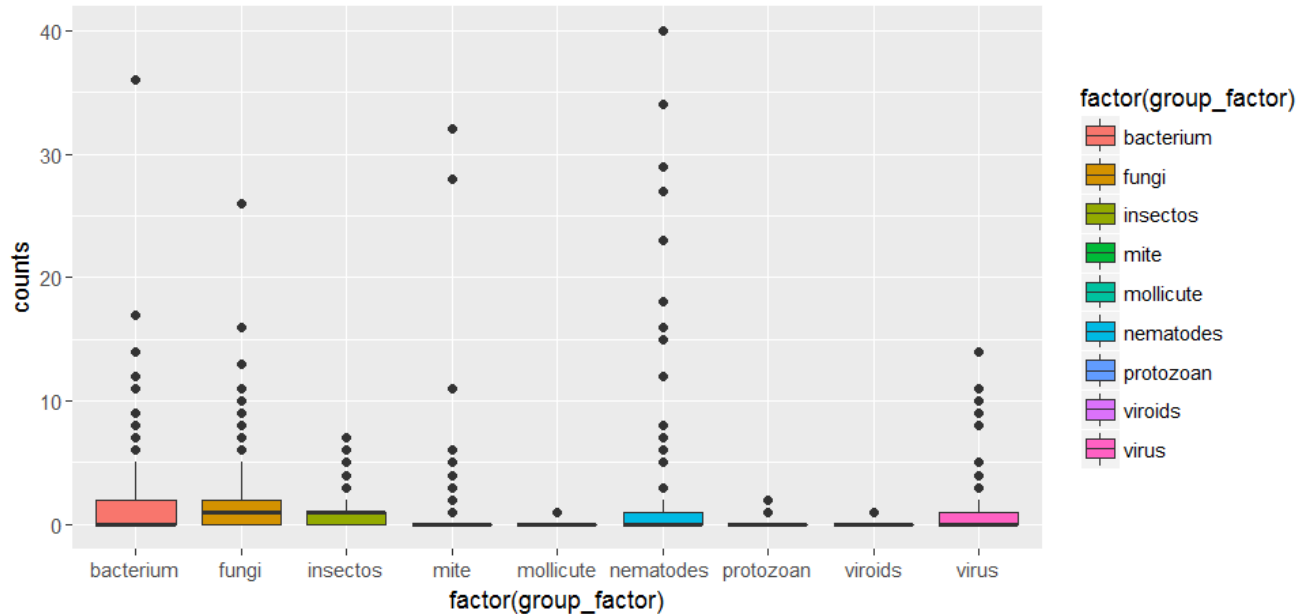


# Predictive phytosanitary model for quarantine pests



Marta Elva Ramírez Guzmán PhD.

June 28<sup>th</sup>, 2017

# Contents

1. Motivation (some questions)
2. Proposal
3. Results
  - 3.1 Data characteristics (**1<sup>st</sup> data: 2001 – 2010**)
  - 3.2 Identification of highest risk pests with NB regression
  - 3.3  $P[X>0]$  and intensity of detections with Hurdle regression
  - 3.4 High risk geographical areas with spatial bayesian regression  
(**2<sup>nd</sup> data shape: 32 Mexican States**)
  - 3.5 Answers
4. Conclusions  
Bibliography

# 1. Motivation

Some questions related to risk base sampling:

1. What are the pests that excess zero detections in probability?
2. What are the high risk pests?
3. What are the low risk pests?
4. What are the high risk geographical areas, where the pests exceed the expected detections with respect the whole detected pests populaton?
5. What is 100% sampling inspecction?

# 1. Motivation

Some questions related to risk base sampling:

6. How to perform sampling inspection of reliable exporters involved in international trade?
7. Is it worthwhile to perform a skip lot sampling?
8. Is the same risk for ports, airports and frontiers?.
9. Which are the high risk products associated with pests detections?.
10. Which OISAS are the hotspots of pest detections?.

# 1. Proposal

## Risk

To define risk statistically (to establish a statistical methodology to estimate the probability of risky pests).

## Samplig

- To establish 2 types of sampling:
  - 1. 100% shipments inspection by sampling for high risk products.
  - 2. Skip lot sampling for low risk products.

## Improvement measurement

- 1. Human and economical savings if focus on risky pests.
- 2. To develop reliable exporters.
- 3. Save around 50% of spendings if skip lot sampling is performed.

# Define risk



Use:

1. ***NB regression*** to detect high quarantine pests.
2. ***Hurdle regression*** to estimate the probability to excess zero detections and to estimate the effectiveness of more strict inspection controls:  $P[X>0]$ .
3. ***STAR models*** to represent relative high phytosanitary risk with respect to the whole population:  $RR=O/E$ . If  $RR$  exceeds 1 means the analysed pest is highly risky.



# Non spatial models for counts

Risk

- Poisson:

$$f(y_i/\underline{x}_i^T, \mu_i) = \frac{\exp(-\mu_i)\mu_i^{y_i}}{y_i!} ; E(y_i/\underline{x}_i^T) = \mu_i$$

- BN:

$$f(y_i/\mu_i, \theta) = \frac{\Gamma(y_i+\theta)}{\Gamma(\theta)y_i!} \frac{\mu_i^y \theta^\theta}{(\mu_i+\theta)^{y+\theta}} ; E(y_i/\underline{x}_i^T) = \mu_i$$

- RIC:

$$f_{\text{zero\_inflation}}(y_i/\underline{x}_i^T, \underline{z}_i^T, \beta, \gamma) = f_{\text{zero}}(0/\underline{z}_i^T, \gamma) I_{\{0\}}(y_i) + (1 - f_{\text{zero}}(0/\underline{z}_i^T, \gamma)) \cdot f_{\text{count}}(y_i/\underline{x}_i^T, \beta)$$
$$E(y_i/\underline{x}_i^T) = \pi_i \cdot 0 + (1 - \pi_i) \cdot \exp(\underline{x}_i^T \beta); \pi_i = f_{\text{zero}}(0/\underline{z}_i^T, \gamma)$$

- Hurdle:

$$f_{\text{hurdle}}(y_i/\underline{x}_i^T, \underline{z}_i^T, \beta, \gamma) = \begin{cases} f_{\text{zero}}(0/\underline{z}_i^T, \gamma), & \text{if } y_i = 0 \\ \frac{(1 - f_{\text{zero}}(0/\underline{z}_i^T, \gamma)) \cdot f_{\text{count}}(y_i/\underline{x}_i^T, \beta)}{(1 - f_{\text{count}}(0/\underline{x}_i^T, \beta))}, & \text{si } y_i > 0 \end{cases}$$
$$E(y_i/\underline{x}_i^T) = \exp[\underline{x}_i^T \beta + \log(1 - f_{\text{zero}}(0/\underline{z}_i^T, \gamma)) - \log(1 - f_{\text{count}}(0/\underline{x}_i^T, \beta))]$$

(1<sup>st</sup> data: 2001 – 2010, without coordinates)

# Empirical Bayes models for mapping high relative risk areas (RR)



- $SMR_i = O_i/E_i$  where  $O_i \sim P(E_i\theta_i)$ ,  $E_i$  is the number of cases in region  $i$  and  $\theta_i$  is relative risk.  $Var(SMR_i) = O_i/E_i^2$  It is less efficient for little population areas.
- EBPG: With Poisson model for likelihood and Gamma for apriori distribution to estimate the parameters:  $\nu$  and  $\alpha$  which smooths rr:  $(O_i + \nu)/(E_i + \alpha)$
- EBLN: with log-Normal Model for both likelihood and apriori (Cressie, 1992). Same failure as EBPG.
- EBMarshall: It considers the regional pattern of the data, however it has the same failure that the EBPG model.
- EBMarsloc: It considers the local regional pattern of the data.

(2<sup>nd</sup> data shape: 32 Mexican States, wth coordinates)





# Bayes Spatial models for mapping high risk areas (RR)

Risk

- PGBAYESX (a Structured Additive Regression models: STAR). A nonlinear GAM model for spatially correlated data with two-dimensional surfaces and heterogeneity among individuals.

$$\eta_r = X\beta + f_{spat}(AREA)$$

$r$  is a generic variable. Function  $f$  can contain non linear, spatial, global and local effects. Local effects as:

$$f_{spat}(AREA) = \beta_x \text{ where } \beta_x \sim N(0, \tau^2)$$

It does not include  $W$ .

- CARBayes: Conditional autoregressive model (hierarchical): Uses  $W$  of neighbors.

$$\eta(\mu_k) = X\beta + \phi_k + O_k$$

$\phi_k$  random effect,  $O_k$  offset (observations). This model captures the spatial local correlation of the data yet after removing the covariables effect. Conditioning is over random effects of the adjacent areas by means of ( $W$ ).

(2<sup>nd</sup> data shape: 32 Mexican States, wth coordinates)

# 1. 100% shipments inspection by sampling for high risk products



## Manuals of statistical methodology for inspection

1. Seeds (2006)
2. Grains (2007)
3. Fruits and vegetables (2007)
4. Dehydrated products (2007)
5. Cut flower and fresh foliage (2007)
6. propagative plant material(2007)

Statistical distributions: binomial, beta-binomial and Poisson.





# 1. 100% shipments inspection by sampling for high risk products

## Manuals of statistical methodology for inspection

Sampling



### Material vegetal propagativo

Tabla 1b. Tamaño de muestra para material vegetal propagativo.  
BAJO RIESGO: Productos que no han presentado plaga cuarentenaria durante los últimos 5 años.

Tamaño de muestra para material vegetal propagativo: $n_c$ : unidades primarias, $n_c$ : muestra combinada.								
$n_c$ : muestra para análisis de laboratorio y $n_{contramuestra}$ : contramuestra.								
OFICIAL DE SEGURIDAD FITOZOOSANITARIA					LABORATORIO			
Paquete o unidad	Unidad de Inspección	Tamaño del lote	$n_p$ : unidades de inspección	$n_c$ : en piezas para enviar al laboratorio	$n_c$ : en gramos	$n_c$ : en gramos	$n_{contramuestra}$ : en gramos	$n_{contramuestra}$ : en gramos
paquetes de: acodo, estacas o varetas, sarmientos, estolones y yemas	paquete o bolsa o caja	Para cualquier tamaño del lote	3	2	1,000	500	500	
			bulbos	bulbos				
bulbo	un bulbo	Para cualquier tamaño del lote	86	14	700	350	350	
			cormos	cormos				
corno o rizoma	un corno o rizoma	Para cualquier tamaño del lote	86	14	500	250	250	
			plántulas	plántulas				
plántula o esqueje o portainjerto o roseta	una plántula o esqueje o portainjerto o roseta	Para cualquier tamaño del lote	8	2	400	200	200	
			tubérculos	tubérculos				
tubérculo	un tubérculo	Para cualquier tamaño del lote	86	14	3,500	1,750	1,750	



### Flor cortada y follaje fresco

Tabla 1a. Tamaño de muestra para flor cortada y follaje fresco.  
ALTO RIESGO: Productos que han presentado plaga cuarentenaria durante los últimos 5 años.

