# SPATIAL PREDICTION OF WEED INTENSITIES FROM EXACT COUNT DATA AND IMAGE BASED ESTIMATES

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# Content

# INTRODUCTION

For recusing the crop from the unwanted plants  ( weeds) farmaers have to use the pesticides in their crops . But when they are using the pesticides in the uniformly amount over the whole field also where their it is nit needed it becomes a harmulfull thing for the soil fertility as welll as the environment.

To be a safe side the if the farmers have the idea where the weeds in the crops then they will use the pesticide on these regions it can helps in maintaining the environment and the soil fertility.

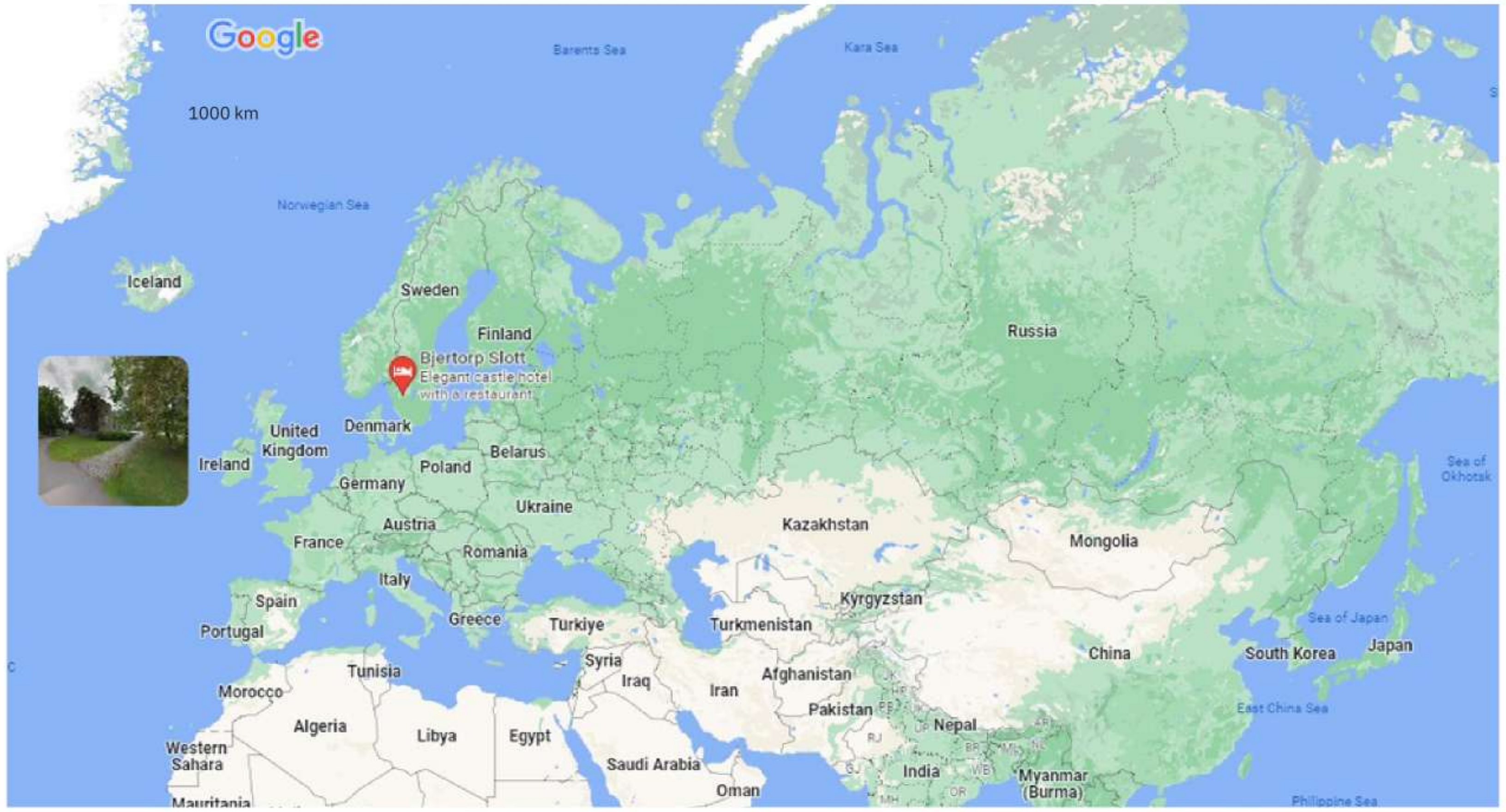
To addresses this issue now the statistical methods are there to get the spatial map of the field and allocate the locations where the weeds are present.

# why do we care about the problem ?

- Environmental Concern
- Issue with Pesticides
- Soil Fertility
- Importance of Weed Location
- Consumer Demands

# Weed Data Set

The analysis is based on data that were collected at the Bjertorp farm located 58.26N–13.13 E in the south-west of Sweden. The data have been collected in a cultivated wheatfield of 30 ha
and consist of exact counts in frames of 0.5 m × 0.75 m taken at 100 sites and estimates
derived from pictures that were taken exactly over these frames.



# Assumption about the dataset

**Green Transformation:**

- Soil and plants distinguished using green transformation and subsequent thresholding.

**Noise Removal:**

- Small objects treated as noise and eliminated from the binary image.

**Crop Row Detection:**

- Hough transform employed to differentiate between crops and rows.

**Weed Identification:**

- Masking utilized to find weeds between crop rows left uncovered by crops.

**Large Weed Extraction:**

- Morphological operations combinations used to extract large weeds covered by crop straws.

