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1 Zero-inflated hierarchical models for faecal egg counts
2 to assess anthelmintic efficacy

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13 **Abstract**

The prevalence of anthelmintic resistance has increased in recent years, as a result of the extensive use of anthelmintic drugs to reduce the infection of parasitic worms in livestock. In order to detect the resistance, the number of parasite eggs in animal faeces is counted. Typically a subsample of the diluted faeces is examined, and the mean egg counts from both untreated and treated animals are compared. However, the conventional method ignores the variabilities introduced by the counting process and by different infection levels across animals. In addition, there can be extra zero counts, which arise as a result of the unexposed animals in an infected population or animals. In this paper, we propose the zero-inflated Bayesian hierarchical models to estimate the reduction in faecal egg counts. The simulation study compares the Bayesian models with the conventional faecal egg count reduction test and other methods such as bootstrap and quasi-Poisson regression. The results show the Bayesian models are more robust and they perform well in terms of both the bias and the coverage. We further illustrate the advantages of our proposed model using a case study

about the anthelmintic resistance in Swedish sheep flocks.

14 *Keywords:* Bayesian hierarchical model, faecal egg count reduction test,
15 anthelmintic resistance, zero-inflated models, statistical analysis

16 **1. Introduction**

17 Gastrointestinal nematodes are parasitic worms that survive in livestock
18 hosts, such as sheep, cattle and horses. The infection is common in the live-
19 stock populations in some regions (Waruiru et al., 2001; Mortensen et al., 2003;
20 Pfukenyi et al., 2007; Tariq, 2014; Zanzani et al., 2014). Such infection can lead
21 to numerous problems including reduction in skeletal growth, live-weight gain
22 and milk yield (Houtert and Sykes, 1996), which can impose great economic
23 burden on ruminant production (Perry and Randolph, 1999). The regular ad-
24 ministration of anthelmintic treatments is a widely used method to control the
25 infection. It aims not to eliminate the infection, but to reduce the infection in-
26 tensity and prevent transmission (Levecke et al., 2012a). However, anthelmintic
27 resistant nematodes appeared in different regions across the globe since late
28 1950s (Kaplan, 2004). The extensive use of anthelmintic treatments has led to
29 an increasing problem of anthelmintic resistance. Once a resistance is detected,
30 alternative treatments are needed in order to avoid any further production losses.
31 Accurate and reliable methods to assess the treatment efficacy are thus essential
32 to effectively control and monitor the infection.

33 The widely used faecal egg count reduction test (FECRT) was established in
34 the early 1990s (Coles et al., 1992). It is a straightforward method to calculate
35 the reduction in faecal egg counts (FECs), by comparing the mean pre-treatment
36 and post-treatment FECs. For sheep and goats, if both the percentage reduction
37 in mean FECs is less than 95% and the corresponding lower confidence limit is
38 less than 90%, then the anthelmintic resistance is declared to be present. A stan-
39 dard method to obtain the FECs, the modified McMaster counting technique, is
40 detailed in the guideline of the World Association for the Advancement of Vet-
41 erinary Parasitology (WAAVP) (Coles et al., 1992). New WAAVP guidelines

42 are not yet developed, but Levecke et al. (2017) have made recommendations
43 to improve and standardize the FECRT.

