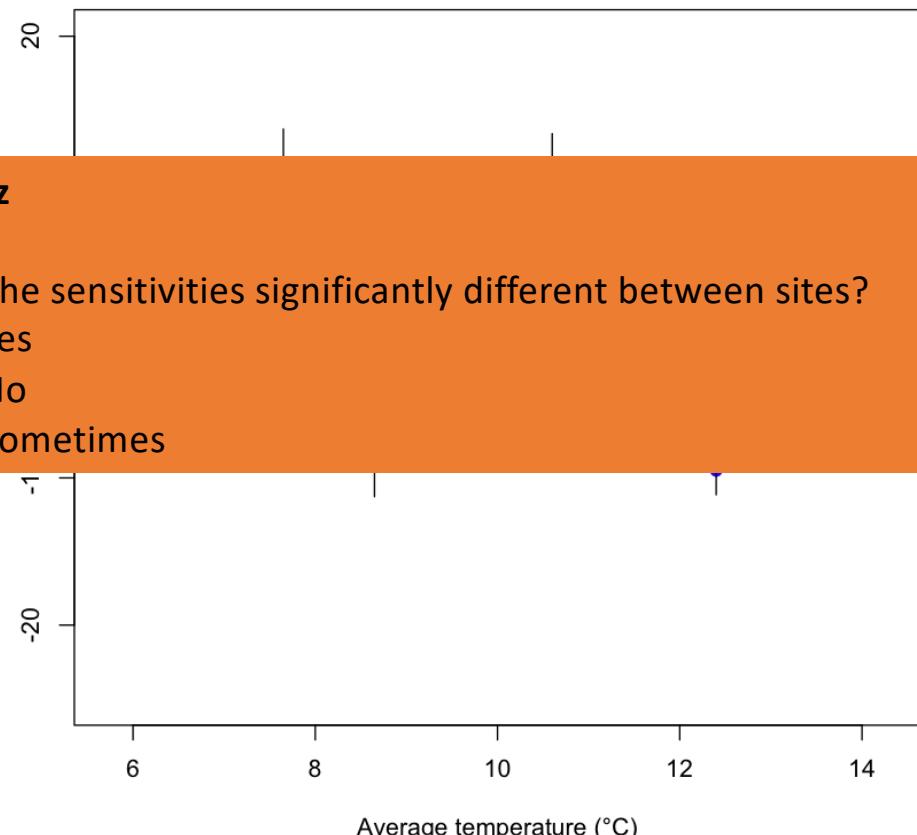
Dingxing (n=2)

Dingxi (n=3)

Yield sensitivities to +1°C by site



Yield sensitivities to +1°C vs. Average temperature



Yield sensitivities to +1°C by site

Yucheng (n=4)

Xidat

Tong

Shan

Nanji

LuluN

Luan

Liany

Guyu

Dingxing (n=2)

Dingxi (n=3)

Quizz

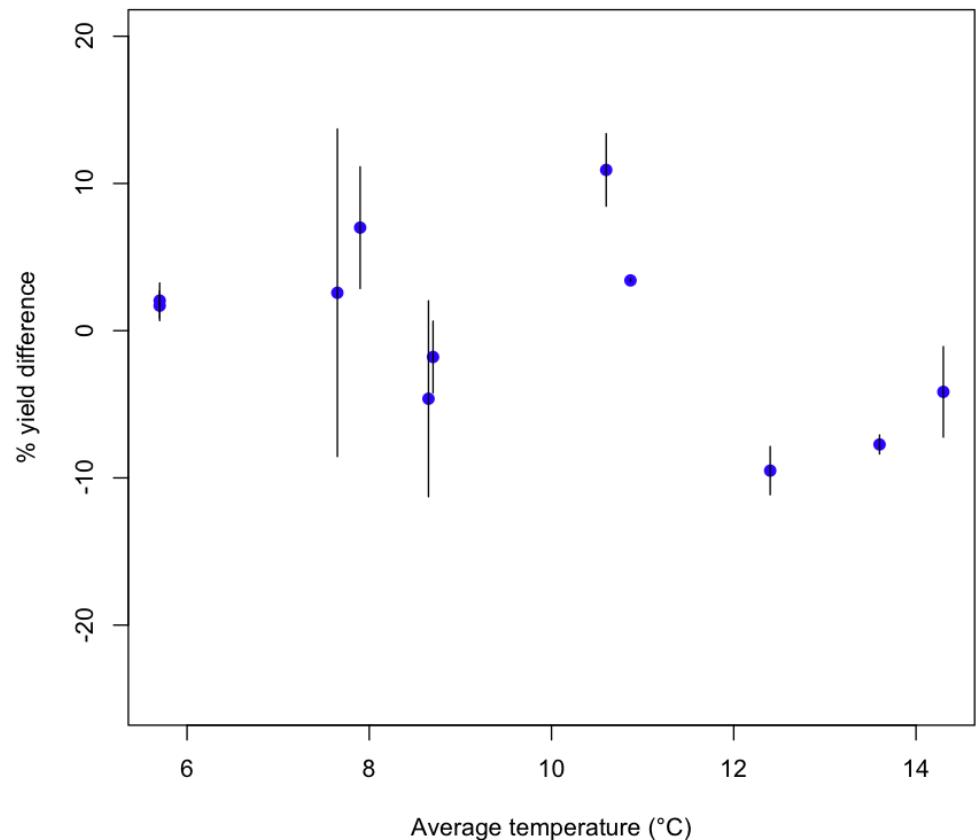
Does the « Mean temperature » explain:

- A. Part of the within-site variability
- B. Part of the between-site variability
- C. Nothing
- D. Don't know

% of yield difference

-20 -10 0 10 20

Yield sensitivities to +1°C vs. Average temperature



Steps

- Explore the dataset
- Define and fit Bayesian models
- Conclude

Hierarchical statistical model

« Random-effect model »

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

Overall mean Effect of study i
Yield sensitivity in study i, replicate j Residual for jth data in study i

The diagram illustrates the hierarchical random-effects model equation $S_{ij} = \mu + b_i + \varepsilon_{ij}$. Red arrows point from the labels to the corresponding components in the equation:

- An arrow points from "Overall mean" to μ .
- An arrow points from "Effect of study i" to b_i .
- An arrow points from "Residual for jth data in study i" to ε_{ij} .
- A fourth red arrow points from "Yield sensitivity in study i, replicate j" to the entire equation $S_{ij} = \mu + b_i + \varepsilon_{ij}$.

Hierarchical statistical model

« Random-effect model »

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

Overall mean Effect of study i

Yield sensitivity in study i, replicate j Residual for jth data in study i

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

Prior: Gaussian and Uniform

Hierarchical statistical model

« Random-effect model »

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

Overall mean Effect of study i

Yield sensitivity in study i, replicate j Residual for jth data in study i

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

Prior: Gaussian and Uniform

Fitting algorithm: MCMC

Hierarchical statistical model (with covariate)

« Random-effect model »

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

↑
Yield sensitivity in
study i, replicate j

↑
Covariate value for study i replicate j

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

Prior: Gaussian and Uniform

Fitting algorithm: MCMC

Open **BayesianRegression_2.R**

This file includes four Bayesian models coded with **rjags**.