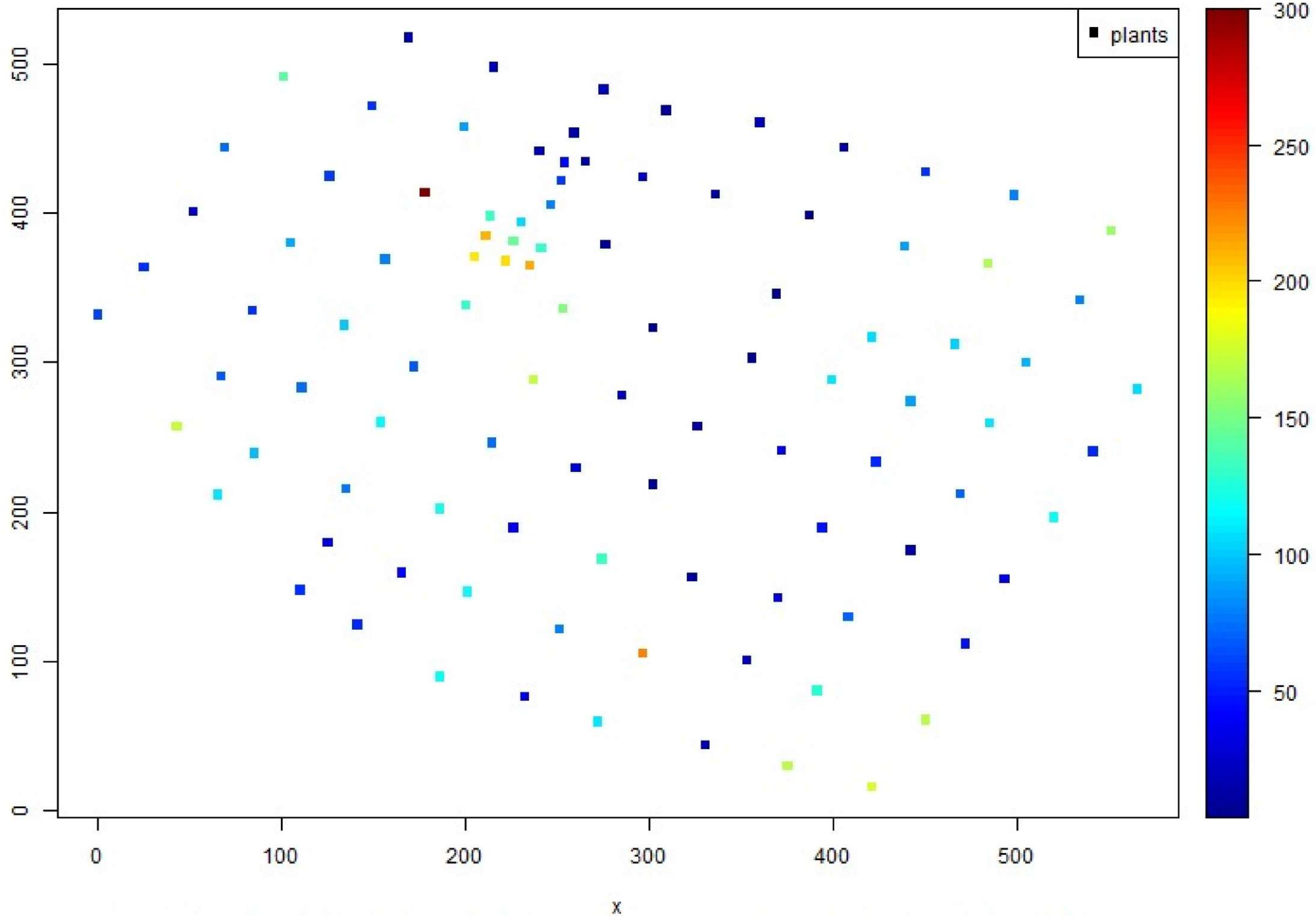
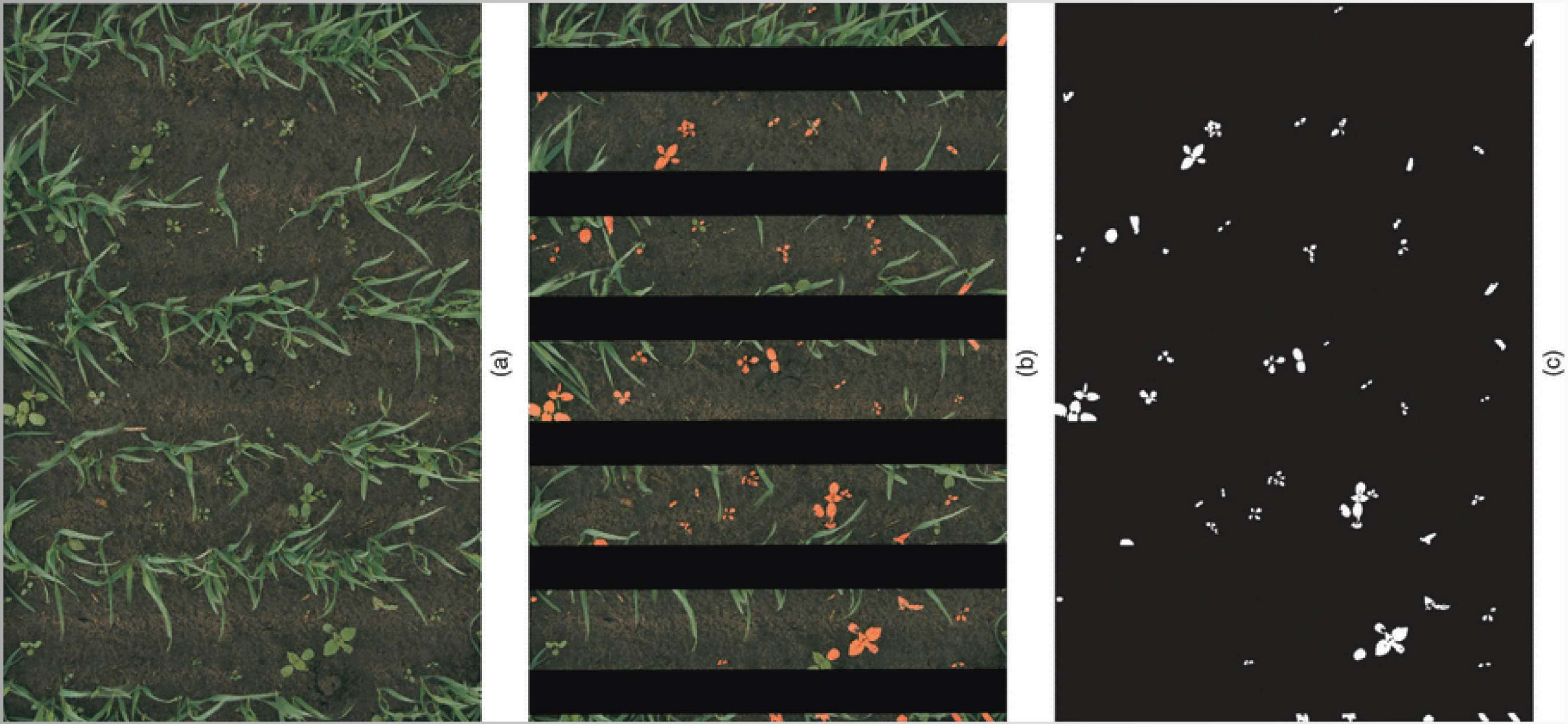