44 Although the FECRT and the McMaster technique were widely used in
45 practice, some limitations have been pointed out in recent years. First of all,
46 the McMaster counting technique introduces substantial variability in the re-
47 sults which is not accounted for in the FECRT (Torgerson et al., 2012). As
48 a consequence of this, the estimated efficacy were found to be quite variable
49 particularly for the samples with low pre-treatment FECs and efficacy in the
50 range between 90%–95% (Miller et al., 2006). The use of refined techniques
51 with a high analytical sensitivity such as FLOTAC (Giuseppe et al., 2010) and
52 Cornell-Wisconsin (Egwan and Slocombe, 1982) can reduce but not eliminate
53 the variability (Torgerson et al., 2012; Levecke et al., 2012b). Secondly, the dis-
54 tribution of egg counts is typically aggregated or overdispersed within the host
55 population (Grenfell et al., 1995). Levecke et al. (2012a) evaluated the FECRT
56 under different scenarios, highlighted that test results should be interpreted
57 with caution when the sample size is small and the aggregation level is high.
58 There were several attempts to propose more elaborate statistical models in the
59 past years. Torgerson et al. (2005) assumed a negative binomial distribution
60 for the counts, and used parametric bootstrap to calculate the confidence in-
61 terval (CI) of the FECs reduction. More recently, methods have emerged that
62 formulate the problem in a Bayesian framework. Denwood et al. (2010) con-
63 sidered a Poisson-gamma distribution for the counts, with the post-treatment
64 mean linked to the pre-treatment mean via a scale factor. The inference is
65 then done using Markov chain Monte Carlo (MCMC). Dobson et al. (2012)
66 proposed a novel way to determine the confidence limits of the FECs reduc-
67 tion using Jeffrey intervals, which is derived from Bayesian procedures using
68 a non-informative prior, however it requires high counts and high analytical
69 sensitivity. Paul et al. (2014) proposed a hierarchical model that uses binomial
70 distribution to capture the counting variability, and a Poisson-gamma distri-
71 bution to model the overdispersion. The posterior median for the reduction
72 and its 95% highest posterior density (HPD) interval is used for its point and

73 interval estimate respectively. An easy-to-use web interface was implemented
74 and made available online (Torgerson et al., 2014). However the models them-
75 selves were not published and well-documented. Levecke et al. (2015) proposed
76 another Bayesian model with a slightly different formulation. It used a Poisson
77 distribution to capture the variability in the counting process and a negative
78 binomial distribution to capture the overdispersion. The Bayesian models do
79 not only provide credible intervals on the reduction, but also generate posterior
80 distributions for each of the model parameters, hence offering a probabilistic
81 view on the efficacy rather than a yes or no answer. To the best of our knowl-
82 edge, a common assumption made by those recent Bayesian models is that all
83 animals in an infected population are exposed. However, Denwood et al. (2008)
84 showed the underlying distribution of the nematodes FECs can be zero-inflated
85 negative binomial (ZINB). The zero-inflation component can arise as a result of
86 the unexposed livestock in an infected population. Models with zero inflation
87 have already been used in the context of disease mapping (Vounatsou et al.,
88 2009; Soares Magalhães et al., 2011).

89 In this paper, we propose zero-inflated Bayesian hierarchical models to es-
90 timate the reduction in FECs. We build on the models in (Paul et al., 2014)
91 and explicitly formulate the model structures. The models account for the extra
92 variabilities that arise from both the sampling process and the between-animal
93 variations. In addition, the models allow for extra zero counts by introducing
94 the zero-inflation components. Overall, the models are more flexible and are
95 suitable for a wide range of scenarios. The rest of this paper is organized as
96 follows. Section 2 briefly reviews the conventional FECRT and efforts made to
97 modify it. Section 3 introduces the zero-inflated Bayesian hierarchical models.
98 Section 4 conducts a simulation study, where the bias and coverage of the esti-
99 mated FECs reduction are compared across different methods. In Section 5, a
100 case study is used to illustrate the proposed methods for estimating the reduc-
101 tion in FECs, where anthelmintic resistance was investigated in Swedish sheep
102 flocks. Finally, Section 6 concludes with a discussion.

103 **2. Faecal egg count reduction test**

104 The FECRT was suggested in the WAAVP guideline for estimating the re-
 105 duction in FECs and its corresponding CI (Coles et al., 1992). In order to reduce
 106 the counting variability, using groups of at least 10-15 animals was suggested.
 107 In addition, the mean pre-treatment FECs should be at least 150 epg, otherwise
 108 the FECRT can give unreliable results.