Tamaño de muestra para material vegetal propagativo: $n_c$ : unidades primarias, $n_c$ : muestra combinada.								
$n_c$ : muestra para análisis de laboratorio y $n_{contramuestra}$ : contramuestra.								
OFICIAL DE SEGURIDAD FITOZOOSANITARIA					LABORATORIO			
presentación (unidad de inspección)	Tamaño del lote: paquetes o piezas	$n_c$ : unidades de inspección	$n_c$ : en piezas para enviar al laboratorio	$n_c$ : en gramos	$n_{contramuestra}$ : en gramos	$n_{contramuestra}$ : en gramos	$n_{contramuestra}$ : en gramos	$n_{contramuestra}$ : en gramos
<b>Flor cortada</b>								
			paquete	paquete	hojas, flores y tallos	hojas, flores y tallos		
flor cortada ramo, combo, bouquet	$N \leq$	100	14	5	250 (Pecilo y al menos 50 hojas jóvenes maduras completamente expandidas) y tallos (al menos 10)	250 (al menos 10 tallos)		
	$<N$		31					
			pieza	pieza	hojas, flores y tallos	hojas, flores y tallos		
flor cortada a granel	$N \leq$	100	14	5	250 (Pecilo y al menos 50 hojas jóvenes maduras completamente expandidas) y tallos (al menos 10)	250 (igual que $n_c$ )		
	$<N$		31					
<b>Follaje fresco</b>								
			paquete	paquete	hojas y tallos	hojas y tallos		
follaje fresco ramo, combo, bouquet	$N \leq$	100	14	5	250 (al menos 100 hojas y 10 tallos)	250 (igual que $n_c$ )		
	$<N$		31					
			pieza	pieza	hojas y tallos	hojas y tallos		
follaje fresco a granel	$N \leq$	100	14	5	250 (al menos 100 hojas y 10 tallos)	250 (igual que $n_c$ )		
	$<N$		31					

Tables

## 2. Skip lot sampling for low risk products



Samplig

1. CSP – 3 continuous sampling for seeds lots with a fraction  $f$  for reliable importers (2013)

Skip lot sampling (Schilling, 1982, Duncan, 1989 y MIL.STD-1235C, 1988).

Sampling: CSP-3



**Senasica**

Dirección General de  
Sanidad Vegetal



# 1. Savings

Estimated savings from 100% sampling to skip lot samplig:

Inspection type	Pesos	%
100% shipments inspection by sampling (DGSV)	\$93,249,085.44	
Skip lot sampling (DGIF)	\$46,820.826.78	
Economical saving	\$46,428,258.66	49.78%

Expected improvements after the proposal:

1. Human and economical savings if focus on risky pests.
2. To develop reliable exporters.
3. Save around 50% of spendings if skip sampling is performed.

Improvement  
measurement

# 3.Results



## 3.1 Descriptive statistics

Pest	mean	sd	min	max	sum
Weeds	6.58	14.69	0	141	2519
Nematodes	2.4	6.76	0	40	286
Fungi	1.73	3.25	0	26	260
Bacteria	1.66	3.97	0	36	232
Insects	1.02	1.43	0	7	164
Virus	1.19	2.63	0	14	146
Mite	1.1	4.24	0	32	121
Protozoan	0.03	0.24	0	2	3
Viroids	0.02	0.15	0	1	2
Mollicute	0.01	0.11	0	1	1
<b>TOTAL</b>	<b>2.58</b>	<b>8.47</b>	<b>0</b>	<b>141</b>	<b>3734</b>

From 2001 to 2010

(1<sup>st</sup> data: 2001 – 2010)



# 3.Results



## 3.1 Excess zeros

SENASICA  
Counts

Freq. Rel (%) Acum. (%)

0	746	53.78514780	53.78515
1	239	17.23143475	71.01658
2	109	7.85868782	78.87527
3	77	5.55155011	84.42682
4	46	3.31651045	87.74333
5	24	1.73035328	89.47368
6	22	1.58615717	91.05984
7	13	0.93727469	91.99712
8	15	1.08147080	93.07859
9	10	0.72098053	93.79957
10	6	0.43258832	94.23216
11	8	0.57678443	94.80894
12	7	0.50468637	95.31363
13	9	0.64888248	95.96251
14	4	0.28839221	96.25090
15	2	0.14419611	96.39510
16	1	0.07209805	96.46720
17	2	0.14419611	96.61139
18	6	0.43258832	97.04398
19	3	0.21629416	97.26027
20	2	0.14419611	97.40447

Counts Freq. Rel (%) Acum. (%)

23	1	0.07209805	97.83706
24	3	0.21629416	98.05335
26	2	0.14419611	98.19755
27	2	0.14419611	98.34174
28	1	0.07209805	98.41384
29	1	0.07209805	98.48594
32	2	0.14419611	98.63014
33	1	0.07209805	98.70224
36	1	0.07209805	98.77433
37	1	0.07209805	98.84643
40	1	0.07209805	98.91853
41	1	0.07209805	98.99063
44	1	0.07209805	99.06273
46	1	0.07209805	99.13482
47	3	0.21629416	99.35112
51	1	0.07209805	99.42322
54	1	0.07209805	99.49531
68	1	0.07209805	99.56741
84	1	0.07209805	99.63951
86	1	0.07209805	99.71161
114	1	0.07209805	99.78371
116	1	0.07209805	99.85580
120	1	0.07209805	99.92790
279	1	0.07209805	100.00000

(1<sup>st</sup> data: 2001 – 2010)