How to install Jags: <https://wiki.student.info.ucl.ac.be/Logiciels/JAGS>

- How many models are coded?
- What are the differences between these models?
- Which one is the simplest?
- Which one is the most complex?

Model 1

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

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

Prior: Gaussian and Uniform

Fitting algorithm: MCMC

Model 2

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

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

Prior: Gaussian and Uniform

Fitting algorithm: MCMC

Model 1bis

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

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

Prior: Gaussian and Uniform

Fitting algorithm: MCMC

Model 2bis

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

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

Prior: Gaussian and Uniform

Fitting algorithm: MCMC

Run model 1

```
Iterations = 100010:2e+05
Thinning interval = 10
Number of chains = 3
Sample size per chain = 10000
```

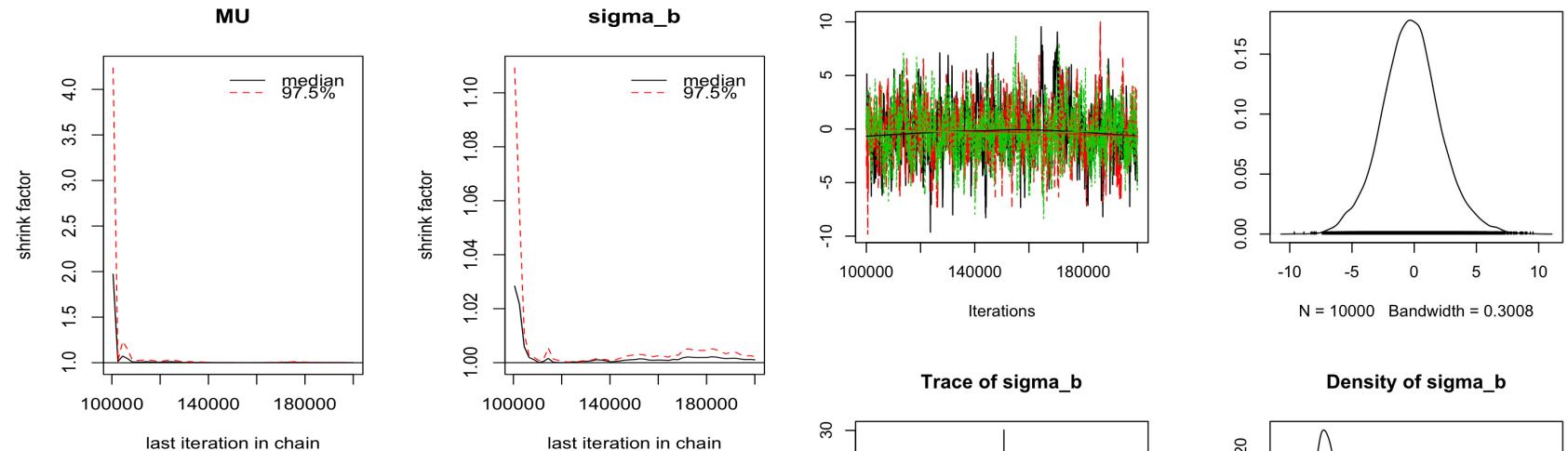
1. Empirical mean and standard deviation for each variable, plus standard error of the mean:

	Mean	SD	Naive SE	Time-series SE
MU	-0.2577	2.362	0.01364	0.09475
sigma_b	7.1907	2.205	0.01273	0.02351

2. Quantiles for each variable:

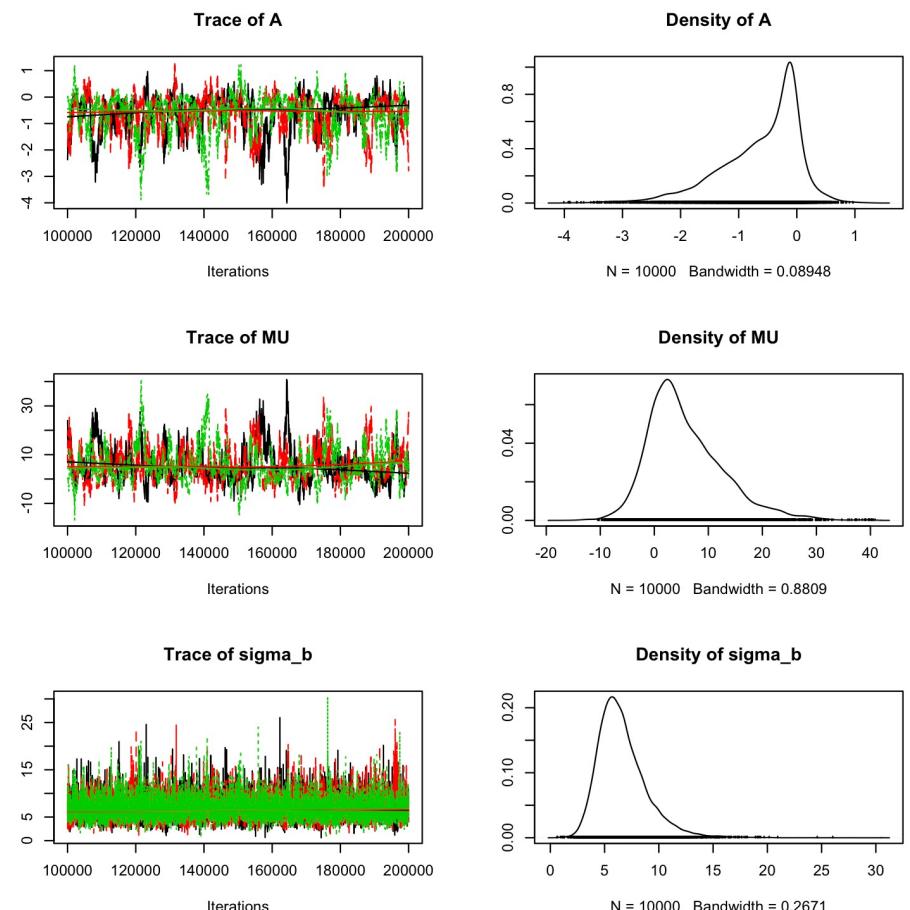
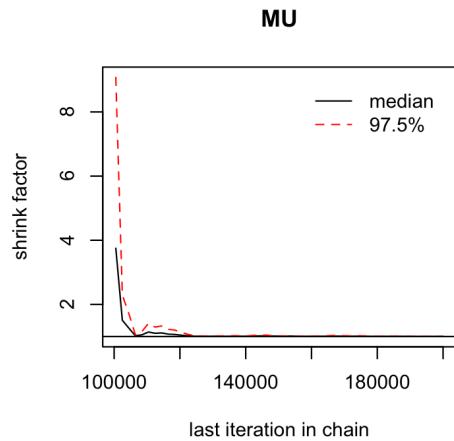
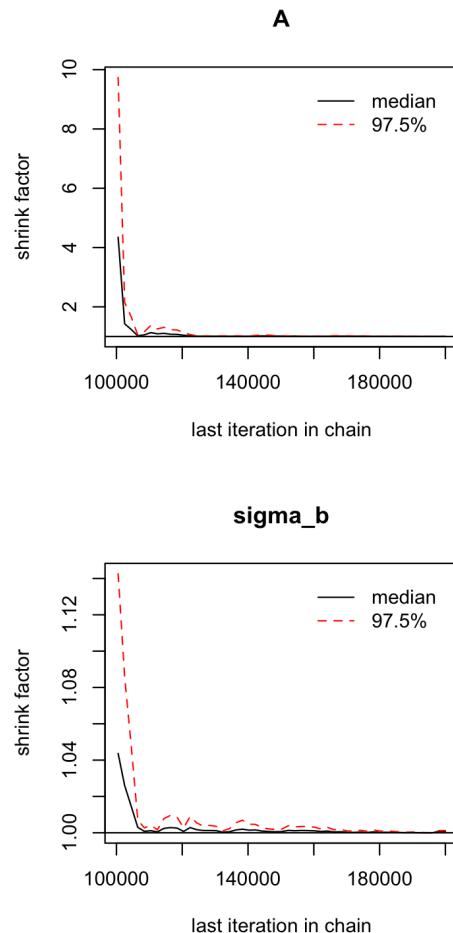
	2.5%	25%	50%	75%	97.5%
MU	-4.985	-1.784	-0.286	1.205	4.668
sigma_b	4.086	5.677	6.798	8.252	12.614

```
> dic.samples(model, 10000)
|*****| 100%
Mean deviance: 236.2
penalty 437.3
Penalized deviance: 673.5
```