109 Suppose a group of n_T animals received anthelmintic treatment and a group
 110 of n_C animals serves as control. The percentage reduction in FECs can be
 111 calculated as

$$\text{Percentage reduction} = 100 \times \left(1 - \frac{\bar{x}_T}{\bar{x}_C}\right), \quad (1)$$

112 where \bar{x}_T and \bar{x}_C denote the mean counts of the treatment and the control
 113 group. Assuming independence, the estimated asymptotic variance of the log
 114 ratio is given by

$$\widehat{\text{Var}} \left(\log \frac{\bar{X}_T}{\bar{X}_C} \right) = \frac{s_T^2}{n_T \bar{x}_T^2} + \frac{s_C^2}{n_C \bar{x}_C^2}. \quad (2)$$

115 where \bar{X}_T and \bar{X}_C denote the means of random samples, s_T^2 and s_C^2 denote the
 116 sample variance of the treatment and the control group counts. The variance
 117 can be used to construct an approximate 95% CI of the log ratio using the 97.5%
 118 and the 2.5% quantile of a Student's t-distribution with $n_T + n_C - 2$ degrees
 119 of freedom. The CI for the log-ratio can be then transformed back to obtain
 120 the 95% CI for the estimated reduction. The WAAVP guideline (Coles et al.,
 121 1992) states that for sheep and goats, the resistance is present if (i) the per-
 122 centage reduction in FECs is less than 95% and (ii) the corresponding lower
 123 95% confidence limit is less than 90%. If only one of these two criteria is met,
 124 then resistance is suspected. Different thresholds have been suggested for other
 125 livestock.

126 Over the past years, modified versions of the FECRT have been proposed in
 127 the literature. Wood et al. (1995) suggested to use the geometric mean in the
 128 FECRT instead of arithmetic mean. Davison and Hinkley (1997) suggested the
 129 95% CI can also be calculated using nonparametric bootstrap. In the unpaired

130 design, there is one group of animals that receives the treatment and another
 131 group is chosen to act as the control group. McKenna (1990) suggested that
 132 instead of taking samples from two groups of animals, the pre-treatment counts
 133 from the treatment group can be used as the baseline, hence eliminated the need
 134 of a distinct control group. We refer to this as the paired design. In this case,
 135 the FECRT becomes inappropriate since it does not take the paired structure
 136 into account in calculating the variance.

137 3. Bayesian hierarchical models

138 There are two designs that can be used for detecting anthelmintic resistance
 139 in a livestock population. For each design, we propose a zero-inflated Bayesian
 140 hierarchical model to estimate the reduction in FECs.

141 3.1. The unpaired design

142 Suppose we have two groups of animals from the same population, a control
 143 group with size n_C and a treatment group with size n_T . A faecal sample from
 144 each animal is collected and counted with an analytical sensitivity f_i , where i
 145 is the index of each animal in the corresponding group. We assume the counts
 146 belong to the same species, more specifically the counts follow a unimodal dis-
 147 tribution. For notational simplicity, we assume every sample has the same
 148 analytical sensitivity, hence the index in f_i is dropped for the rest of the paper.
 149 The faecal sample is thoroughly mixed after dilution, hence we assume the eggs
 150 are homogeneously distributed within each sample. A proportion of the diluted
 151 sample $p = 1/f$ is then counted. Denote the raw number of eggs in the diluted
 152 sample of the i th control animal as Y_i^{*C} , with $i = 1, 2, \dots, n_C$. Given the true
 153 number of eggs per gram of faeces Y_i^C , the raw count Y_i^{*C} follows a binomial
 154 distribution with size Y_i^C and probability p . This captures both the dilution
 155 and the McMaster counting variability. Then the true epg Y_i^C follows a zero-
 156 inflated Poisson (ZIP) distribution with mean μ_i^C and zero-inflation parameter
 157 ϕ , it implies Y_i^C is 0 with probability ϕ , and follows the Poisson distribution

158 with mean μ_i^C with probability $(1 - \phi)$. The zero-inflation component captures
 159 the excess number of zero counts that could come from unexposed animals, while
 160 the Poisson component captures the animals with zero counts that are below the
 161 detection limit. Finally the mean μ_i^C is gamma-distributed with shape κ and
 162 rate κ/μ . It has mean μ and variance μ^2/κ , the gamma distribution captures
 163 the overdispersion of the egg counts. This yields the following model for the
 164 control group animals,

$$\begin{aligned} Y_i^{*C} | Y_i^C &\sim \text{Bin}(Y_i^C, p), \\ Y_i^C | \mu_i^C, \phi &\sim \text{ZIP}(\mu_i^C, \phi), \\ \mu_i^C | \kappa, \mu &\sim \text{Gamma}(\kappa, \kappa/\mu). \end{aligned} \quad (3)$$