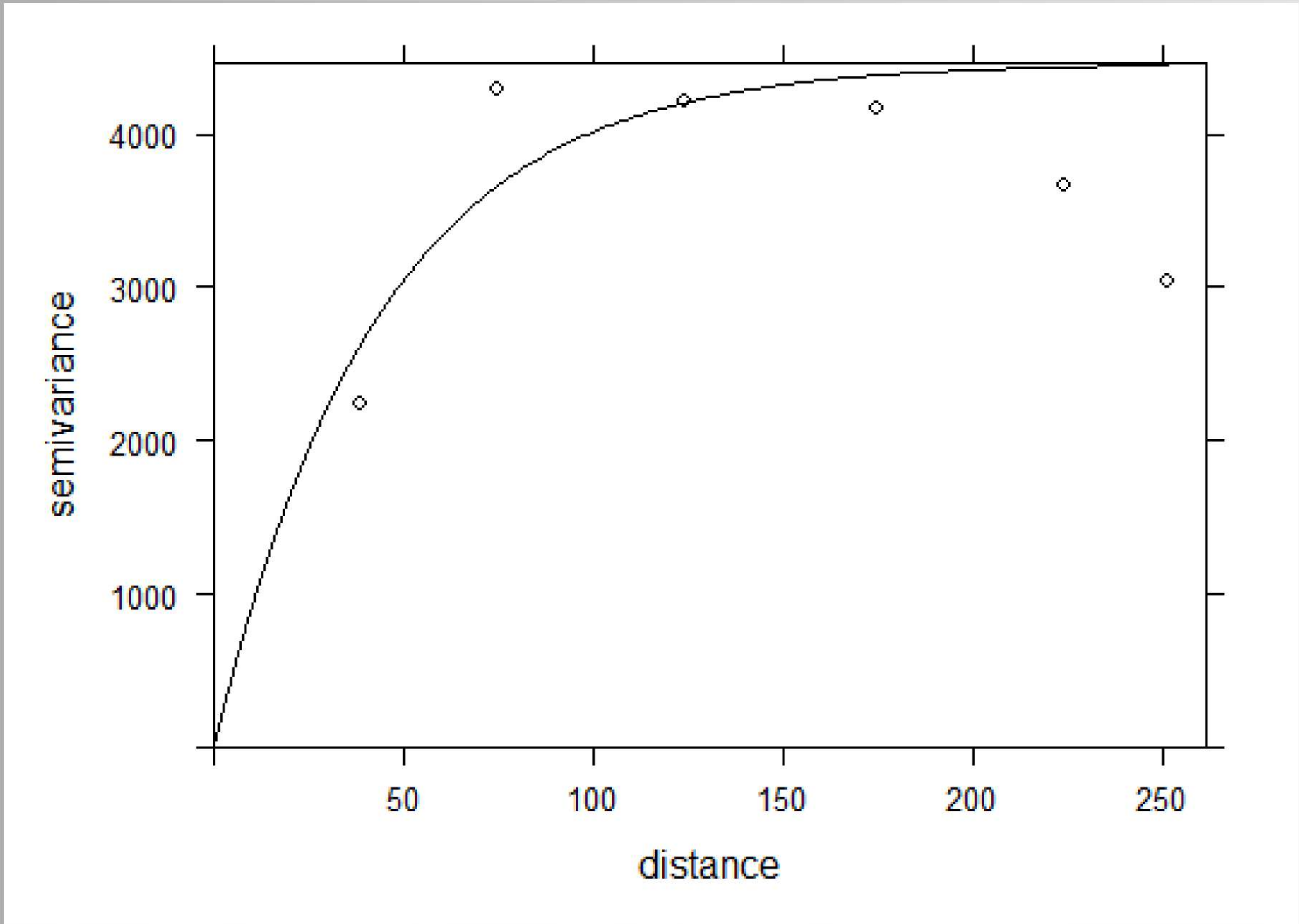