- What is the posterior mean of the yield sensitivity?
- What is the 95% credibility interval?
- Practical conclusion?
- Modify the code to look at the within-study variances

Run model 2



- What are the meanings of A, MU, sigma_b?
- Does the model includes other parameters?
- Modify the code to look at the within-study variances

Run model 2

```
> summary(samples)
```

Iterations = 1000010:2e+05
Thinning interval = 10
Number of chains = 3
Sample size per chain = 10000

1. Empirical mean and standard deviation for each variable, plus standard error of the mean:

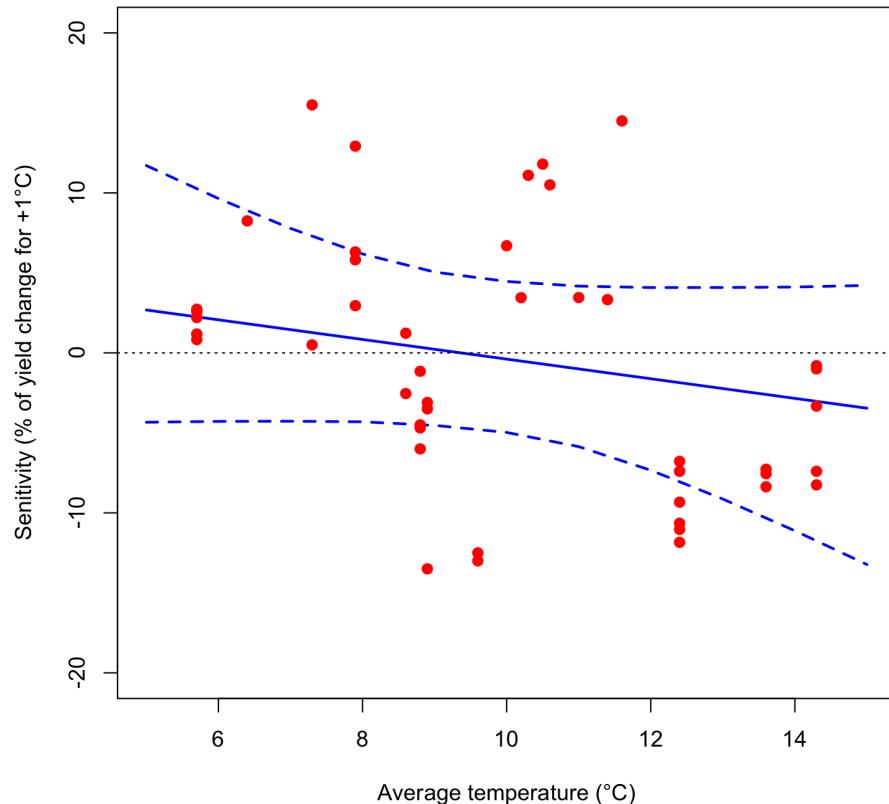
	Mean	SD	Naive SE	Time-series SE
A	-0.6139	0.689	0.003978	0.04979
MU	5.7506	7.015	0.040500	0.49460
sigma_b	6.6276	2.280	0.013165	0.04103

2. Quantiles for each variable:

	2.5%	25%	50%	75%	97.5%
A	-2.293	-1.0024	-0.4249	-0.1132	0.3409
MU	-4.960	0.8774	4.3804	9.6299	22.8198
sigma_b	3.276	5.0932	6.2541	7.7468	12.1035

```
> dic.samples(model, 10000)
|*****| 100%
```

Mean deviance: 243.4
penalty 1146
Penalized deviance: 1389



- What is the effect of the average temperature?
- Does this variable explain a big part of the between-site variability?

Run model 1bis

```
> summary(samples)
```

Iterations = 100010:2e+05
Thinning interval = 10
Number of chains = 3
Sample size per chain = 10000

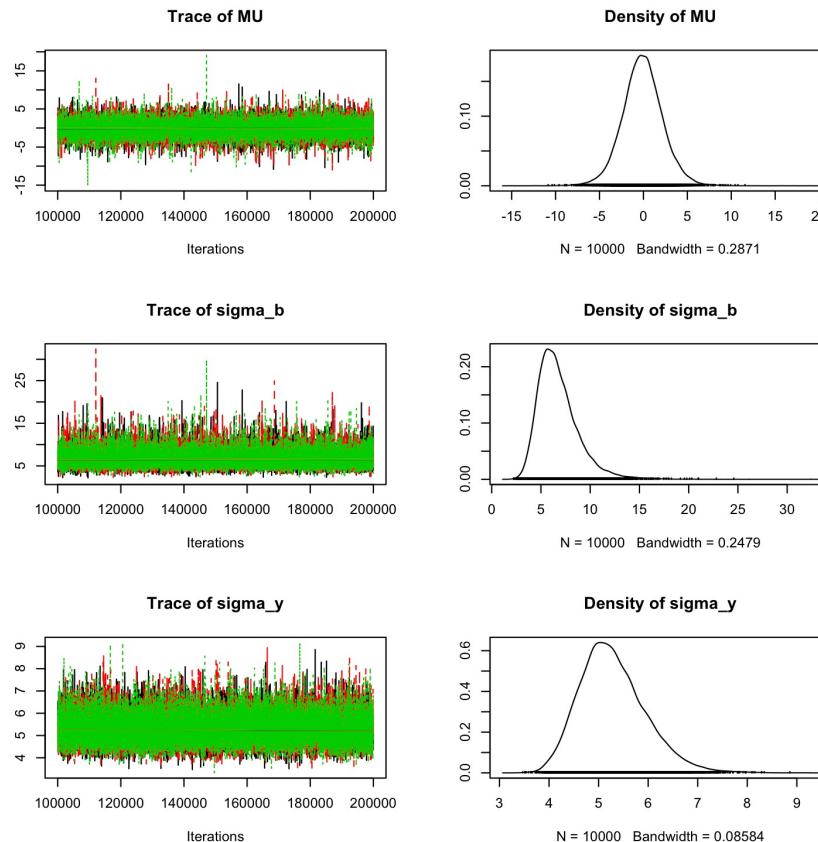
1. Empirical mean and standard deviation for each variable, plus standard error of the mean:

	Mean	SD	Naive SE	Time-series SE	SE
MU	-0.09876	2.2985	0.013270	0.01889	
sigma_b	6.76543	2.1056	0.012157	0.01323	
sigma_y	5.28503	0.6643	0.003836	0.00380	

2. Quantiles for each variable:

	2.5%	25%	50%	75%	97.5%
MU	-4.593	-1.536	-0.1248	1.317	4.528
sigma_b	3.751	5.320	6.4026	7.783	11.902
sigma_y	4.173	4.823	5.2160	5.676	6.772

```
> dic.samples(model, 10000)
|*****| 100%
Mean deviance: 275.9
penalty 11.3
Penalized deviance: 287.2
```



- How does this model compare with model 1?
- Is it relevant to consider different within-site variances?

Run model 2bis

```
> summary(samples)
```

```
Iterations = 100010:2e+05
Thinning interval = 10
Number of chains = 3
Sample size per chain = 10000
```

1. Empirical mean and standard deviation for each variable, plus standard error of the mean:

	Mean	SD	Naive SE	Time-series SE
A	-2.045	0.8503	0.004909	0.027451
MU	19.581	8.3981	0.048487	0.266484
sigma_b	7.273	2.6770	0.015456	0.054430
sigma_y	4.679	0.6271	0.003621	0.006523

2. Quantiles for each variable:

	2.5%	25%	50%	75%	97.5%
A	-3.917	-2.552	-1.974	-1.461	-0.5895
MU	5.001	13.773	18.979	24.668	37.8528
sigma_b	3.719	5.435	6.748	8.501	13.8902
sigma_y	3.632	4.234	4.614	5.055	6.0909

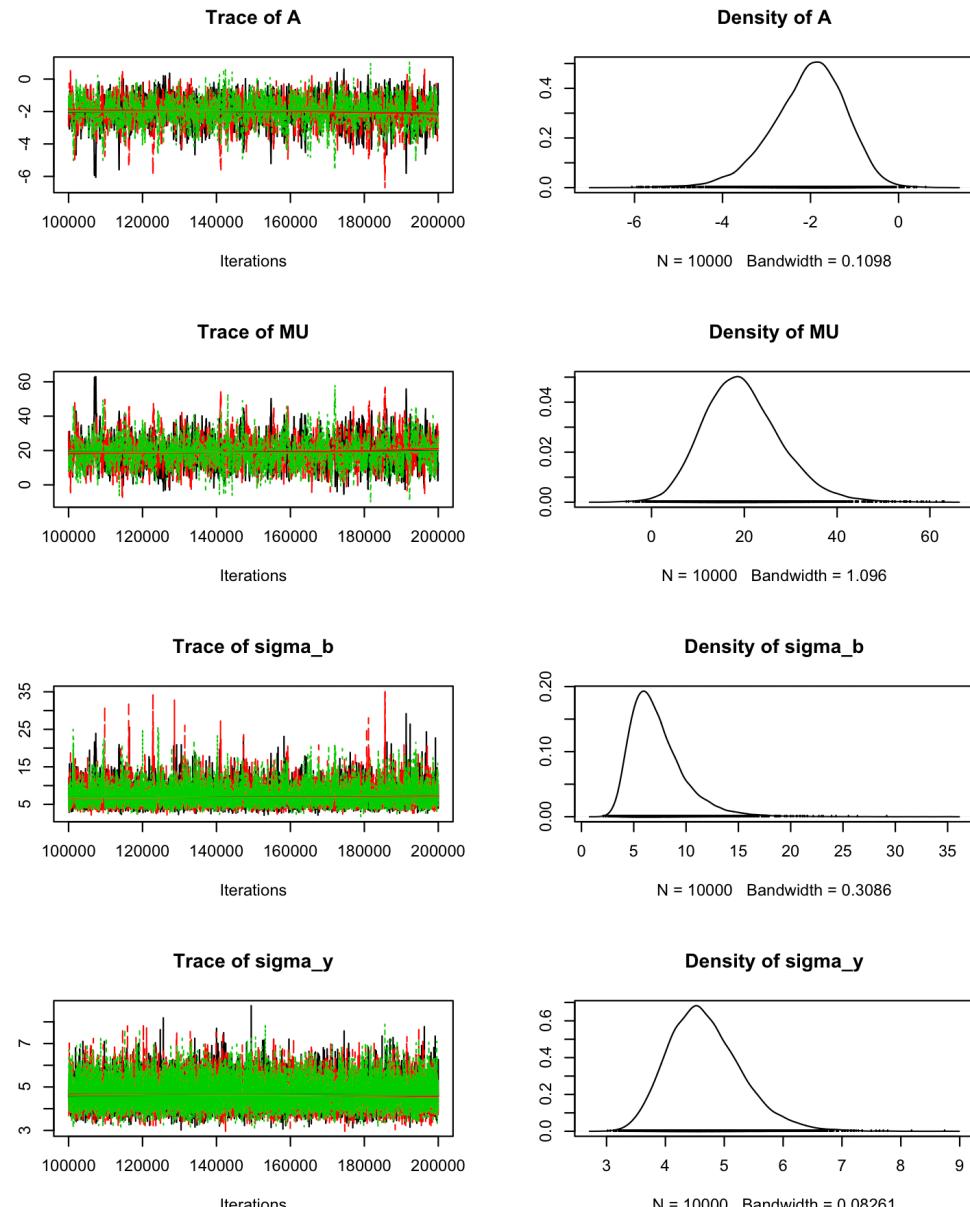
```
> dic.samples(model, 10000)
|*****| 100%
```

```
Mean deviance: 264.7
```

```
penalty 12.43
```