165 For the treatment group, the number of eggs in faecal samples is likely to de-
 166 crease after some days receiving the treatment, hence we introduce a reduction
 167 factor $(1-\delta)$ where δ represents the proportion of eggs remaining. The treatment
 168 may significantly reduce the infection level but it is very unlikely to completely
 169 eliminate the infection, hence the zero-inflation component remains the same.
 170 In addition, we assume the reduction in FECs occurs at individual level, such
 171 that the parameters μ and κ also stay the same. This yields the following model
 172 for the treatment group,

$$\begin{aligned} Y_i^{*T} | Y_i^T &\sim \text{Bin}(Y_i^T, p), \\ Y_i^T | \mu_i^T, \phi &\sim \text{ZIP}(\delta\mu_i^T, \phi), \\ \mu_i^T | \kappa, \mu &\sim \text{Gamma}(\kappa, \kappa/\mu). \end{aligned} \quad (4)$$

173 where the superscript T denotes the parameters for the treatment group. The
 174 priors for the flock parameters μ , κ and ϕ need to be specified in advance.
 175 If previous knowledge about the distribution of those parameters is available,
 176 they can be taken into account in the model as priors. Otherwise, diffuse priors
 177 should be used.

178 *3.2. The paired design*

179 In the paired design, there is only one group of animals of size n . A faecal
 180 sample from each animal is counted twice, once before the treatment and once
 181 some days after the treatment. The baseline counts of each animal is used as
 182 the corresponding control. The model for the paired design is

$$\begin{aligned}
 Y_i^{*C} | Y_i^C &\sim \text{Bin}(Y_i^C, p), \\
 Y_i^C | \mu_i^C, \phi &\sim \text{ZIPois}(\mu_i^C, \phi), \\
 Y_i^{*T} | Y_i^T &\sim \text{Bin}(Y_i^T, p), \\
 Y_i^T | \mu_i^C, \phi &\sim \text{ZIPois}(\delta \mu_i^C, \phi), \\
 \mu_i^C | \kappa, \mu &\sim \text{Gamma}(\kappa, \kappa/\mu).
 \end{aligned} \tag{5}$$

183 The only difference in the model comparing with the unpaired design is that,
 184 the pre-treatment epg Y_i^C and post-treatment epg Y_i^T are now based on the
 185 same Poisson mean μ_i^C to indicate that they belong to the same animal. The
 186 priors for the flock parameters should be specified in a similar way as for the
 187 unpaired design.

188 The hierarchical model given in Eq. (5) without zero-inflation in Y_i^C and
 189 Y_i^T was proposed in (Paul et al., 2014), however the authors used the posterior
 190 median as the point estimate for the reduction, and the 95% HPD credible in-
 191 terval as the interval estimate. The model was implemented in the “eggCounts”
 192 package version $\leq 0.4-1$ (Wang and Paul, 2016) in R along with the hierarchical
 193 model for the unpaired design without zero-inflation. In addition, the authors
 194 used $(1 - \bar{Y}_i^C / \bar{Y}_i^T)$ as the posterior samples for the reduction in the unpaired
 195 model rather than using $(1 - \delta)$ directly. Typically, the posterior mode is used
 196 in conjunction with the HPD interval. In the simulation study, we show that
 197 using the posterior mode of the reduction parameter as the estimate gives a
 198 smaller bias compared to using the posterior median.

199 **4. Simulation study**

200 In order to investigate the performance of the proposed Bayesian models, we
 201 conduct a simulation study to estimate the FECs reduction. We first simulate
 202 the FECs data under different scenarios, then use our proposed models and
 203 other methods to estimate the reduction. The bias and the coverage of the 95%
 204 CIs or credible intervals are compared across different methods.