Fig. 1. Spatial distribution of the exact weed count; the colour code denotes the number of observed plants




**Taken from the paper**

# Empirical variograms of the exact count data

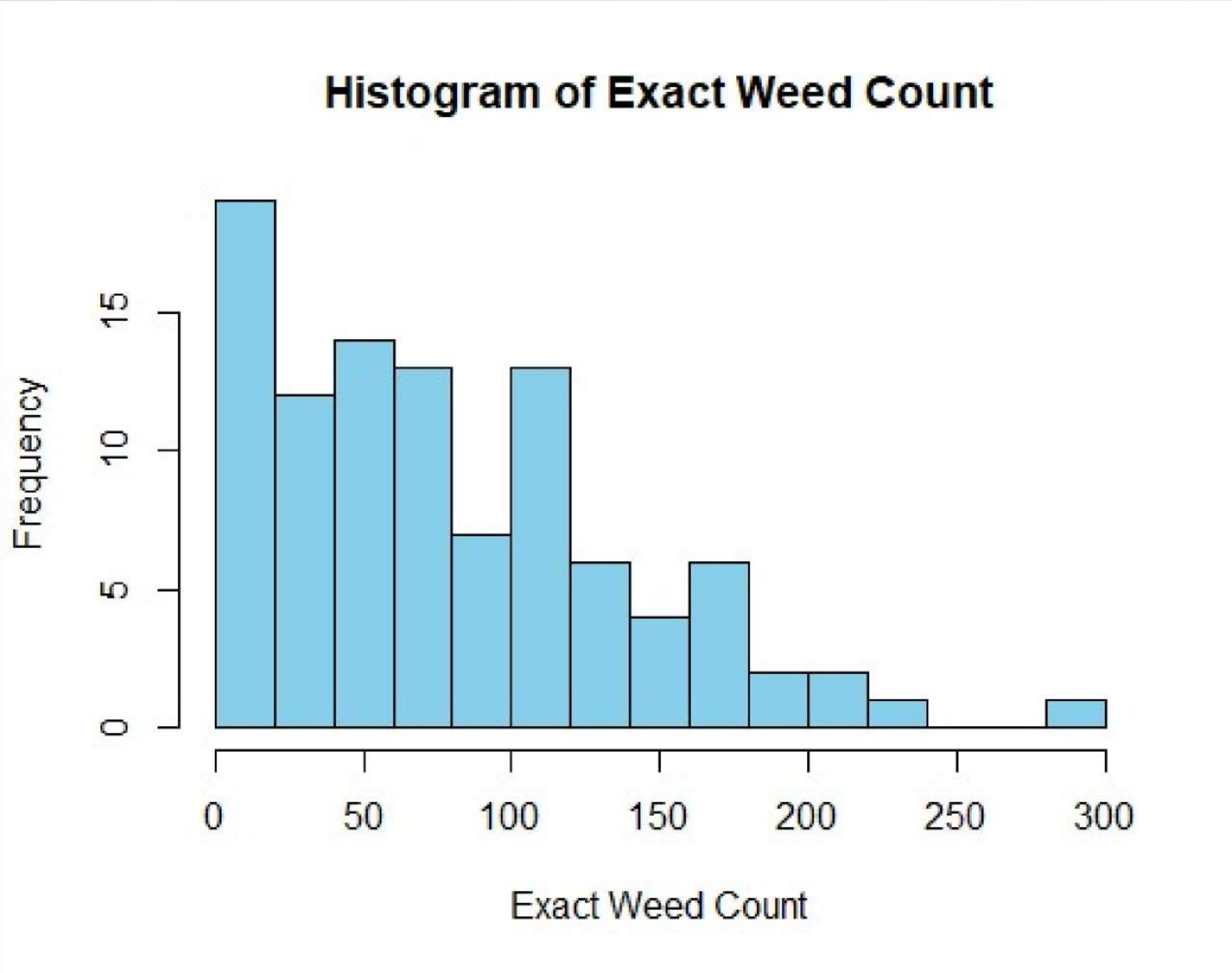


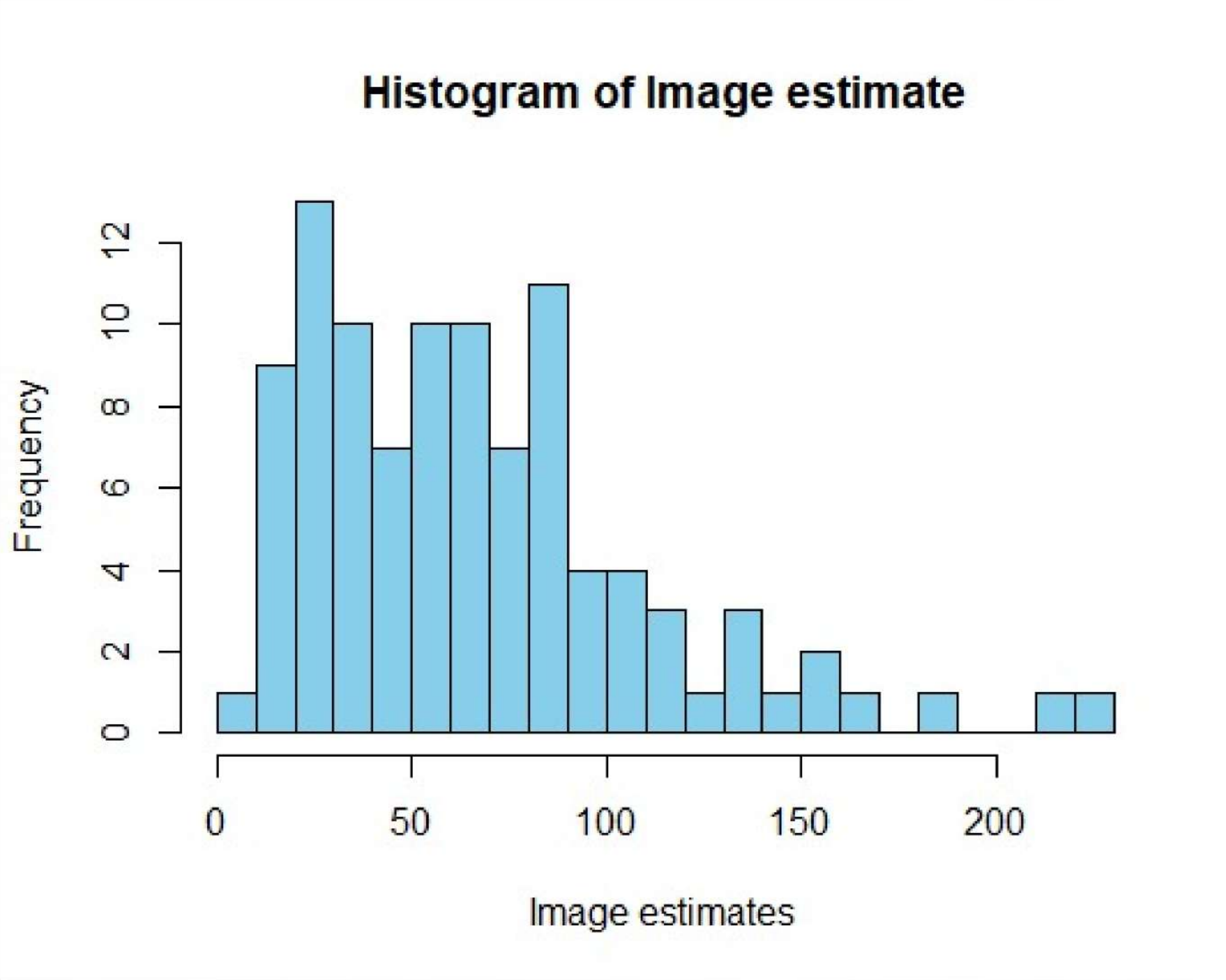
# Modelling

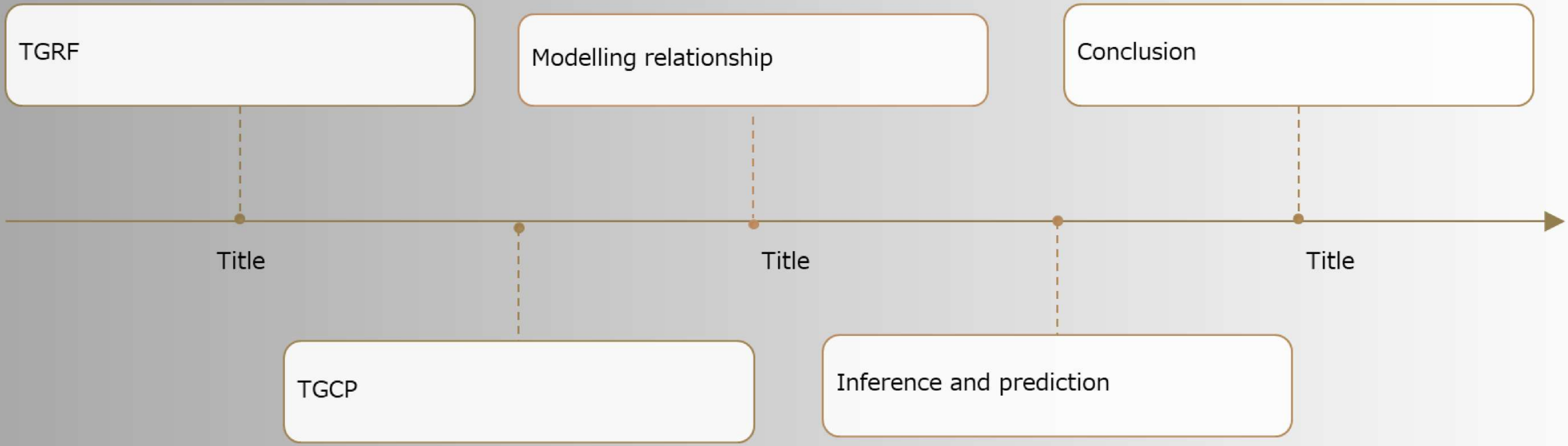
Exact weed counts are obseved at a set of sites
S= (s1,s2....,sns) denoted by Cs=(c(s1)....c(sn))