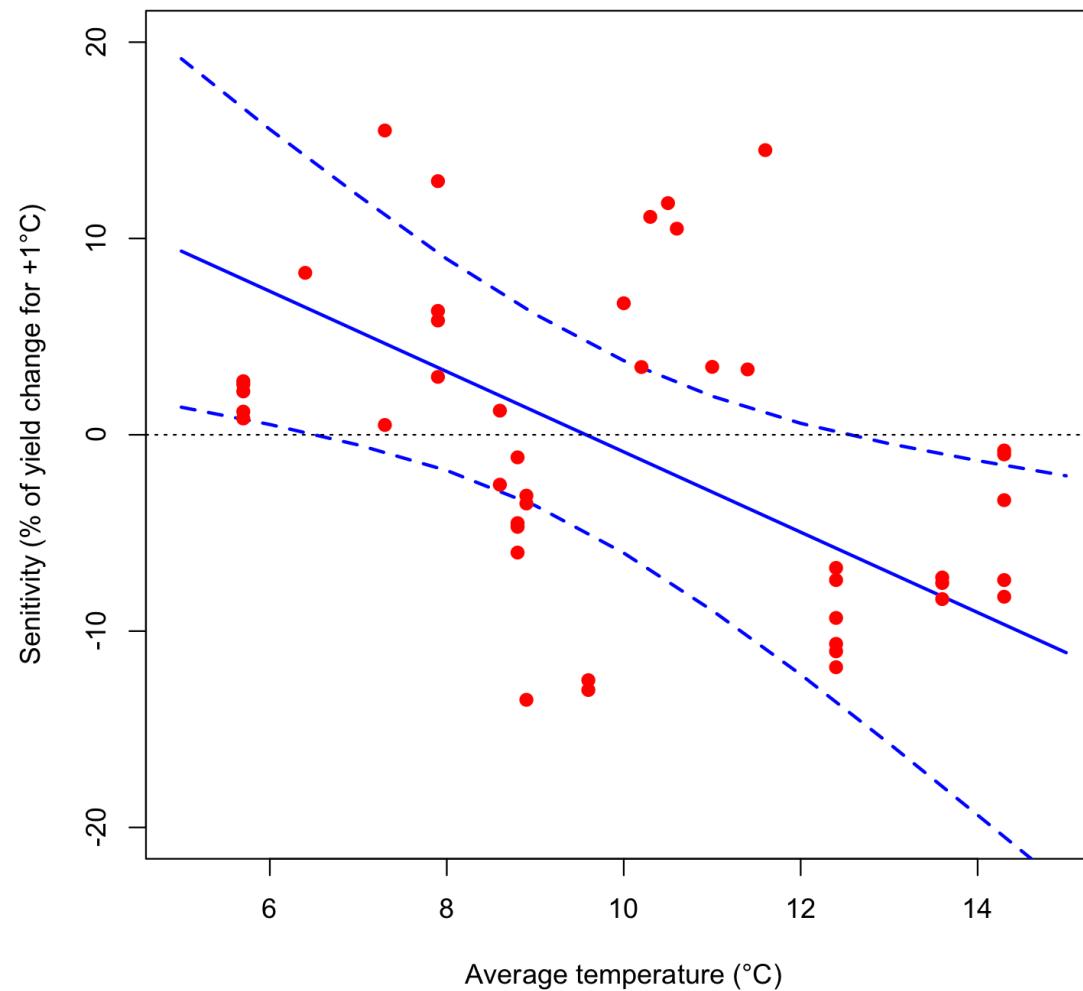
```
Penalized deviance: 277.2
```

- How does this model compare with the other models?
- What is the effect of the average temperature?



Run model 2bis

- What is the yield sensitivity when the average temperature is of 6°C or of 14°C?
- Can you anticipate a shift of the wheat growing area due to climate change based on this model?



If you had 2 days available, how will you improve this model?