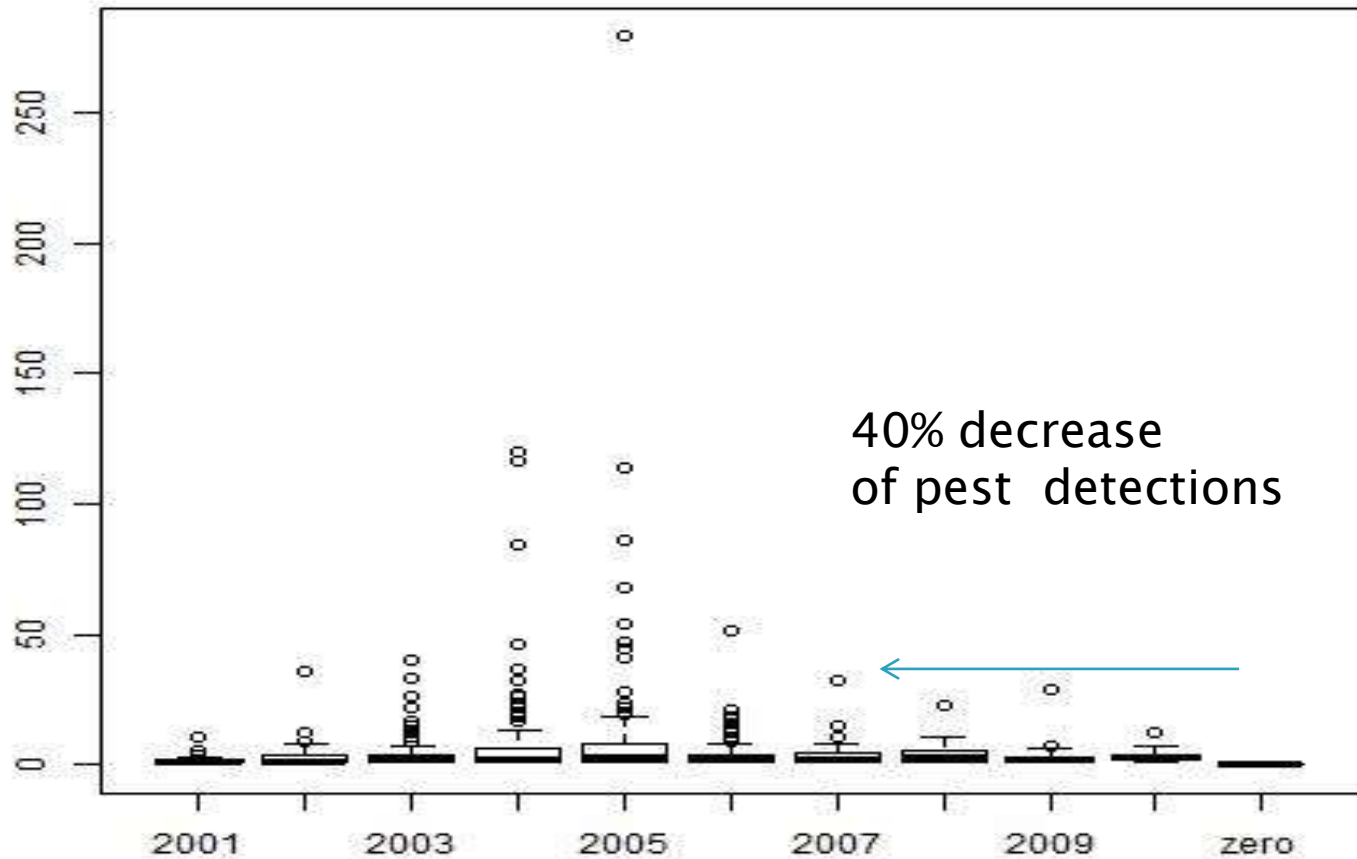
▶ Zero excess: 54%

▶ expected zeros =  $3734 * \exp(-2.58) = 282.94 < 746$

# 3.Results

## 3.1 Box plots **by time**

Box plot of detections by year



← Before the sampling manuals

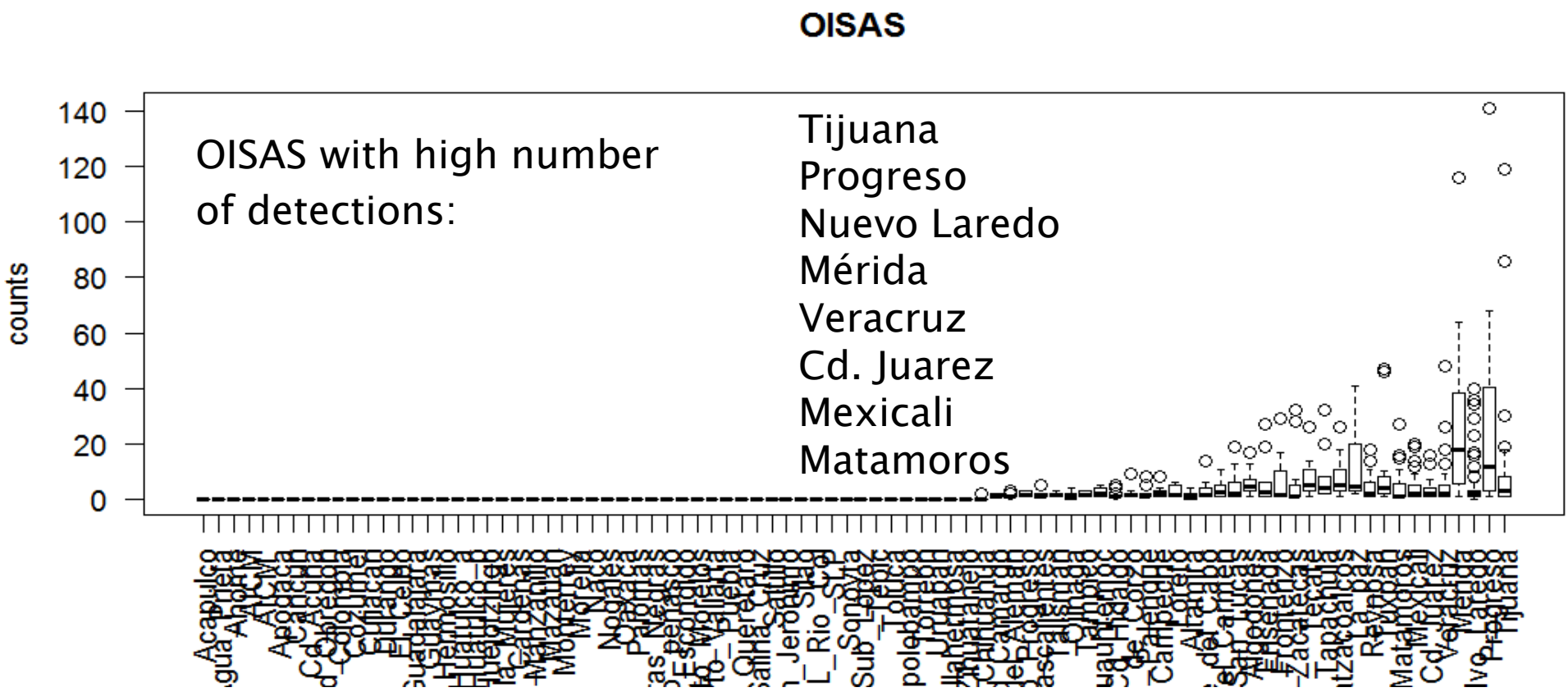
→ After the intervention of new sampling inspection schemes.





# 3.Results

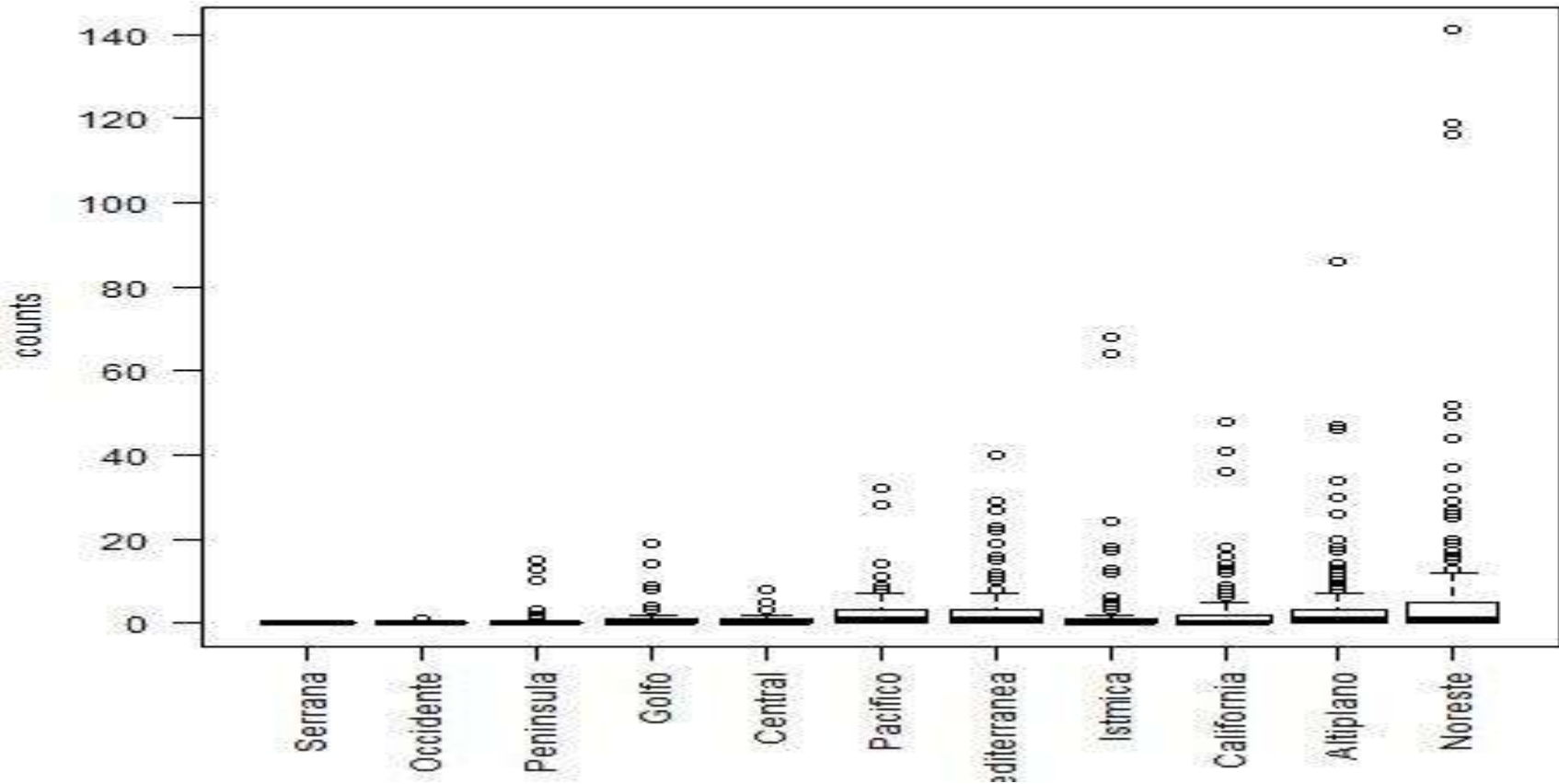
## 3.1 Box plots by OISA



# 3.Results

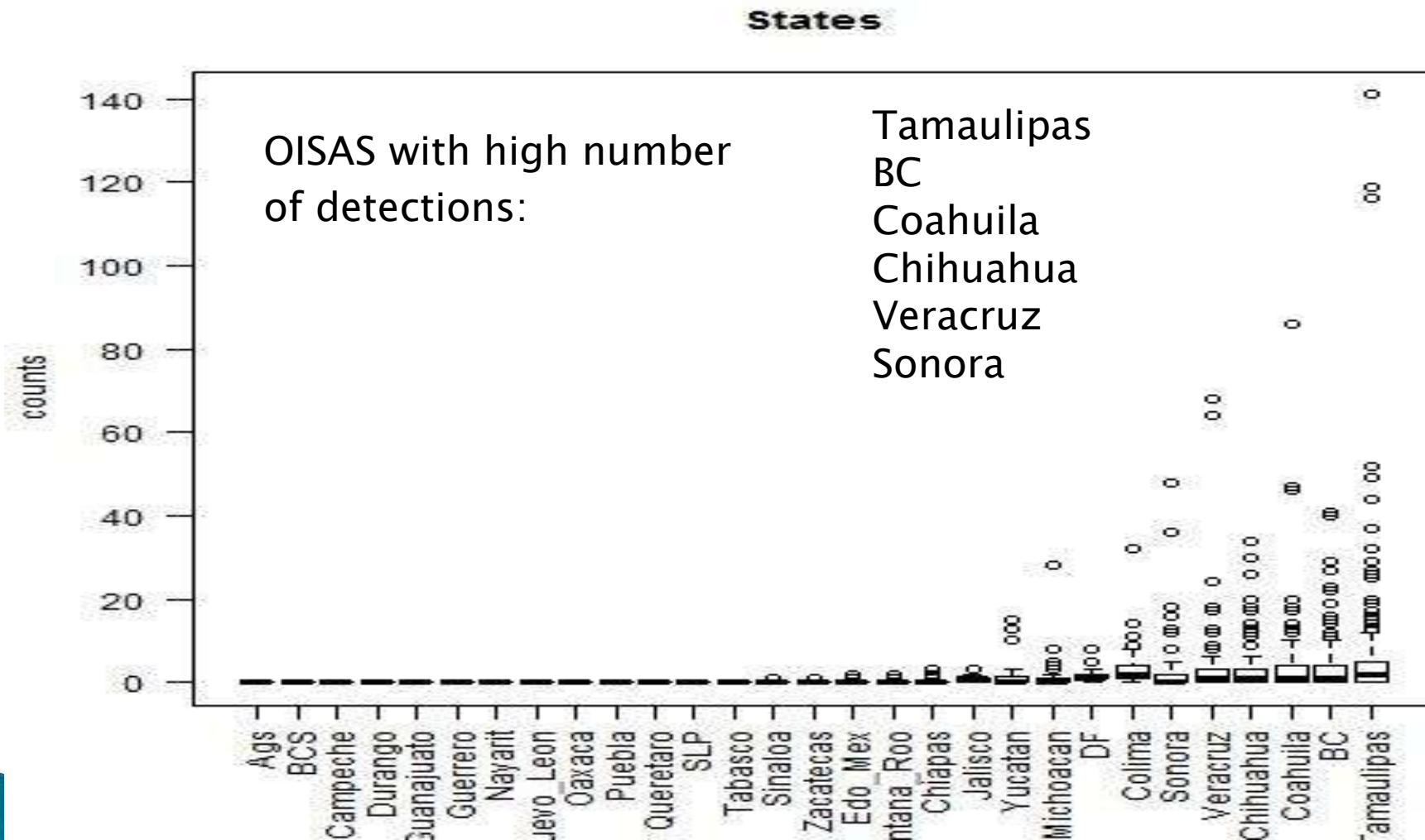
## 3.1 Box plot by epidemiological regions