Image estimates are at a set sites T= (t1,.....tnt)
denoted by i=(i(t1),.......i(tnt))

Spatial prediction of the weed field c is sought U=(u1,....unu) denoted by
(c(u1).....c(un))


Histogram of Exact Weed Count
Frequency
0
5
10
15
0
50
100
150
200
250
300
Exact Weed Count


Histogram of Image estimate
Frequency
0
2
4
6
8
10
12
0
50
100
150
200
Image estimates


TGRF
Modelling relationship
Conclusion
Title
Title
Title
TGCP
Inference and prediction

In our dataset, the sets S and T are identical but there might be a case occurs that two sets do not necessarily coincide so we indivially modelling for exact counts &Image count

- **Modelling for Exact weed counts**

TGRF Model

TGCP Model

## TGRF Model

- TGRF model actually accounting for spatial auto- correlation and non- gaussian marginal distribution.
- Assumption is same as geostatistics
- They assume y(s)~N(0,1) s ∈ R^2
- There exist a function ψ:R→R s.t

$$c(s) = \psi(y(s))$$

  for large class of continuous transformation ψ
- Also assume that y is stationary and isotropic correlation function ρ(h) with exponetial decay

$$\mathrm{corr}\{y(s), y(s+h)\} = \exp(-||h||/\kappa)$$

where k is spatial correlation parameter

# TGCP Model

The previous TGRF model place a continuous distribution on c although the TGCP model for discrete variable.

$$c(s) \sim \text{poisson}\{w(s)\}$$

where $w(s) = \psi\{y(s)\}$

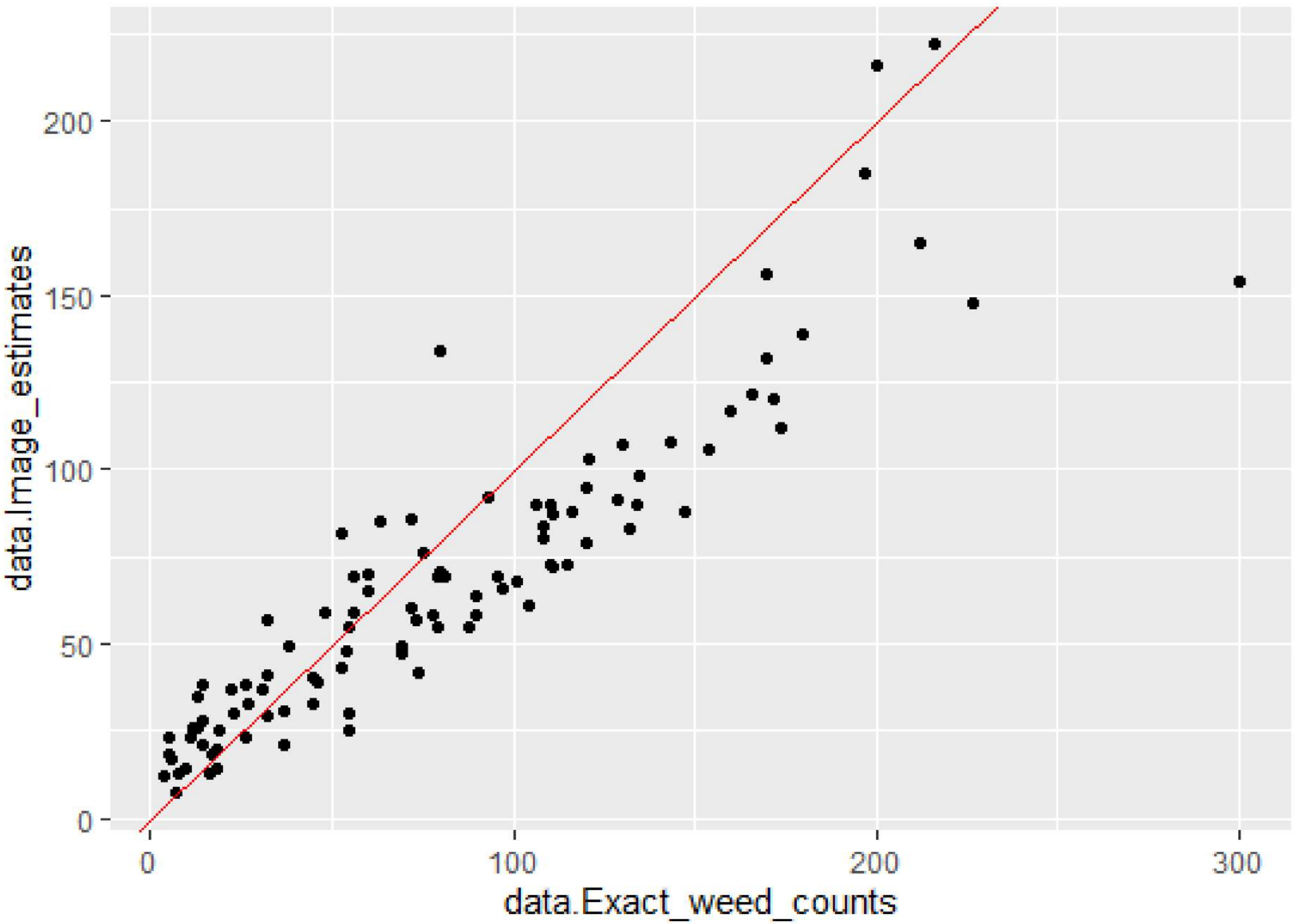
- This is a special case of the spatial generalized linear model where weed counts are assumed to arise from a spatial generalized linear mixed model with a Gaussian random field.
- Under this Poisson regression model there is a relationship

$$\text{cov}\{c(s), c(s+h)\} = \text{cov}\{w(s), w(s+h)\} \qquad h>0$$

$$\text{var}\{c(s)\} = E[w(s)] + \text{var}[w(s)]$$

we consider $\psi\{y(s)\}$ is long- normal marginal distribution with stationary mean u and variance sigma sq.

