

# Quasi-Poisson regression models for radiation dose estimation from biomarkers

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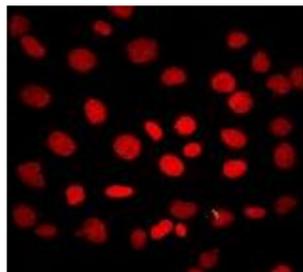
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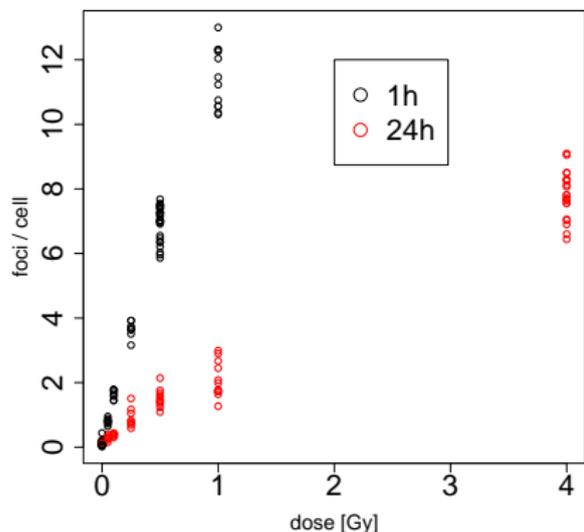
- Radiation incident leading to (potentially) exposed individuals
- Contracted radiation dose can be estimated retrospectively by exploiting the radiation-induced change in certain **biomarkers**
- ‘Gold-standard’: Dicentric chromosomes (resulting from unsuccessful DNA-damage response)
- However: time- and work-intensive and expensive methodology



- Biomarkers based on **proteins** have recently emerged as a quicker and cheaper alternative
- The H2AX–histone responds to radiation–induced double strand breaks with **phosphorylation**, in this state then referred to as  $\gamma$ -H2AX
- $\gamma$ -H2AX foci can be counted manually (immunofluorescence microscopy) or automated (flow cytometers)



Foci 'yield' (that is foci/cell, out of 500 sample cells) versus design dose:



- Strong (linear?) dose–response relationship; strong decay from 1h to 24h after exposure
- H2AX-based dose estimation has to happen within 24 hours of exposure!
- Considerable variation, so Uncertainty Quantification crucial

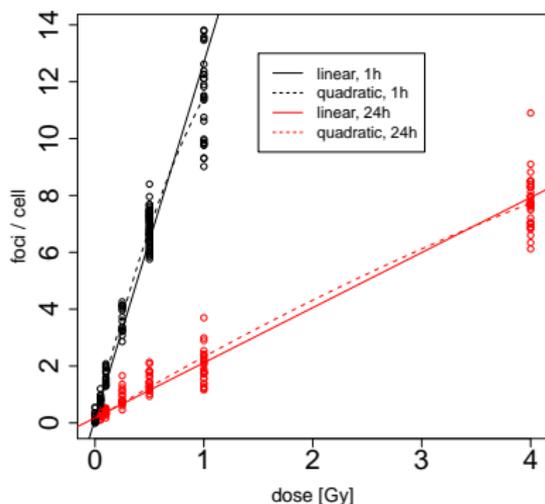
- For fixed time after exposure, calibration data  $(x_i, y_{ij})$ ,  $j = 1, \dots, n_i$ , with  $y_{ij}$  “yield of the  $j$ -th sample (of  $n$  cells) for dose  $x_i$ ”.

- Count data (Poisson) regression with ‘identity link’

$$\mu_i \equiv E(y_{ij}|x_i) = A + Bx_i$$

(Quadratic models also considered, but discarded)

- Huge overdispersion ( $\hat{\phi} \approx 60!$ )



- Overdispersed Poisson model for  $Y_{ij} = ny_{ij}$ ,

$$E(Y_{ij}|x_i) = nA + B(nx_i); \quad \text{Var}(Y_{ij}|x_i) = \phi E(Y_{ij}|x_i)$$

Score equations for this model (with  $\mu_i = A + Bx_i$ ),

$$\frac{1}{\phi} \sum_{i=1}^d \sum_{j=1}^{n_i} \begin{pmatrix} 1 \\ x_i \end{pmatrix} (Y_{ij} - n\mu_i) / \mu_i = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

... so the estimates of  $A$  and  $B$  do not depend on  $\phi$ !