Epidemiological Regions



# 3.Results

## 3.1 Box plot by State

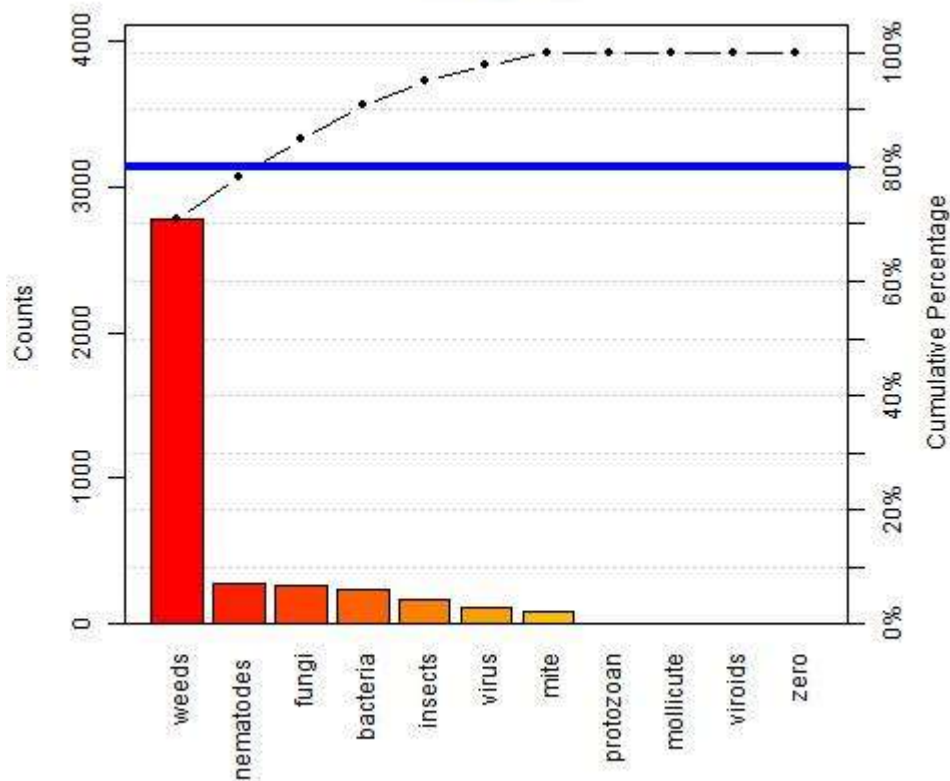


# 3.Results



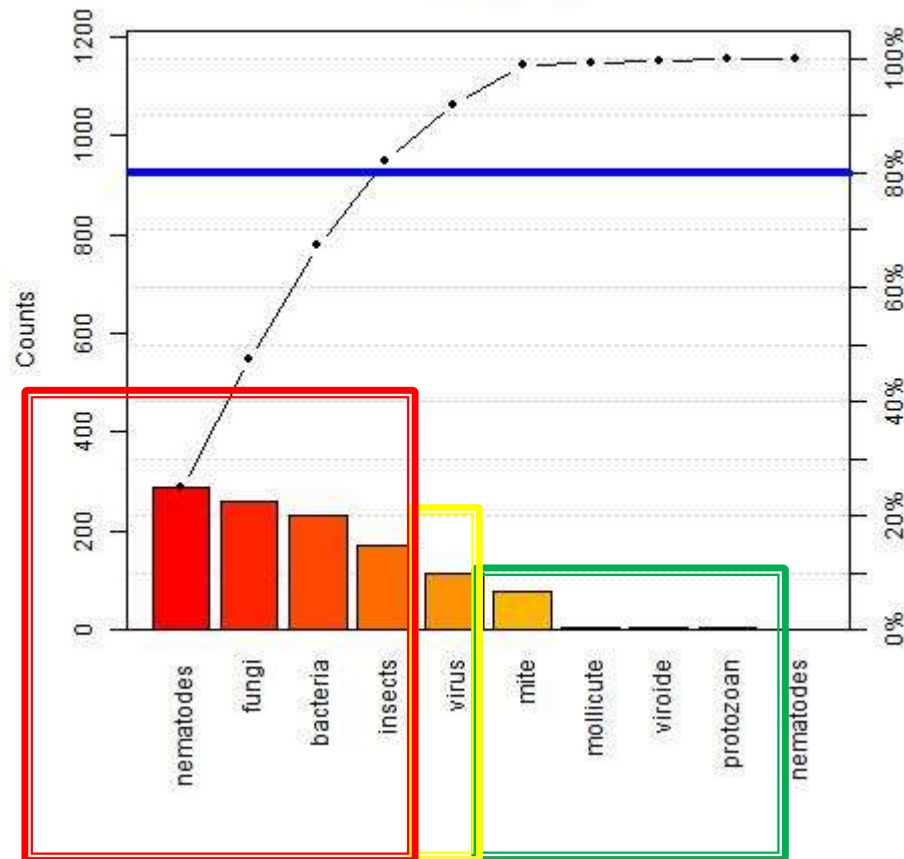
## 3.1 Pareto by pest

Pareto by pest



80%: Weeds and nematodes

Pareto by pest

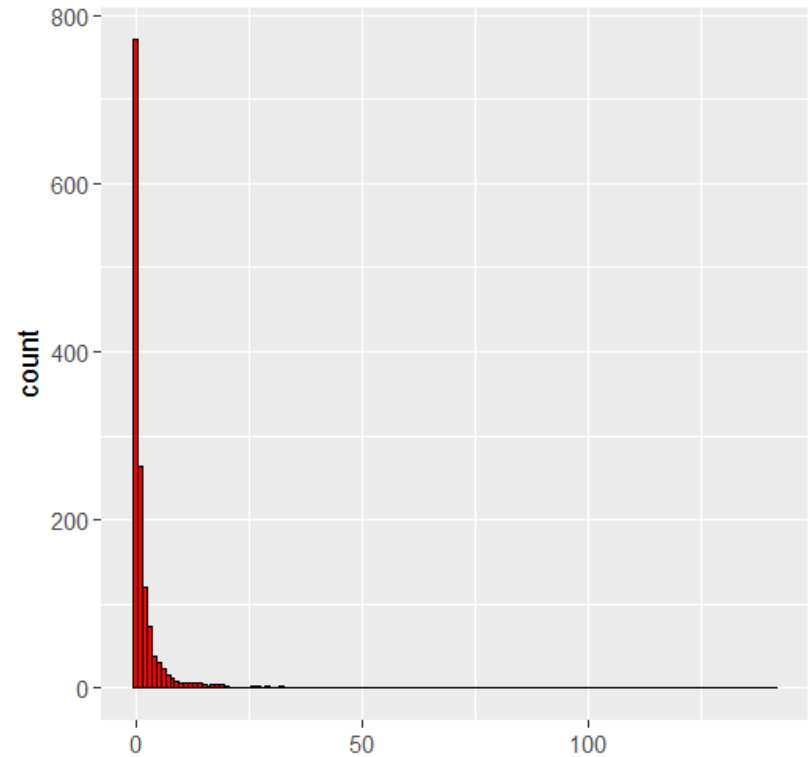
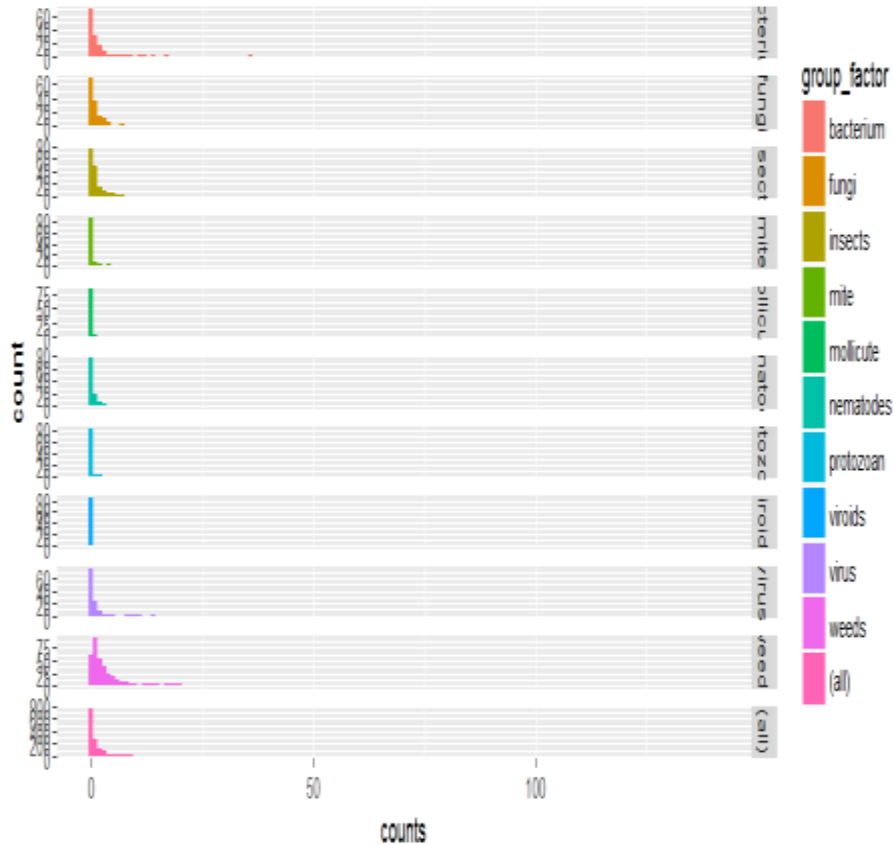


80%: Nematodes, fungi, bacteria and insects (after removing weeds)