# Modelling relationship between exact counts and image estimates




We assume a poisson regression model for the Image estimates

$$i(s)|c \sim \text{Poisson}\{\gamma\, c(s)^{\delta}\}$$

where γ and δ are parameters that slightly departure from linearity

# Inference and prediction

so our full inference will be modeled as :

Data that is provided to us is as is = (i(s1),i(s2),i(s3,...i(sns ).

The relations that are provided are : i(s)|c poi sson(γc(s) δ )

c(s)|w(s) poisson(w(s))

w = ψ(y) Y (.) GP(μ(.),

k(s,s ′ ) = exp(−||h|/κ))

A total of parameters that we need to estimate are θ = (μ,σ 2 ,κ,γ,δ) The likelihood function is given by :

L(μ,σ,κ,γ,δ) = π((i(sj),c(sj)), j = 1,2,3,..n;μ,σ,γ,κ,δ)

= π(i(s1),i(s2)...i(sns )|c(s1),c(s2),c(s3)...c(sns );γ,δ)×π(c(s1),c(s2),c(s3)....c(sns );μ,σ,κ)

= Yns j=1 π((i(sj)|c(sj));γ,δ)×π(c(s1),c(s2)...(sns );μ,σ,κ)

Yns j=1 π((i(sj)|c(sj));γ,δ)× Z Z ···Z π(c(s1)...c(sns )|(Y (s1),Y (s2)),...Y (sns ))×π((Y (s1))...Y (sns );μ,σ,κ)dY (s1)...d(y(sns ))

Yns j=1π((i(sj)|c(sj));γ,δ)× Z Z ···Z

Yns j=1 π(c(sj)|Y (sj))× 1 |2πσ2 P κ)| exp −1 2σ2 (Y −μ) T P−1 κ (Y −μ) dY

This integral is over Y = (Y (s1),Y (s2)...Y (sn)

In this likelihood function

π((i(sj)|c(sj));γ,δ) = e −γc(sj ) δ (γc(sj) δ ) i(sj ) i(sj)! π((c(sj)|Y (sj)))

= e −ψ(Y (sj ) (ψ(Y (sj)))c(sj ) c(sj)!

# Estimations of parameters

- For the estimation of the kappa : we used the profile likelihood estimation of the the parameter involves in the correlation function (kappa)

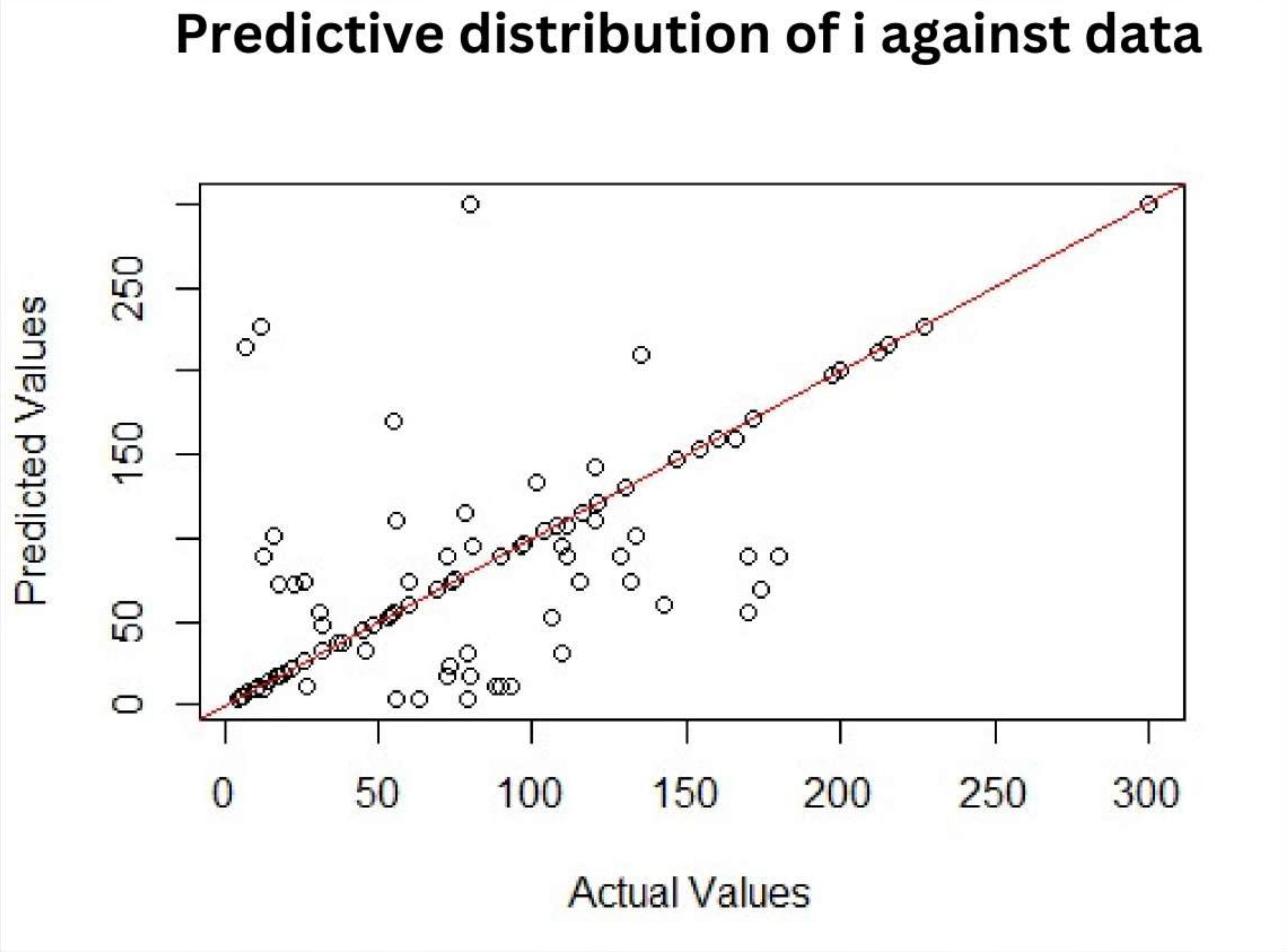
- For the estimation of the gamma and delta : For estimating the gamma and delta parameters that are involved in the relation between the image estimates and the exact count, we used probit GLM method.