Another package with a different phylosophy:
MCMCglmm

```
#Data and their summaries
TAB<-read.table("Data_Zhao_Wheat.txt", sep="\t", header=T)
summary(TAB)

###Data###

Y=TAB$Sensitivity
Temp=TAB$TGS
REF=as.numeric(as.factor(as.character(TAB$Site_name)))

DATA=data.frame(REF, Y, Temp)
```

```
library(MCMCglmm)
Mod_mcmc<-MCMCglmm(Y~1+Temp,random=~REF, data=DATA,verbose=F, nitt=50000, thin=10, burnin=10000, pr=TRUE)

#Visualisation du résumé de l'ajustement
summary(Mod_mcmc)

#Graphique de la chaîne de valeur pour le paramètre mu
plot(Mod_mcmc)
```

```
> summary(Mod_mcmc)

Iterations = 10001:49991
Thinning interval  = 10
Sample size  = 4000

DIC: 274.9552

G-structure: ~REF

      post.mean l-95% CI u-95% CI eff.samp
REF       56.5     7.024    145.6     3454

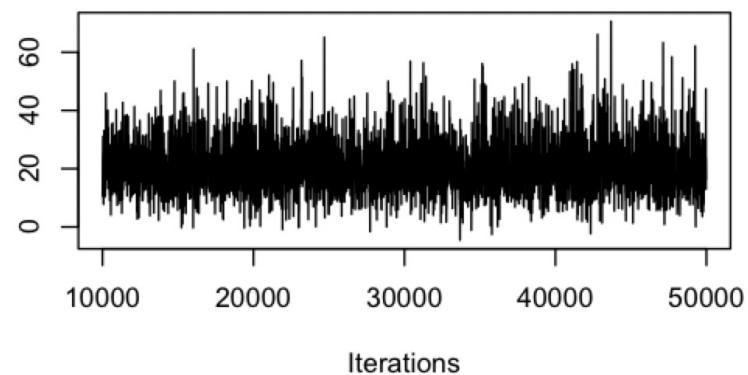
R-structure: ~units

      post.mean l-95% CI u-95% CI eff.samp
units     21.6     11.74    33.75     3512

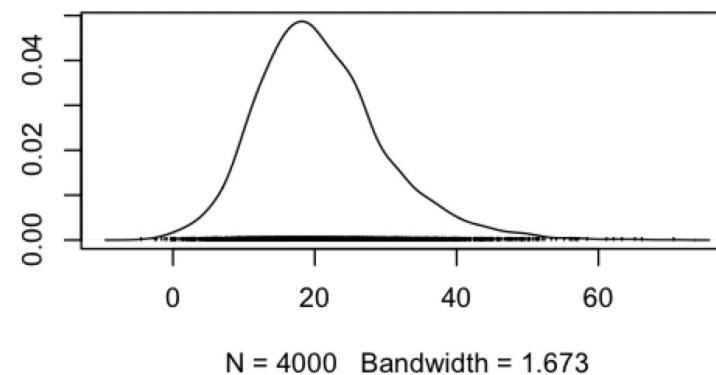
Location effects: Y ~ 1 + Temp

      post.mean l-95% CI u-95% CI eff.samp pMCMC
(Intercept)  20.8669   4.6540   40.0615    4000 0.0050 ***
Temp        -2.1598  -4.0221  -0.5079    4000 0.0035 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

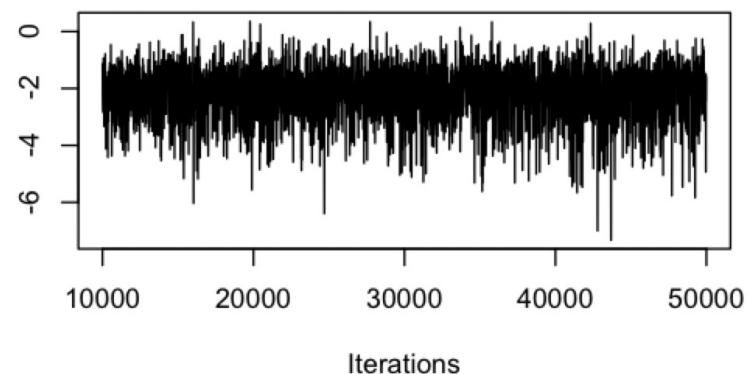
Trace of (Intercept)



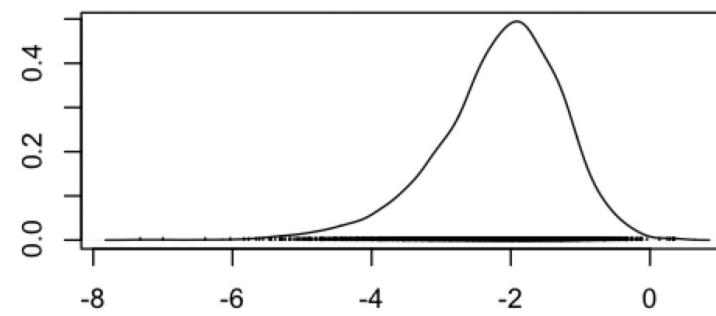
Density of (Intercept)



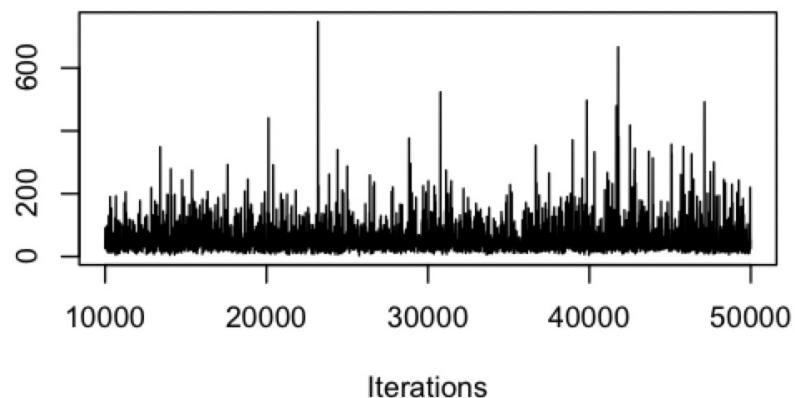
Trace of Temp



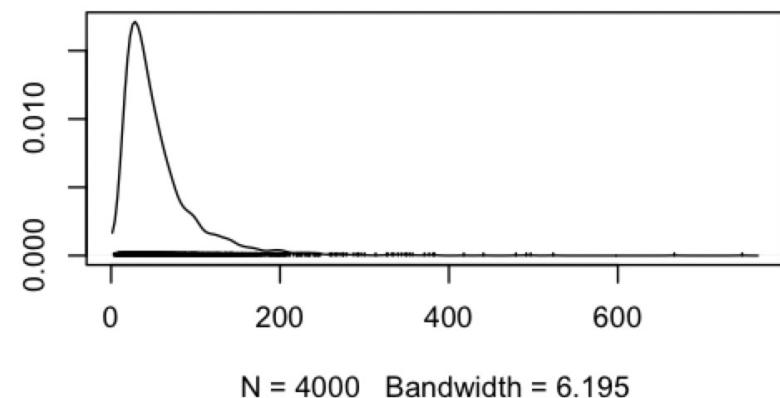
Density of Temp



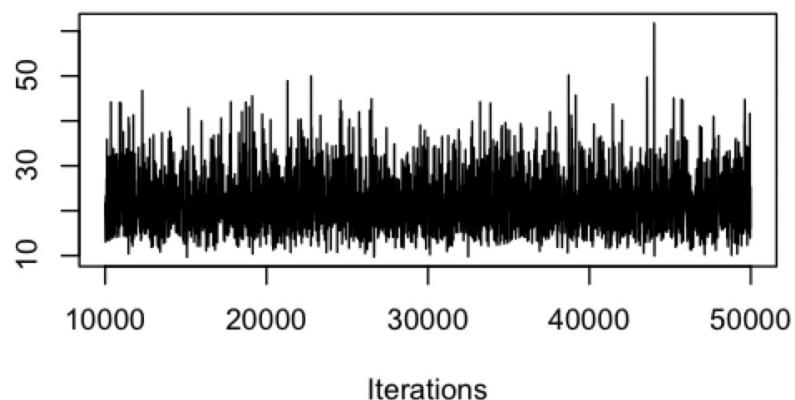
Trace of REF



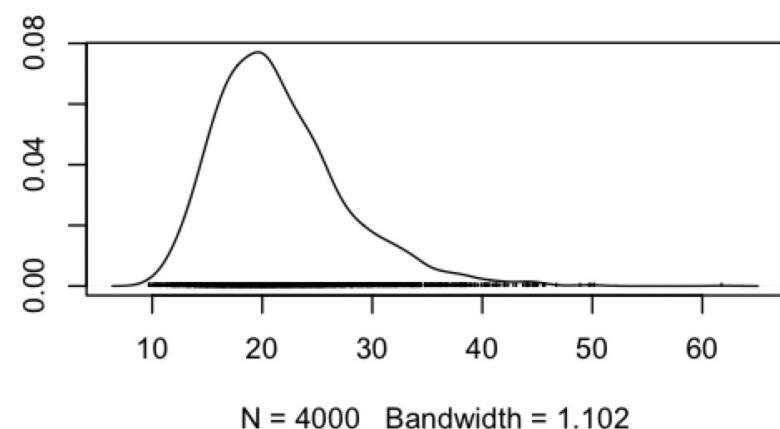
Density of REF



Trace of units



Density of units

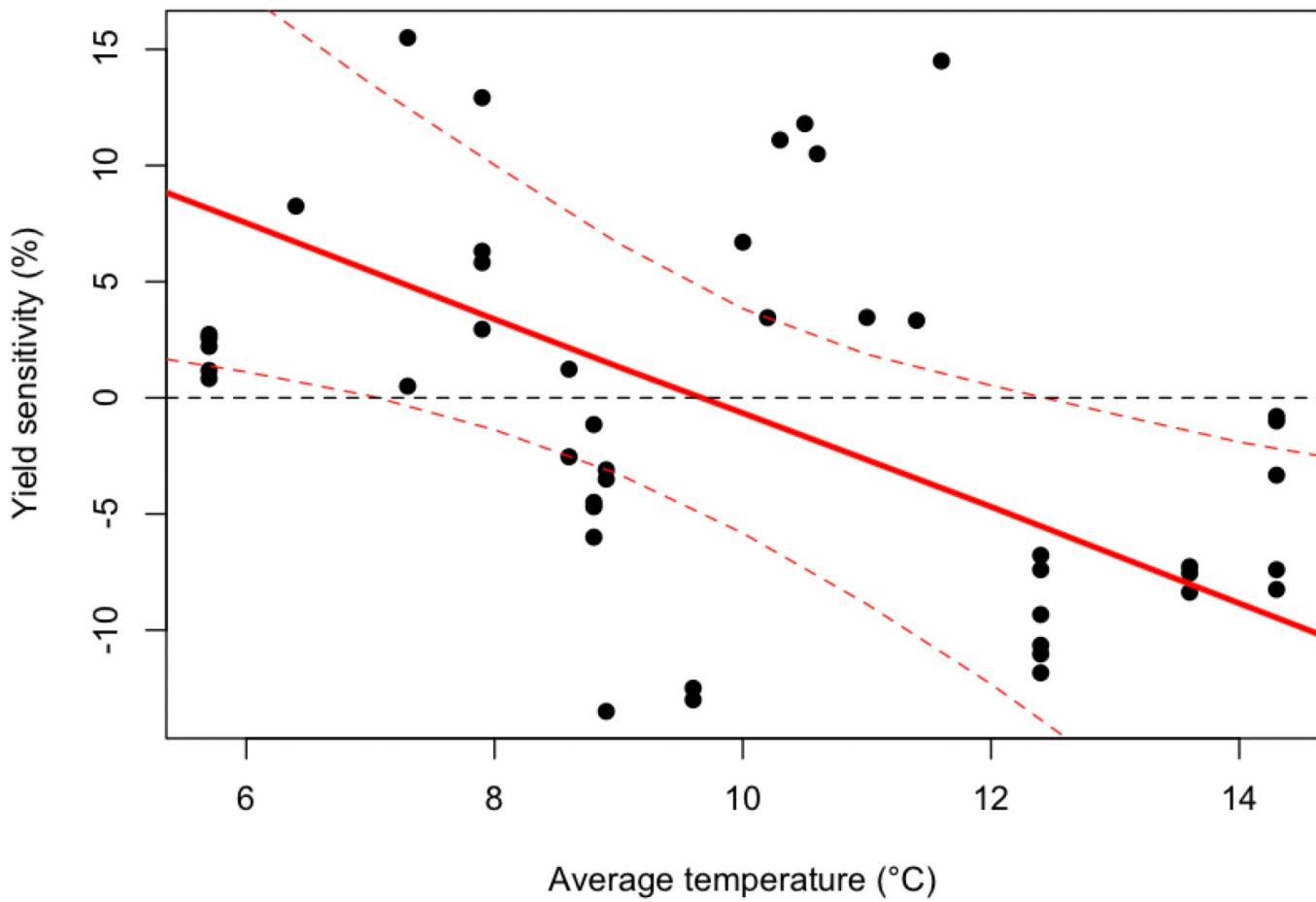