# 3.Results



## 3.1 Statistical distribution



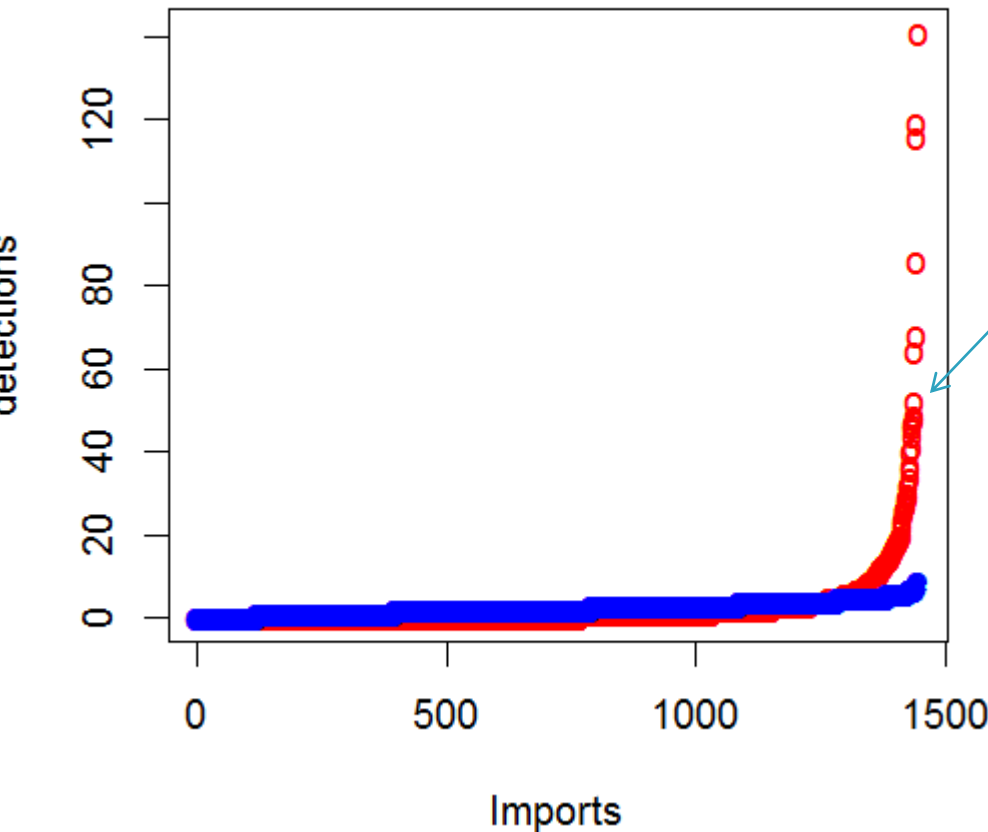
**Asimmetrical distribution**

# 3.Results



## 3.1 Overdispersion

Detections (red)- Expected by Poisson (blue)



It is confirmed the **overdispersion** in contrast with Poisson distribution

Ho: Overdispersion does not exist  
Ha: Overdispersion exists

Overdispersion test	Obs.Var/Theor.Var	Statistic	p-value
poisson data	44.96191	62317.21	0

We reject Ho, so there exists evidence of overdispersion.

# 3.1 Data characteristics



Weeds

Nematodes

Fungi



Bacteria

Insects

Virus





# 3.1 Data characteristics



**Mite**



**Protozoan**



**Viroids**



**Mollicute**



# 3.Results



## 3.1 Data characteristics

Overdispersion, excess of zeros and asymmetrical distribution implies to work with alternative regression models:

- ▶ NB
- ▶ Zero inflation
- ▶ Hurdle
- ▶ Empirical bayes models
- ▶ Structured additive regression (Bayes)

## 3.2 Identification of highest risk pests with NB (includes weeds)



The incident rate for **weeds**, **nematods**, **fungi** and **bacteria** are 5.98, 2.18, 1.58 and 1.51 times the incident rate for mites (1.1). Likewise, the incident rate for **protozoan**, **viroids** and **mollicute** are 0.03, 0.02 and 0.01 times the incident for mites.

Insects and virus have similar incidence rate as mites (1.1).

Group	$x'\beta$		$E(Y)=\exp(x'\beta)$
mite	0.0953 (0.1750)		1.10
<b>bacteria</b>	0.4098 (0.2291)	.	<b>1.51</b>
<b>fungi</b>	0.4547 (0.2255)	*	<b>1.58</b>
insects	-0.0768 (0.2280)		0.93
<b>weeds</b>	1.7882 (0.1935)	***	<b>5.98</b>
<b>mollicute</b>	-4.5612 (1.0290)	***	0.01
<b>nematods</b>	0.7816 (0.2341)	***	<b>2.18</b>
<b>protozoan</b>	-3.4626 (0.6263)	***	0.03
<b>viroids</b>	-3.8565 (0.7478)	***	0.02
virus	0.0761 (0.2397)		1.08
dispersion parameter	0.39		
2xlog_likelihood	-4,714.40		
AIC	4,776.80		

§ In parenthesis SE.

\*  $p < 0.005$ ; \*\*  $p < 0.001$ ; \*\*\*  $p < 0.0001$

## 3.2 Identification of higher risk pests with **NB** (includes weeds)



### Incidente rate ratio

Cluster	Pest	Incident rate with respect the reference pest=mites (1.1)
1	weeds	5.98
2	nematodes	2.18
3	bacterias	1.58
4	virus, mites and insects	1.1
5	protozoan, viroids and mollicute	0.02

# OISA and Products comparison (includes weeds)



## Comparison between OISA types

Detections increase by 17.43 and 8.19 times with respect to airport (0.27) if goods come through *frontier* and *port*, respectively.

## Comparison between products

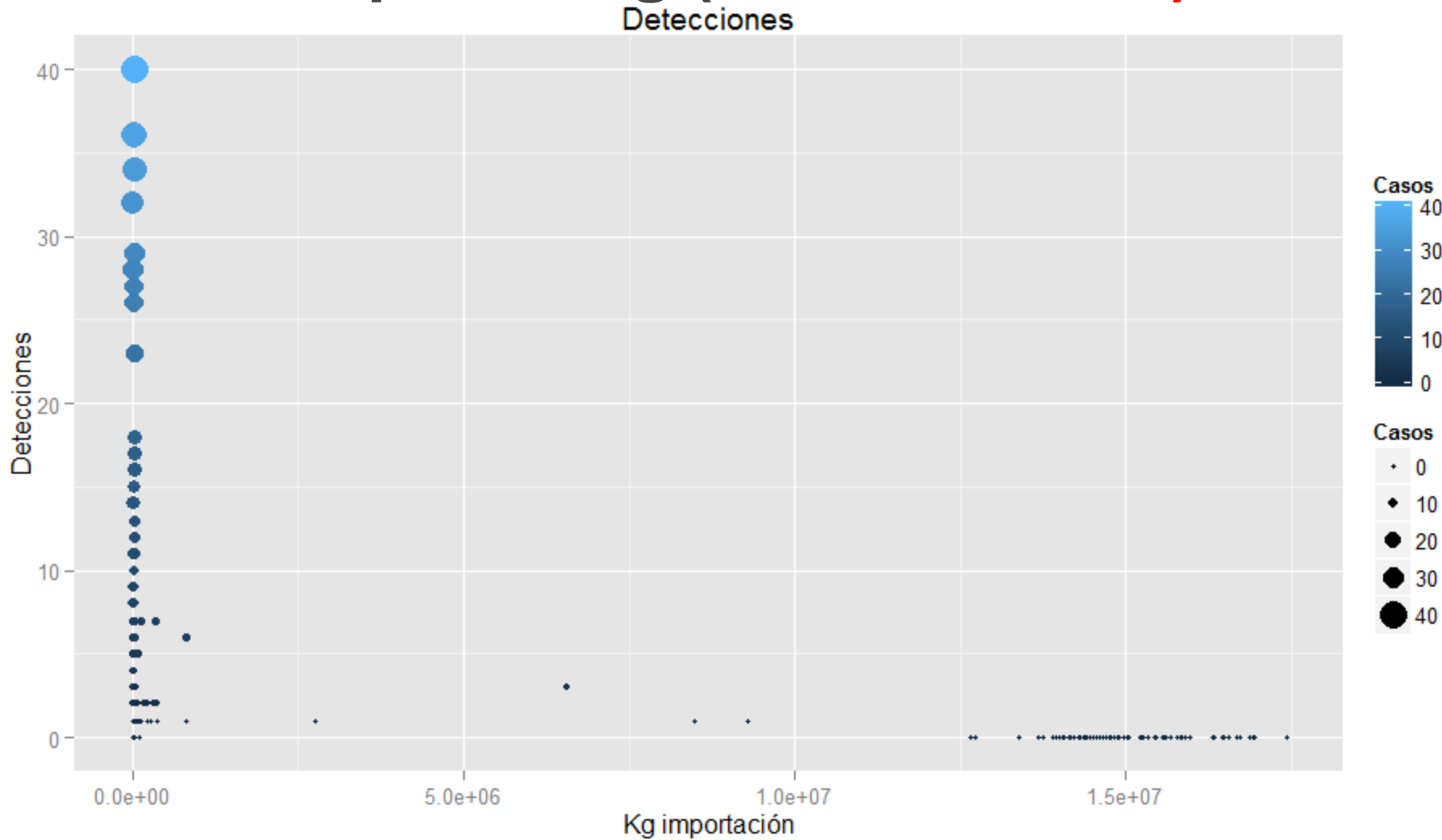
Detections increase by 8.93, 7.81, 7.72, 7.11, 6.48 times for barley, potato, linseed, lentil, oats with *respect to garlic (1)*.