- However, standard errors do depend on  $\phi$ , namely

$$SE(\hat{A}) = \sqrt{\hat{\phi}} SE_P(\hat{A}); \quad SE(\hat{B}) = \sqrt{\hat{\phi}} SE_P(\hat{B}).$$

- ‘Quick-and-dirty’, from estimated Poisson model

$$\hat{\phi} = \frac{\text{Deviance}}{N - 2}$$

- We use

$$\hat{\phi} = \frac{1}{N - 2} \sum_{i=1}^d \sum_{j=1}^{n_i} \frac{(Y_{ij} - n\hat{\mu}_i)^2}{n\hat{\mu}_i} = \frac{n}{N - 2} \sum_{i=1}^d \sum_{j=1}^{n_i} \frac{(y_{ij} - \hat{\mu}_i)^2}{\hat{\mu}_i}$$

where  $\hat{\mu}_i = \hat{A} + \hat{B}x_i$  and  $N = \sum_{i=1}^d n_i$ .

- Each additional covariate will increase the value ‘2’ in the denominator by 1.

- Dispersion estimates can become poor if data are aggregated.

- Simulation example:

10000 data sets of size 100 from

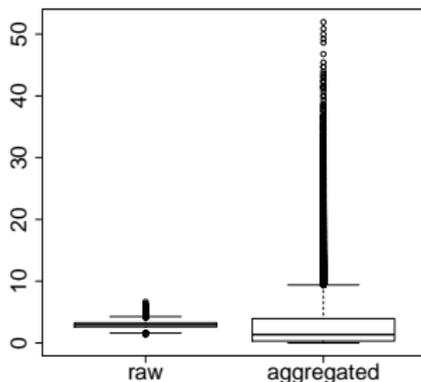
$y_i \sim \text{NB1}(\mu_i, 2)$ , with

$\mu_i = 2 + 5x_i$  and

$x_i \sim \text{Bin}(2, 0.5)$ .

- That is,  $\phi = 3$  known.

Dispersion estimates before and after aggregation over  $x$

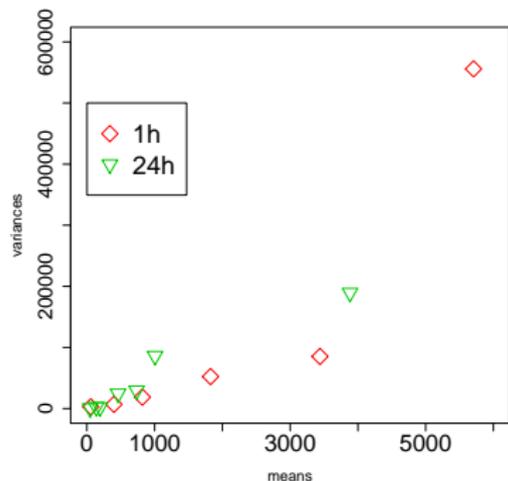


- Even though the average of estimates  $\hat{\phi}$  are almost identical (2.96 and 2.98, resp.), *each individual dispersion estimate from the aggregated data is close to useless.*

- Our calibration data are 'half-aggregated' (over cells; not over dose).

- Estimated dispersions:

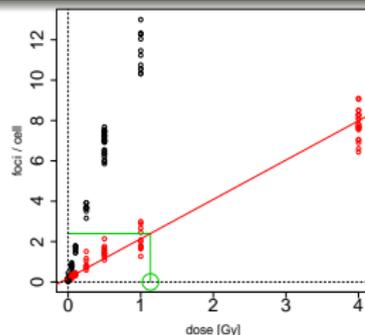
$\hat{\phi}$	1h	24h
'quick-and-dirty'	57.91	54.26
GLM-based	59.56	57.55



- $\hat{\phi} \approx 60$  appears a reasonable assumption.

- Inverse regression: For a new yield  $y_*$ , one has

$$x_* = \frac{y_* - \hat{A}}{\hat{B}}.$$



- UQ via delta-method:

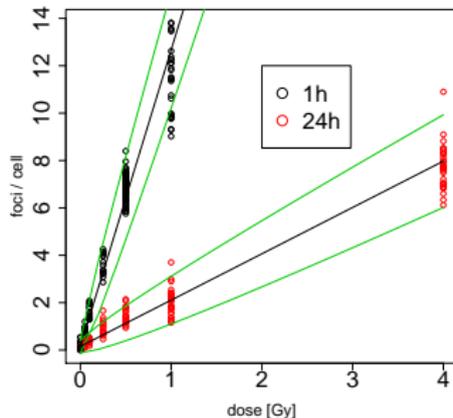
$$\begin{aligned} SE^2(x_*) &= \left(\frac{\partial x_*}{\partial \hat{A}}\right)^2 SE^2(\hat{A}) + \left(\frac{\partial x_*}{\partial \hat{B}}\right)^2 SE^2(\hat{B}) + \left(\frac{\partial x_*}{\partial y_*}\right)^2 SE^2(y_*) \\ &= \frac{1}{\hat{B}^2} SE^2(\hat{A}) + \frac{(y_* - \hat{A})^2}{\hat{B}^4} SE^2(\hat{B}) + \frac{1}{\hat{B}^2} \frac{\hat{\phi} y_*}{n_*} \end{aligned}$$

- This accounts for intra- and inter-individual variation, but still requires calibration curve to be 'correct'

Complication: The calibration curve may vary with laboratory, scorer, equipment etc. Hence, a given calibration curve needs to be **validated before use**.