```
plot(Temp,Y, xlab="Average temperature (°C)", ylab="Yield sensitivity (%)", pch=19)

Temp_vec=5:15
Response=Mod_mcmc$Sol[,1]+as.matrix(Mod_mcmc$Sol[,2])%*%t(Temp_vec)

med_rep=apply(Response, 2, median)
q2.5_rep=apply(Response, 2, quantile, 0.025)
q97.5_rep=apply(Response, 2, quantile, 0.975)

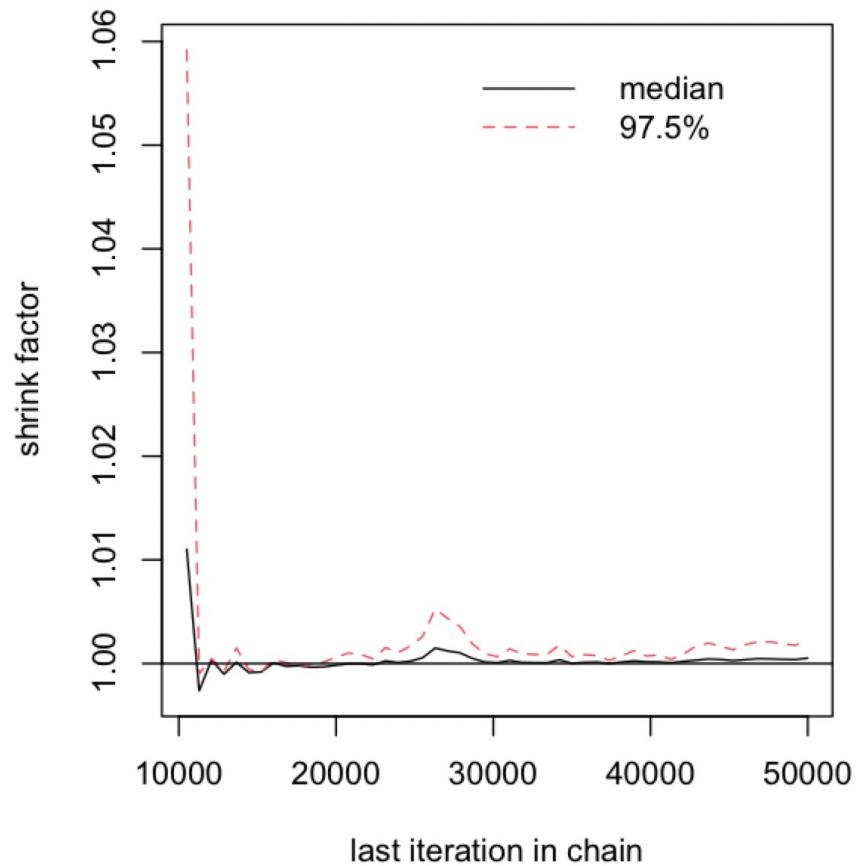
lines(Temp_vec, med_rep, col="red", lwd=3)
lines(Temp_vec, q2.5_rep, col="red", lty=2)
lines(Temp_vec, q97.5_rep, col="red", lty=2)
abline(h=0, lty=2)
```



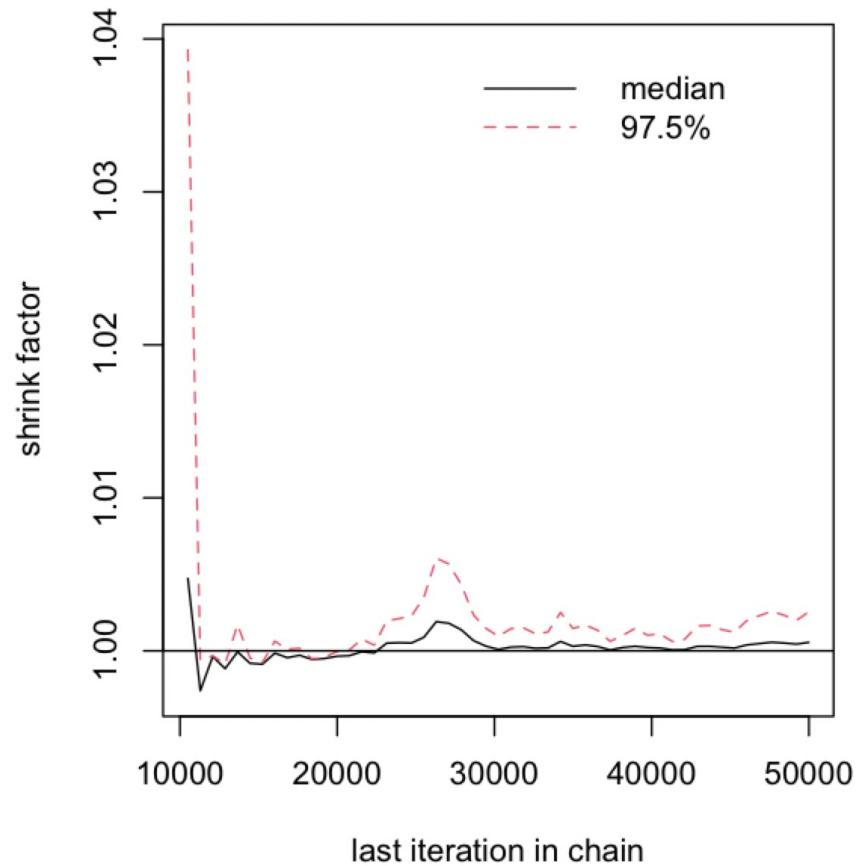
```
Mod_mcmc_1<-MCMCglmm(Y~1+Temp,random=~REF, data=DATA,verbose=F, nitt=50000, thin=10, burnin=10000)
Mod_mcmc_2<-MCMCglmm(Y~1+Temp,random=~REF, data=DATA,verbose=F, nitt=50000, thin=10, burnin=10000)
Mod_mcmc_3<-MCMCglmm(Y~1+Temp,random=~REF, data=DATA,verbose=F, nitt=50000, thin=10, burnin=10000)