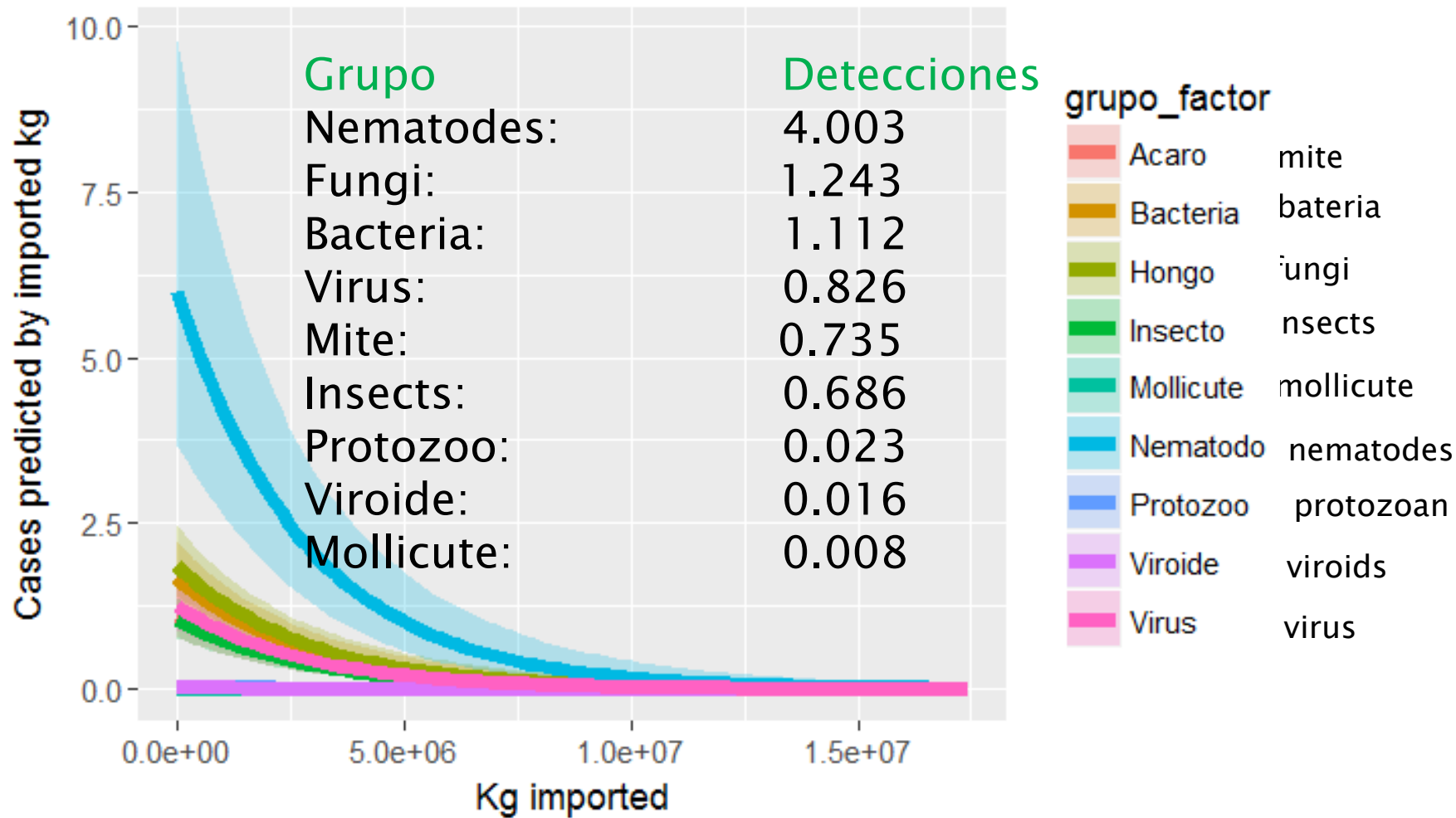
# 3.4 Observed detections by imported kg (**without weeds**)



SE



# 3.4 Predicted detections for imported products (without weeds)



The increment percentage of detections is of 1% by kg of imported kg. Expected detections for weeds=6 with other data.

# 3.3 Hurdle model (includes weeds)



1. Weeds, fungi, insects, bacteria, virus and nematods have a **Prob[Y>0]**, which indicates that a pest will be presented.

2. **E(Y)=exp(X' β)** determines how many cases will be detected of this pests.

Pest	Prob[Y>0]		X' β	E(Y)=exp(X' β)
Mite	-1.224 (0.2275)	***	-7.145 18.085	0.0008
<b>Bacteria</b>	<b>1.195</b> (0.283)	***	-0.593 0.484	<b>0.5527</b>
<b>Fungi</b>	<b>1.411</b> (0.281)	***	-0.695 0.474	<b>0.4992</b>
<b>Insects</b>	<b>1.311</b> (0.277)	***	-1.672 0.473	*** 0.1879
<b>Weeds</b>	<b>2.868</b> (0.267)	***	<b>0.714</b> 0.435	<b>2.0430</b>
Mollicute	-3.230 (1.031)	**	-10.923 93.843	0.0000
<b>Nematods</b>	<b>0.618</b> (0.298)	*	<b>0.512</b> 0.535	<b>1.6686</b>
Protozoo	-2.526 (0.751)	***	-2.400 1.600	0.0907
Viroids	-2.514 (0.751)	***	-18.215 2585.607	0.0000
<b>Virus</b>	<b>0.743</b> (0.294)	*	-0.731 0.511	<b>0.4813</b>
Dispersion parameters	1e-04»		0.40	

2 x log-likelihood: -2251

§ Standar error in parenthesis

\* p<0.005; \*\* p<0.001; \*\*\* p<0.0001

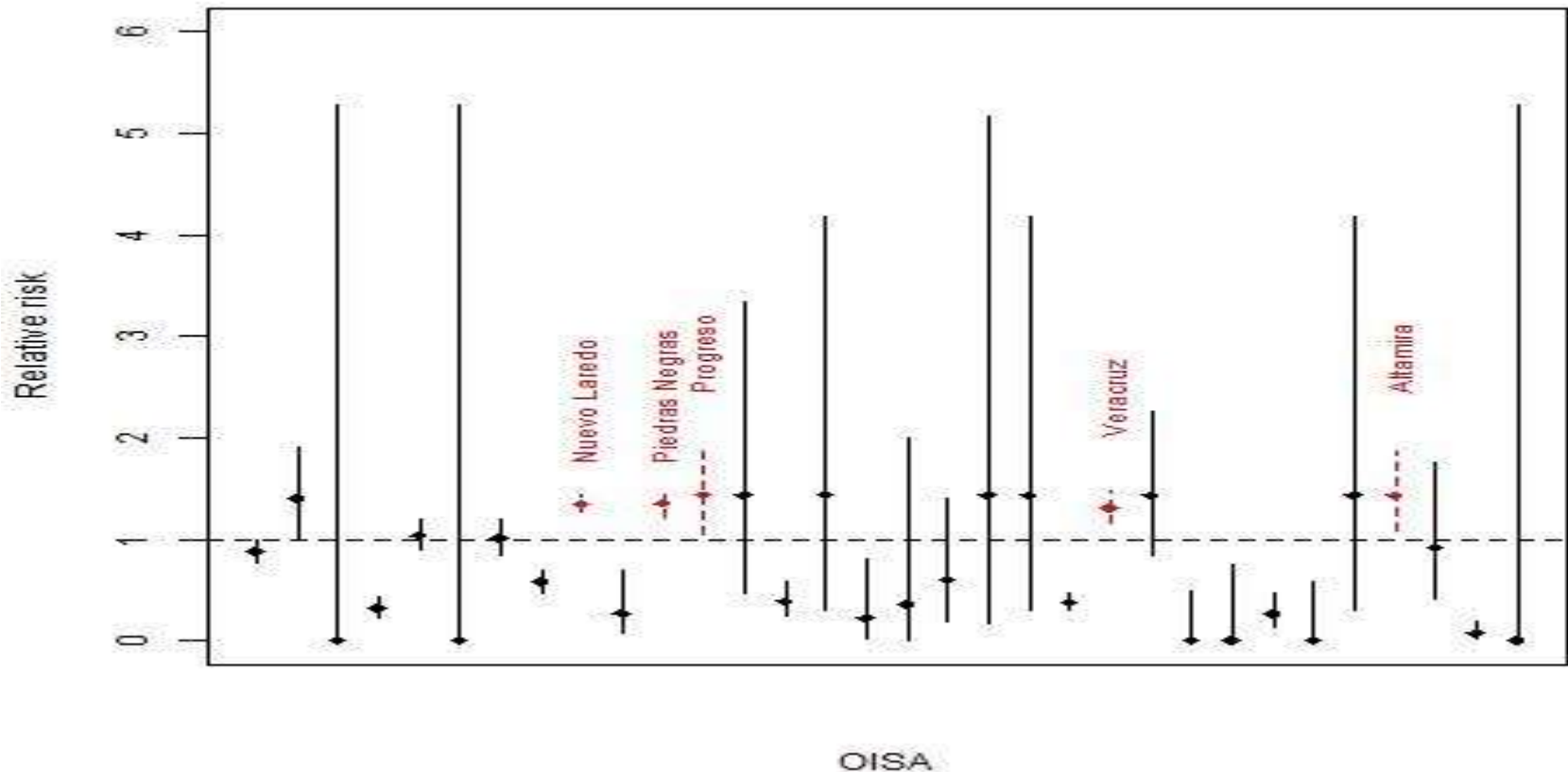


# 3.4 Searching the best estimator of relative risk = O/E



Weeds excess

95% Confidence Intervalo of weeds rate



	mean	sd	min	max	sum
Weeds	89.06	211.09	0	1,119	2,850
Total	127.66	232.93	1	1,185	4,085

# 3.4 Spatial analysis

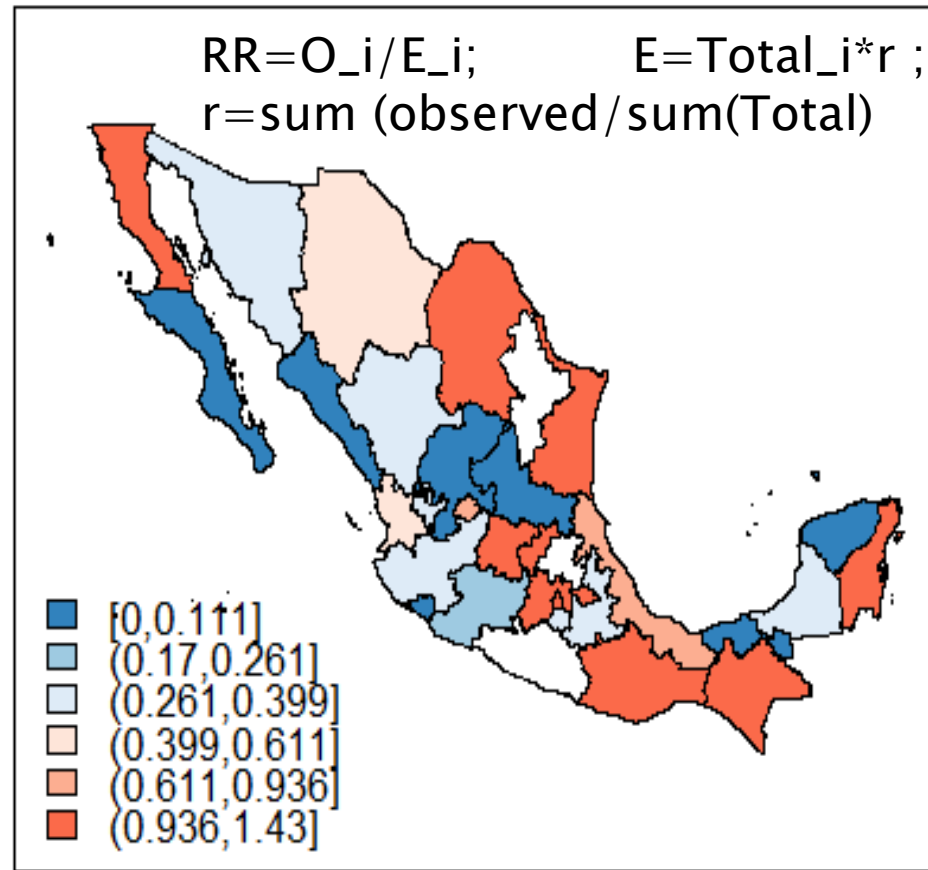
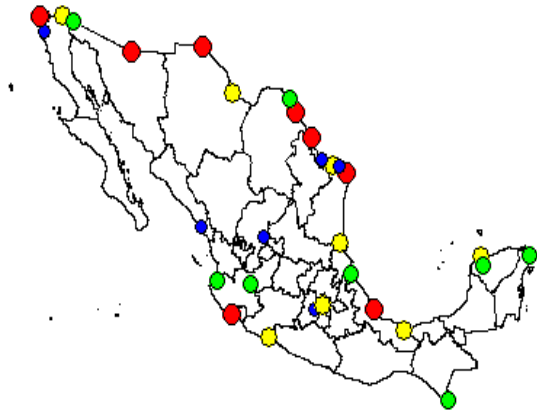


## Relative weeds risk (RR)

Risk strata:

- Low
- Low medium
- High medium
- High

Four stata detections



$RR = (\text{weeds} / \text{total pest}) = 2850 / 4085 = 0.70$   
 If  $RR > 1$ , implies «excess of weeds»  
 According to Poisson distribution.