205 *4.1. Simulation setup*

206 FECs for both unpaired and paired designs are simulated. For each design,
 207 we consider 16 different scenarios that vary in terms of the baseline mean count
 208 μ (150 epg or 500 epg), the dispersion κ (1 or 2), the reduction $(1 - \delta)$ (90%
 209 or 95%) and the zero-inflation ϕ (0 or 30%). Sample size is chosen to be 15
 210 for all scenarios, and the analytical sensitivity is 50. For each scenario in each
 211 design, 1000 dataset are simulated. The pre-treatment FECs are simulated
 212 as follows: we firstly draw the mean epg μ_i^C from a gamma distribution with
 213 shape κ and rate κ/μ . Then the true number of eggs y_i^C are drawn from a ZIP
 214 distribution with mean μ_i^C and zero-inflation ϕ . Finally, the observed counts
 215 are drawn from another Poisson distribution with mean y_i^C/f where f is the
 216 analytical sensitivity. The post-treatment FECs are simulated in a similar way
 217 but with different parameters. Note the process of simulating the data does not
 218 exactly match our proposed model. In addition, the simulation parameters are
 219 chosen such that the FECRT is suitable to use under the guideline of WAAVP.
 220 This encourages a fair comparison across the different methods. If we simulate
 221 exactly as our model specifications, we expect the results will be even more
 222 favorable.

223 We compare several different methods for estimating the mean FECs re-
 224 duction and its confidence interval. For the unpaired design, we consider the
 225 FECRT with the approximate CI (FECRT); the hierarchical model in Eq. (3)–
 226 (4) without zero-inflation and using posterior median as the point estimate, as
 227 implemented in (Wang and Paul, 2016) (PoGa(median)) and the same model

228 but using posterior mode as the point estimate (PoGa(mode)); our proposed
229 zero-inflated hierarchical model for the unpaired design (ZIPoGa); and finally
230 parametric bootstrap, assuming zero-inflated negative binomial distributions
231 and using 1999 bootstrap samples (pBoot).

232 The FECRT does not distinguish between paired and unpaired designs,
233 hence it is applicable to both. The zero-inflated negative binomial regression
234 does not perform well when the sample size is small, and it sometimes does not
235 produce sensible results (Denwood et al., 2008). Hence for the paired design,
236 in addition to the FECRT, we consider a quasi-Poisson regression, excluding
237 zero pre-treatment counts and using log pre-treatment counts as the offset term
238 (qPois); the proposed hierarchical model in (Paul et al., 2014) using posterior
239 median as the point estimate (PoGa(median)) and the same model but using
240 posterior mode as the point estimate (PoGa(mode)); and finally our proposed
241 zero-inflated hierarchical model for the paired design (ZIPoGa).

242 The Bayesian models are implemented in the “eggCounts” package version
243 1.1-1 (Wang and Paul, 2016) using the modelling language Stan (Carpenter,
244 2015), Stan uses an effective MCMC sampling technique and is available through
245 the “stan” package (Guo et al., 2015) in R (R Core Team, 2015). The prior for
246 the reduction follows a Beta(1, 1) distribution, which assigns uniform density
247 between 0 and 1. For the parameters μ and κ , we use Gamma(1, 0.001) and
248 Gamma(1, 0.7) prior respectively. For each Bayesian model, 12,000 MCMC
249 samples are generated with 2,000 samples for burn-in without thinning. The
250 posterior mode is used as the estimate for the reduction parameter in our pro-
251 posed models, and the 95% HPD interval of the posterior samples was obtained.
252 All the simulations are conducted in R version 3.2.1.

253 4.2. Simulation results

254 Fig. 1 and Fig. 2 show the bias and the coverage probability of 95% CIs or
255 95% HPD interval for the FECs reduction, in the case of unpaired designs. The
256 PoGa(median) model slightly underestimate the reduction in most cases, how-
257 ever it is improved by using the posterior mode as the point estimate as shown

Fig. 1: Boxplots of the estimated FECs reduction in the paired design, using FECRT with approximated CI (FECRT); the hierarchical model without zero-inflation (Paul et al., 2014) and using the posterior median as the point estimate (PoGa(median)); the hierarchical model without zero-inflation (Paul et al., 2014) and using the posterior mode as the point estimate (PoGa(mode)); our proposed zero-inflated hierarchical model for the paired design (ZIPoGa); and quasi-Poisson regression (qPois). The horizontal line indicates zero bias.

Fig. 2: Barplots of the coverage probability of the 95% CIs, or HPD credible intervals for the FECs reduction in the unpaired design. The error bars are calculated based on the 95% binomial confidence interval. The horizontal line indicates 95% coverage. The methods are the same as described in Fig. 1.