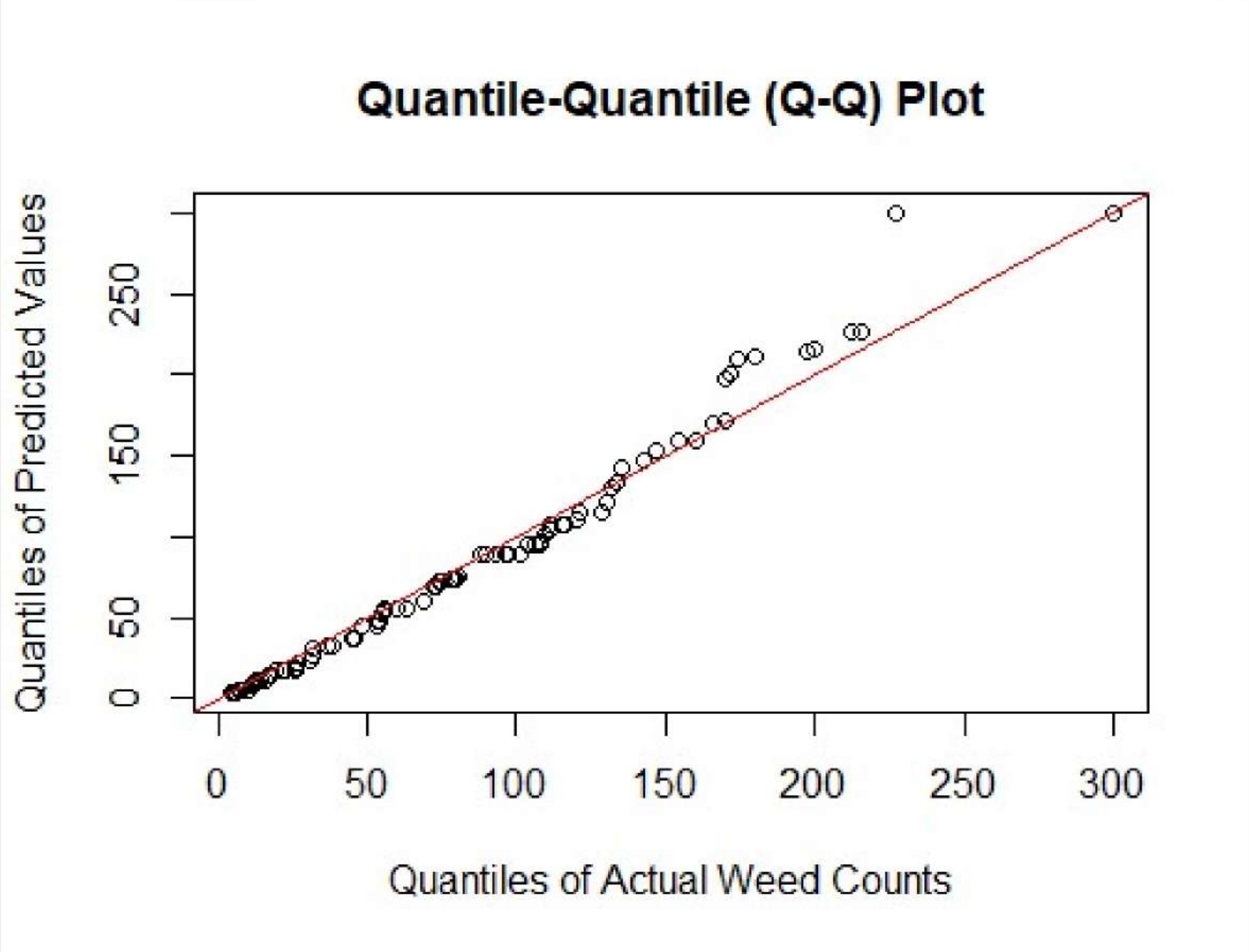
- For the estimation of μ and σ : For the estimation of μ and σ we used the simple Monte carlo estimation approach.

# Obtained values of estimates of the parameters

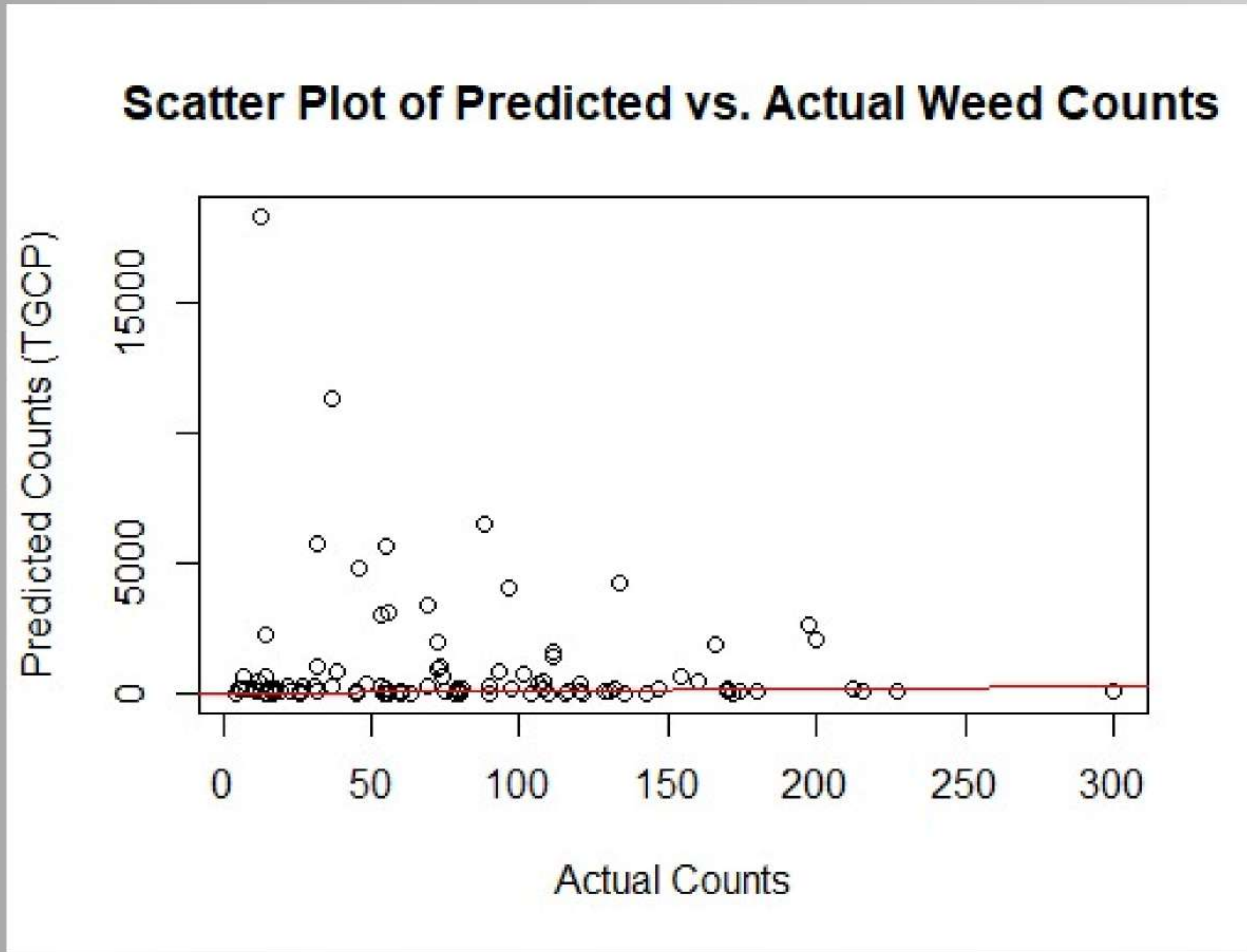
- The value of the $\kappa$, we get from the estimation is 1.13
- The estimated value for the parameter $\mu$ is 2.32
- The estimated value for the $\sigma2$ is 26.56
- The estimated value for the parameter $\gamma$ is 3.90
- The estimated value for the parameter $\delta$ is 0.725