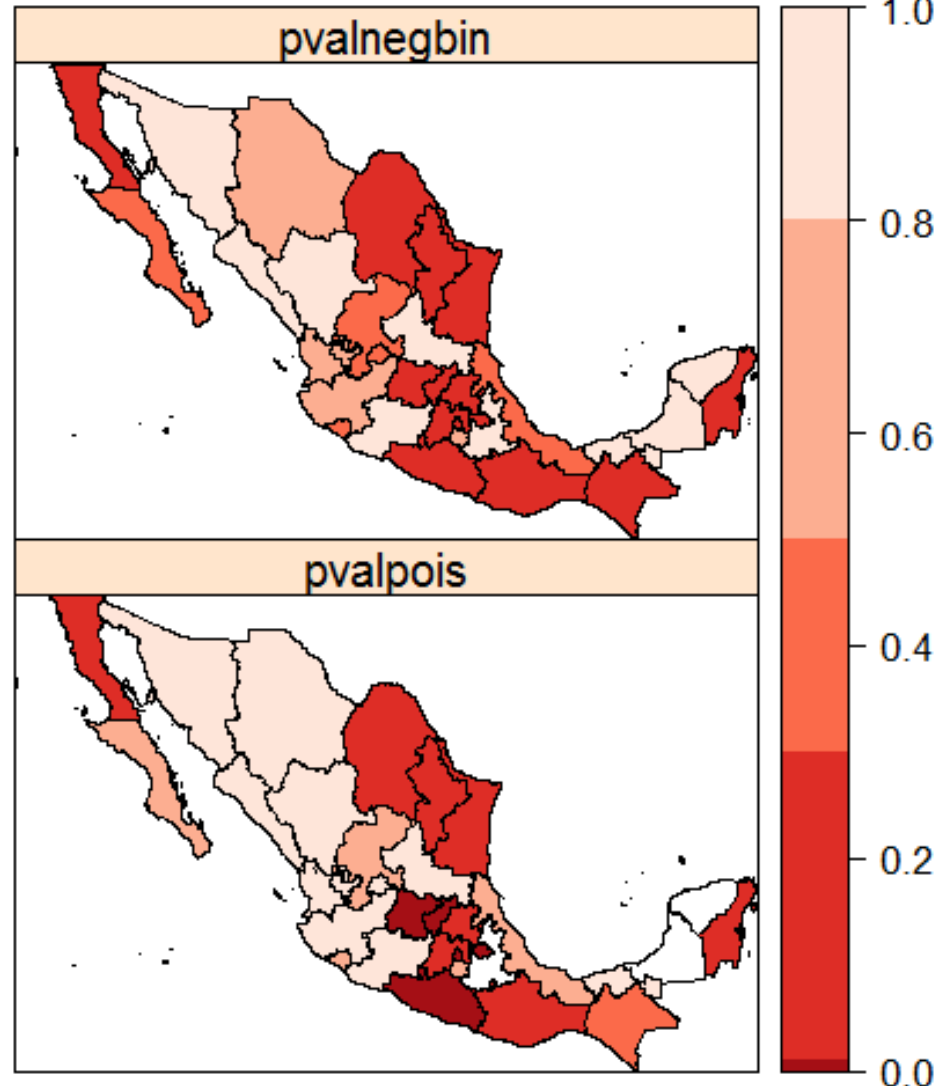
# 3.4 Spatial analysis



$H_0: P(\theta \leq 1)$ , Where  $\theta = RR$ : relative risk

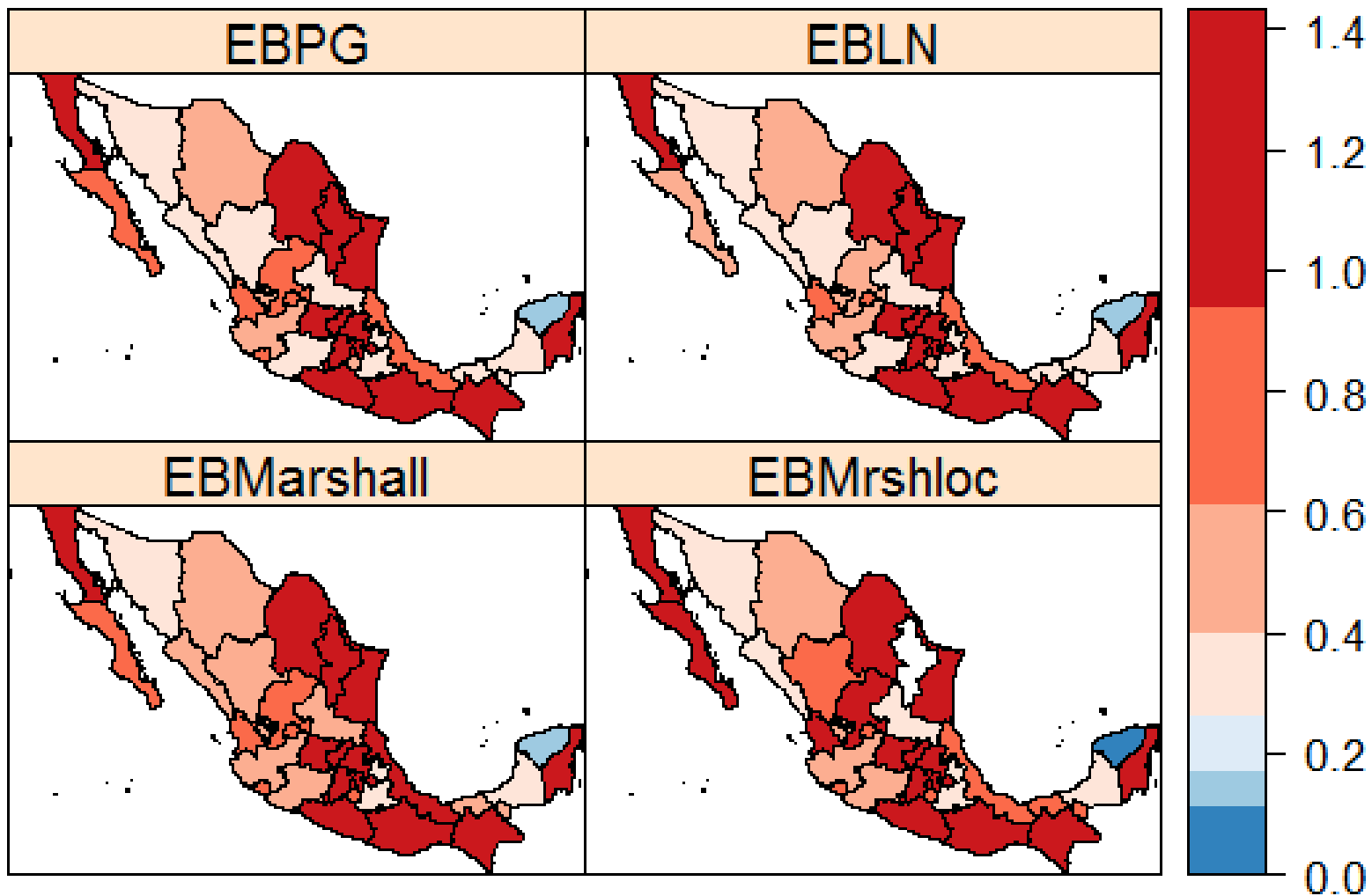
p-values  $< 0.05$  means rejection of low RR

P-values from **NB** distribution (NB alert more than Poisson distribution)



P-values from **Poisson** distribution

# 3.4 Spatial analysis EB Risk estimates



Empirical bayesian modelling

(2<sup>nd</sup> data shape)