258 in PoGa(mode). All the other methods have small biases. Both the FECRT and
 259 the parametric bootstrap method have inaccurate coverage probabilities when
 260 the pre-treatment mean count is low. As expected, the FECRT has accurate
 261 coverage when the pre-treatment mean is high, since the asymptotic variance
 262 improves. The PoGa(median) model provides low coverage probability when the
 263 pre-treatment mean count is high, and it is improved by using $(1 - \delta)$ as the
 264 posterior samples for the reduction directly. In contrast, our proposed zero-inflation
 265 models offers good coverage while maintaining small bias. Note the Bayesian
 266 credible intervals do not have a long-run property like the CIs where 95 per-
 267 cent of the 95% CIs should cover the true parameter value (Spiegelhalter et al.,
 268 2004), but the coverage probability for the Bayesian methods can still be used
 269 as a rule of thumb to assess the models.

Fig. 3: Boxplots of the estimated FECs reduction in the paired design, using FECRT with approximated CI (FECRT); the hierarchical model without zero-inflation (Paul et al., 2014) and using the posterior median as the point estimate (PoGa(median)); the hierarchical model without zero-inflation (Paul et al., 2014) and using the posterior mode as the point estimate (PoGa(mode)); our proposed zero-inflated hierarchical model for the paired design (ZIPoGa); and quasi-Poisson regression (qPois). The horizontal line indicates zero bias.

270 Fig. 3 and Fig. 4 show the bias and the coverage probability for the paired
 271 designs. The biases are small for all the methods except the PoGa(median)
 272 model. It is improved again by using the posterior mode as the estimate. In

Fig. 4: Barplots of the coverage probability of the 95% CIs, or HPD credible intervals in the case of Bayesian models, for the FECs reduction in the paired design. The error bars are calculated based on the 95% binomial confidence interval. The horizontal line indicates 95% coverage. The methods are the same as described in Fig. 3.

273 term of the coverage, the FECRT method tends to have wide confidence intervals
274 since they do not take the paired structure into account, resulting almost 100%
275 coverage when the pre-treatment mean is high. The Bayesian models provide
276 slight over-coverage in all the scenarios.

277 Overall, the zero-inflated Bayesian models are robust methods. They consis-
278 tently provide small bias and accurate coverage in the simulated scenarios. In
279 the following case study, we further illustrate the advantages of the zero-inflated
280 hierarchical models.

281 5. Case study: anthelmintic resistance in Swedish sheep flocks

282 In order to illustrate our proposed model, we re-analyze the data in a
283 study where the prevalence of anthelmintic resistance in parasitic nematodes
284 in Swedish sheep flocks was investigated (Höglund et al., 2009). The FEC data
285 was collected and analyzed using both the FECRT and molecular testing meth-
286 ods. In the study, a total of 45 farms were randomly selected throughout Swe-
287 den, each with a minimum of 20 ewes. During the grazing season of 2006 and
288 2007, two flocks of approximately 15 lambs were selected from each farm, each
289 flock was treated with either a benzimidazole (BZ), albendazole (Valbazen[®],
290 Pfizer) or a macrocyclic lactone, ivermectin (Ivomec[®], Merial). In this paper,
291 we only consider the efficacy of BZ, which was received by 45 out of all 90
292 flocks selected. However the model is applicable for other treatments as well as
293 other livestock. Each lamb was sampled before treatment using the modified
294 McMaster technique with an analytical sensitivity of 50. 39 out of 45 flocks
295 with mean of at least 50 epg was re-sampled using the same setting 7-10 days
296 after treatment, with flock sizes varying between 10 to 17 animals. In addition
297 to the McMaster counting technique, the BZ-resistance of parasites was tested

298 using a pyrosequencing assay. Larval cultures indicated that *Teladorsagia* and
299 *Trichostrongylid* nematode infection were predominant.