ChainList<-mcmc.list(Mod_mcmc_1$Sol,Mod_mcmc_2$Sol,Mod_mcmc_3$Sol)
gelman.plot(ChainList)
```

(Intercept)



Temp



Prior

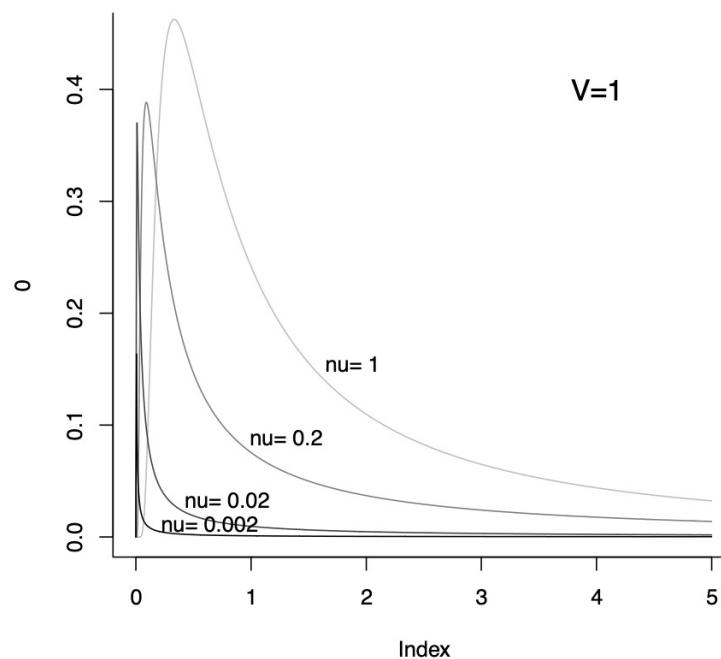


Figure 1.5: Probability density function for a univariate inverse Wishart with the variance at the limit set to 1 ($V=1$) and varying degree of belief parameter (ν). With $V=1$ these distributions are equivalent to inverse gamma distributions with shape and scale parameters set to $\nu/2$.

```

prior1<-list(B=list(mu=c(0,0),V=diag(c(10^8,10^8))), R=list(V=1,nu=1),G=list(G1=list(V=1,nu=1)))

Mod_mcmc<-MCMCglmm(Y~1+Temp,random=~REF, data=DATA,verbose=F, nitt=50000,
thin=10, burnin=10000, pr=TRUE, prior=prior1)

Iterations = 10001:49991
Thinning interval = 10
Sample size = 4000

DIC: 275.2081

G-structure: ~REF

post.mean l-95% CI u-95% CI eff.samp
REF      43.94     5.529     106     3705

R-structure: ~units

post.mean l-95% CI u-95% CI eff.samp
units    21.23    11.38     32.2     4000

Location effects: Y ~ 1 + Temp

post.mean l-95% CI u-95% CI eff.samp pMCMC
(Intercept) 19.4293   4.6279  36.3057     3489 0.0040 **
Temp        -2.0153  -3.6662 -0.5011     3075 0.0025 **
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
prior1<-list(B=list(mu=c(0,0), V=diag(c(10^8,10^8))), R=list(V=1,nu=1), G=list(G1=list(V=1,nu=1)))
```

```
Mod_mcmc<-MCMCglmm(Y~1+Temp, random=~REF, data=DATA, verbose=F, nitt=50000,  
thin=10, burnin=10000, pr=TRUE, prior=prior1)
```

Iterations = 10001:49991
Thinning interval = 10
Sample size = 4000

DIC: 275.2081

G-structure: ~REF

	post.mean	l-95% CI	u-95% CI	eff.samp
REF	43.94	5.529	106	3705

R-structure: ~units

	post.mean	l-95% CI	u-95% CI	eff.samp
units	21.23	11.38	32.2	4000

Location effects: Y ~ 1 + Temp

	post.mean	l-95% CI	u-95% CI	eff.samp	pMCMC
(Intercept)	19.4293	4.6279	36.3057	3489	0.0040 **
Temp	-2.0153	-3.6662	-0.5011	3075	0.0025 **

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

```

prior1<-list(B=list(mu=c(0,-10),V=diag(c(10^8,1))), R=list(V=1,nu=1),G=list(G1=list(V=1,nu=1)))

Mod_mcmc<-MCMCglmm(Y~1+Temp, random=~REF, data=DATA,verbose=F, nitt=50000,
                      thin=10, burnin=10000, pr=TRUE, prior=prior1)

summary(Mod_mcmc)
Iterations = 10001:49991
Thinning interval = 10
Sample size = 4000

DIC: 269.5588

G-structure: ~REF

post.mean l-95% CI u-95% CI eff.samp
REF      409.2    79.22   861.1     4000

R-structure: ~units

post.mean l-95% CI u-95% CI eff.samp
units     18.04   10.04   27.53     3780

Location effects: Y ~ 1 + Temp

post.mean l-95% CI u-95% CI eff.samp pMCMC
(Intercept) 69.792  50.498  90.452    4000 <3e-04 ***
Temp        -7.238  -8.905  -5.572    4000 <3e-04 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
prior1<-list(B=list(mu=c(0,-10),V=diag(c(10^8,1))), R=list(V=1,nu=1),G=list(G1=list(V=1,nu=1)))
```

```
Mod_mcmc<-MCMCglmm(Y~1+Temp,random=~REF, data=DATA,verbose=F, nitt=50000,  
thin=10, burnin=10000, pr=TRUE, prior=prior1)
```

```
summary(Mod_mcmc)
```

Iterations = 10001:49991

Thinning interval = 10

Sample size = 4000

DIC: 269.5588

G-structure: ~REF

	post.mean	l-95% CI	u-95% CI	eff.samp
REF	409.2	79.22	861.1	4000

R-structure: ~units

	post.mean	l-95% CI	u-95% CI	eff.samp
units	18.04	10.04	27.53	3780

Location effects: Y ~ 1 + Temp

	post.mean	l-95% CI	u-95% CI	eff.samp	pMCMC
(Intercept)	69.792	50.498	90.452	4000	<3e-04 ***
Temp	-7.238	-8.905	-5.572	4000	<3e-04 ***

Signif. codes:	0 ***	0.001 **	0.01 *	0.05 .	0.1 ' '