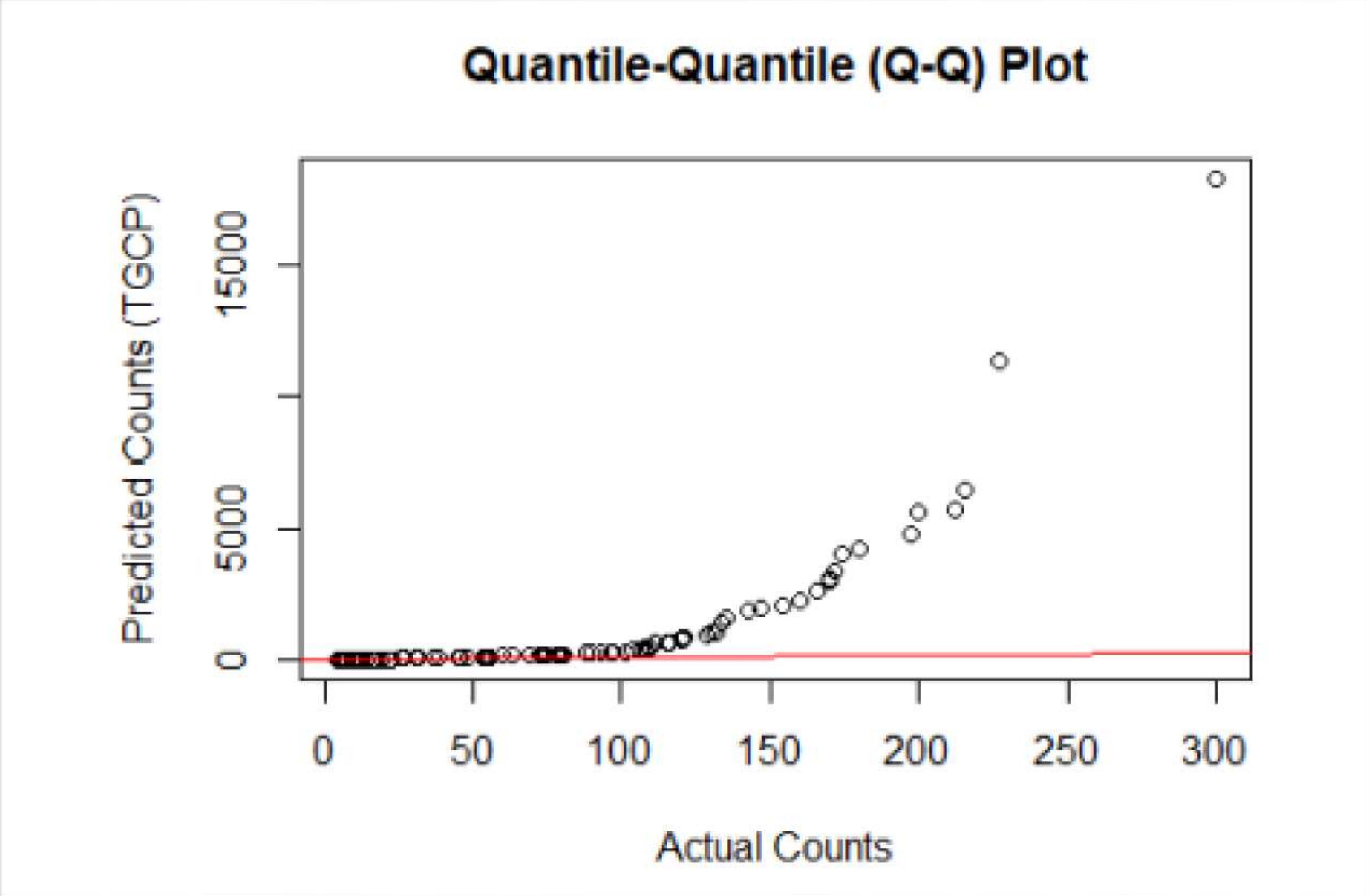
# TGRF model plot



# TGCP model plot



# Conclusion

1)

- when we use Image data its clearly improves the accuracy of prediction compared with exact counts.
- Throughout this study some of the image data were collected at the same sites as exact counts data. All computations are based on such data.
- where S∩T=∅ that prediction was less accurate than where S⊂T in the TGRF and TGCP model.
- we also note that there was a poisson regression relationship between image and counts data, where

$$\mathrm{var}(i) = \gamma E[c^{\delta}] + \gamma^2 \mathrm{var}(c^{\delta}).$$

- If γ and δ closs to 1 then var(i) ~ E(c) + var(c)

  ⇒ var(i) > var(c)

  but in present data var(i)< var(c)

2)

- when we use complex model TGRF &TGCP model on a given small dataset TGRF model give more accurate prediction than TGP model.
- When we increase the datapoints then the models will give the results with more accuracy .

# Reference


- https://rss.onlinelibrary.wiley.com/doi/10.1111/j.1467-9876.2009.00664.x#pane-pcw-figures

- https://rss.onlinelibrary.wiley.com/doi/10.1111/1467-9876.00419


Thank you!