Before examining a patient sample, lab should irradiate two reference samples at 0Gy and 1.5Gy and compare yields with prediction interval:

- If inside, validated
- If outside, a new calibration curve can be computed from the reference samples which still allows dose estimation, albeit at a higher variance



The screenshot shows a Google Chrome browser window with the URL `shivar.untoja.es/app/h2axDE/`. The page title is "DoseEstimateH2AX". The interface is divided into a left-hand control panel and a right-hand results area.

**Calibration**

- Own calibration curve?  Yes  No
- Time after exposure  1h  24h
- Reference samples available?  Yes  No
- $y_0$ :   $n_0$ :
- $r$ :   $y_r$ :   $n_r$ :
- Dispersion index available?  Yes  No

**Observed sample**

- $y^*$ :   $n^*$ :
- 
- Download report?  Yes  No

**Main | Plot | Information**

**Calibration curve:  $A + B D$**

Background yield, A: 0.1496 (0.0131).  
Linear dose effect, B: 1.9559 (0.0366).  
Dispersion index,  $\Phi$ : 55.6753.  
Note: The built-in calibration curve, PHE's 24h X-rays calibration curve has been validated for the introduced reference samples, and consequently used in this dose estimation.

**Summary of dose estimation**

Point estimate: 0.3171 Gy.  
Standard error: 0.2452 Gy.  
95% confidence interval: (-0.1595, 0.7937) Gy.



## DoseEstimateH2AX

**Calibration**

Own calibration curve?  Yes  No

Time after exposure  1h  24h

Reference samples available?  Yes  No

$Y_0$    $n_0$

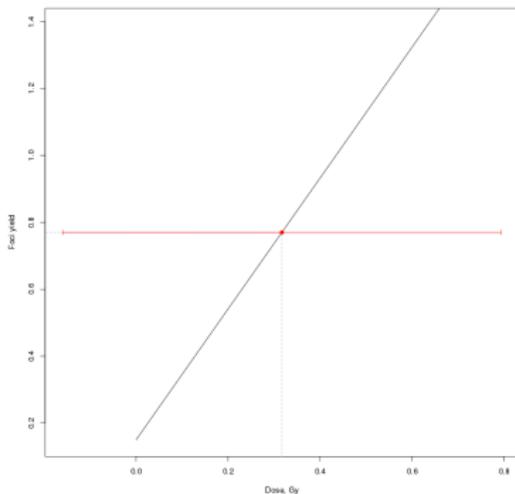
$r$    $Y_r$    $n_r$

Dispersion index available?  Yes  No

**Observed sample**

$Y^*$    $n^*$

Main Plot Information



We believe to have solved the questions regarding

- ... the incorporation of overdispersion
- ... the validation of the calibration curve
- ... the quantification of uncertainty in this process

Open questions are

- Is the dispersion a 'universal property of foci counts', or a feature of the scoring mechanism?
- Partial body exposure cannot be easily identified since overdispersion will be present either way

- Micronuclei: Overdispersion usually present but small ( $\approx 1.5$ ), risk of incorrect estimation of  $\phi$  possibly larger than benefits. If full count data distributions available then NB model preferable.
- Dicentric chromosomes
  - under partial body exposure: Overdispersion is due to zero-inflation; so direct use of ZIP models preferable.
  - under densely ionizing radiation: Overdispersion present but situation similar to micronuclei.
- Other protein-based biomarkers, such 53PB1
  - here probably useful, but yet to be tried...

- Combinations of Biomarkers

Idea: Use quick and cheap (but potentially high variance) biomarkers such as H2AX for the triage step, and a more precise biomarker (such as the dicentric assay) as a second step, depending on the first outcome. Bayesian approach favorable here.

- Why always estimate 'dose'?

It seems to be an irrevocable standard to always estimate *dose*. Why not triage directly based on the H2AX count? This removes need for inverse regression, and reduces uncertainties. Could be dealt with easily through ordinal logistic regression.

- Ainsbury EA et al** (2017). Uncertainty of fast biological radiation dose assessment for emergency response scenarios. *International Journal of Radiation Biology* **93**, 127–135.
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- Einbeck J et al** (2018). A statistical framework for radiation dose estimation from the  $\gamma$ -H2AX assay. *PLoS ONE* **13**(11):e0207464.
- Oliveira M et al** (2016). Zero-inflated regression models for radiation-induced chromosome aberration data: A comparative study. *Biometrical Journal* **58**, 259-79.