# 3.4 Spatial analysis (STAR and neighborhood bayesian model )

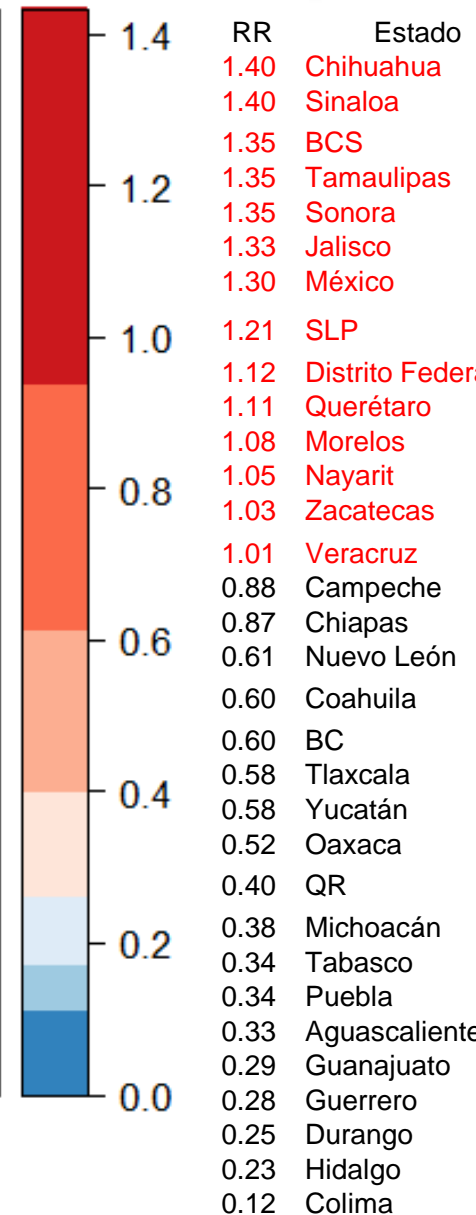
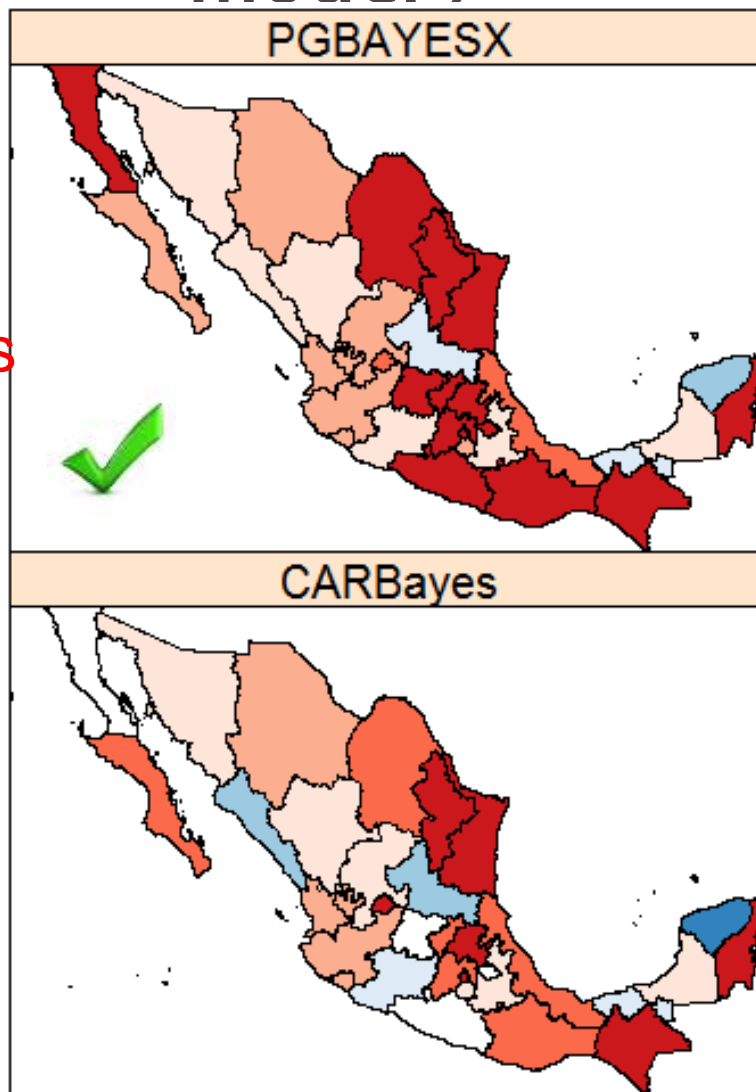


DIC= 61.45

Bayesian modelling with **smooth functions** (STAR: Generalized Additive model).

DIC= 487.05

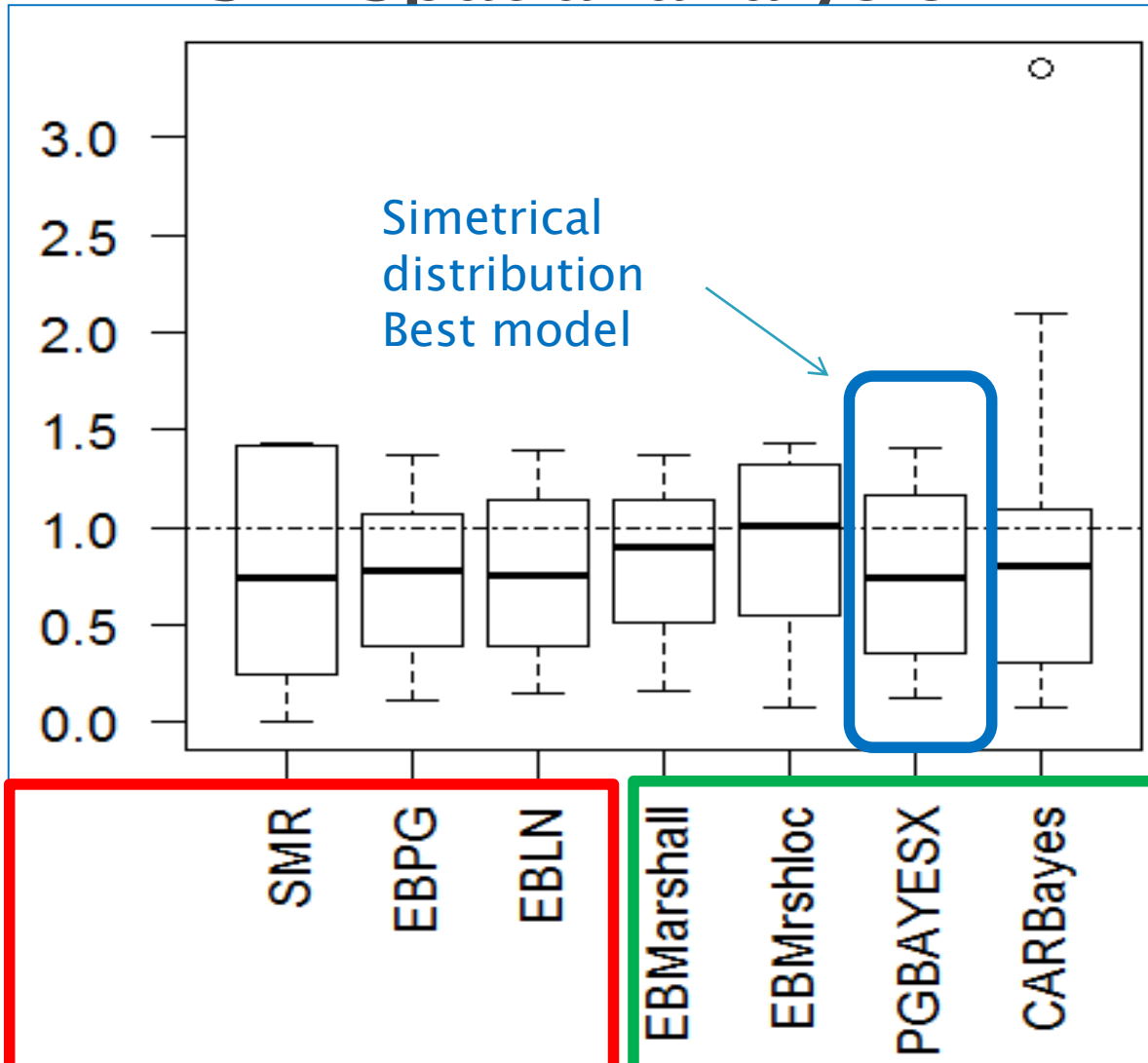
Bayesian modelling with **W neighborhood matrix**



# 3.4 Spatial analysis



Structural  
Regression  
model:  
Statistical  
Analysis of  
Discrete  
Structures



Non spatially correlated

Spatially correlated

S: Spline

W: neighborhood matrix

## 3.5 Answers



1. What are the pests that excess zero detections in probability?:  
Weeds, Nematodes, fungi, bacteria, virus, mite and insects.
2. What are the high risk pests?: weeds (6), nematodes (4), fungi (1.24), bacteria (1.11). In parenthesis: predicted detections.
3. What are the low risk pests?: protozoo, viroids and mollicute
4. What are the high risk geographical areas where the pests exceed the expected detections with respecto the whole detected pests popilation?: Chihuahua, Sinaloa, BCS, Tamaulipas,...,Veracruz
5. What is 100% sampling inspecction?. [Guías](#)

## 3.5 Answers



6. How to perform sampling inspection of reliable exporters involved in international trade? Skip sampling inspection CSP-3
7. Is it worthwhile to perform a skip lot sampling?: 50% of saving
8. Is the same risk for ports, airports and frontier?. : No. Detections increase by 17.43 and 8.19 times factor with respect to airport (0.27) if goods come through frontier and port, respectively.
9. Which are the high risk products associated with pests detections?: barley, potato, linseed, lentil, oats increase by 8.93, 7.81, 7.72, 7.11, 6.48 times with respect to garlic (1).
10. Which OISAS area the hotspots of pest detections?.: Nuevo Laredo, Piedras Negras, Progreso, Veracruz y Altamira.



## 4. Conclusions



- NB regression is recommended to estimate de risk probability for quarantine pests.
- Hurdle regression would be useful to estimate the probability risk to excess threshold of zero detections and to estimate the intensity of expected detections once the zero detections has been crossed. It could be useful to measure effectiveness of more strict inspection controls.
- STAR models are a good option to represent graphical variation of the phytosanitary risk.
- Propose a NOM in the Diario Oficial that includes the NB,, Hurdle and STAR regression models to monitor and represents the relative risk geographicaly of quarantine pests.

# Bibliography



- ✚ Best, N., Richardson, S. and Thomson, A. (2005). A comparison of bayesian spatial models for disease mapping. *Statistical Methods in Medical Research* 14, 35 – 59.
- ✚ Cressie N (1992) Smoothing regional maps using empirical Bayes predictors. *Geographical Analysis* 24:75 – 95
- ✚ Hodges J. and Reich B. (2010). Adding spatially–correlated errors can mess up the fixed effect you love. *The American Statistician*, 64(4):325–334, 2010. [p1, 3]
- ✚ Marshall R. M. (1991) Mapping disease and mortality rates using Empirical Bayes Estimators, *Applied Statistics*, 40, 283 – 294.
- ✚ McCullagh, P. and Nelder, J.A. (1989). *Generalized Linear Models*, Second Edition. London: Chapman and Hall.

- ✚ Mullahy J (1986). "Specification and Testing of Some Modified Count Data Models." *Journal of Econometrics*, 33, 341–365.
- ✚ Klein, N., Kneib, T. and Lang, S.(2014). Bayesian Generalized Additive Models for Location, Scale and Shape for Zero–Inflated and Overdispersed Count Data. To appear in *Journal of the American Statistical Association*.
- ✚ Zeileis A, Croissant Y (2010). "Extended Model Formulas in R: Multiple Parts and Multiple Responses." *Journal of Statistical Software*, 34(1), 1{13. ISSN 1548–7660. URL <http://www.jstatsoft.org/v34/i01>, <http://CRAN.R-project.org/package=Formula>.
- ✚ Zeileis A, Kleiber C, Jackman S (2008). "Regression Models for Count Data in R." *Journal of Statistical Software*, 27(8), 1{25. ISSN 1548–7660. URL <http://www.jstatsoft.org/v27/i08>.



**[martharg@colpos.mx](mailto:martharg@colpos.mx)**