300 There are 39 flocks consisting of 575 animals in total, all of them were treated
301 with BZ. The post-treatment FECs are missing in 28 animals, hence they are
302 excluded from the analysis. In addition, one animal had a pre-treatment egg of
303 30, which is not possible with a correction factor of 50. In this case, the author
304 clarified that 3 eggs were observed outside the grid area on the McMaster slide,
305 hence a correction factor of 10 was applied. However according to WAAVP
306 guideline, eggs outside the grid should not be counted, hence this particular
307 observation was set to zero. Using FECRT, we first calculate the reduction
308 in FECs and its approximate 95% CI. The decision rule for sheep and goats
309 suggested in the WAAVP guidelines is used for deciding anthelmintic resistance.
310 In 35 flocks, all of the post-treatment counts were zero which resulted 100%
311 reduction in each flock. The CI for those flocks cannot be computed using the
312 FECRT. Out of the remaining 4 flocks, the parasite in 2 flocks (flock 33 and 39)
313 are anthelmintic resistant according to the FECRT. The results based on the
314 molecular testing suggested 5 out of 39 flocks (flock 24, 33, 36, 37 and 39) have
315 anthelmintic resistance present using the codon 200 TAC allele frequency of
316 $\geq 95\%$ as the indicator. In the end, the authors concluded that the prevalence
317 of anthelmintic resistance in the Swedish sheep population is relatively low,
318 however it is more widespread than the FECRT indicated. The paper pointed
319 out the urgent need to develop alternative diagnostic procedures. The quasi-
320 Poisson regression gave similar results, failing to detect the remaining resistance.

321 In the following, we re-analyze the FECs data from the Swedish sheep study
322 using our proposed model. The worm burden differs depending on the animals
323 and the type of parasites eggs that is being counted, hence the choice of hy-
324 perparameters for the prior should be based on similar studies. According to
325 another study of the distribution of trichostrongylid eggs in the sheep flocks
326 (Morgan et al., 2005), the mean pre-treatment FECs ranged from 43 to 1915,
327 and the estimated dispersion parameter based on negative binomial regressions
328 ranged from 0.18 (95% CI: 0.10 to 0.32) to 2.3 (95% CI: 0.2 to 4.2). Hence we

Flock	FECRT	quasi-Poisson	PoGa(mode)	ZIPoGa
24	99.0 (96.3, 99.8)	99.0 (97.2, 99.7)	99.0 (98.5, 99.4)	97.8 (95.8, 98.9)
33	82.2 (65.4, 90.8)	82.2 (68.6, 90.0)	81.3 (77.4, 85.9)	76.8 (70.6, 81.8)
36	97.5 (90.6, 99.4)	97.5 (93.2, 99.1)	97.6 (93.1, 99.2)	97.4 (93.1, 99.2)
37	100.0 (–, –)	100.0 (100.0, 100.0)	<i>99.3 (89.5, 100.0)</i>	<i>98.8 (49.3, 100.0)</i>
39	92.3 (62.9, 98.4)	93.9 (90.1, 96.3)	92.6 (89.0, 94.8)	93.1 (89.7, 95.6)

Table 1: Analysis results for the five BZ treated flocks which the molecular testing indicated anthelmintic resistance are present. Results are shown for the estimated percentage reduction in FECs using the FECRT, quasi-Poisson regression, the PoGa and the ZIPoGa hierarchical models. The 95% CI are shown for the first two methods, while the 95% HPD intervals are shown for the hierarchical model. The text is in **bold** if a resistance is detected, and is in *italic* if a resistance is suspected.

329 assign a weakly informative prior $\text{Gamma}(1, 0.001)$ to μ , where 90% of the prob-
330 ability mass lies between 59 and 2996, and assign a $\text{Gamma}(1, 0.7)$ prior for κ ,
331 where 90% of the probability mass lies between 0.1 and 4.3 with a prior median
332 of 1. We assume the overall level of infection does not increase after treatment
333 is applied, hence the reduction should always be between 0 to 100%. A non-
334 informative prior $\text{Beta}(1, 1)$ is assigned to the parameter δ , such that all the
335 values between 0 and 1 are equally likely a priori. Finally for the zero-inflation
336 parameter ϕ , we assign a non-informative $\text{Beta}(1, 1)$ prior.

337 We apply the zero-inflated Bayesian model for the paired design separately to
338 each flock. In order to diagnose the potential non-convergence, 4 MCMC chains
339 were requested. Each has 12,000 MCMC samples, 2,000 samples for burn-in and
340 without thinning. There was no evidence of non-convergence with potential scale
341 reduction factors (Brooks and Gelman, 1998) approximately equal to 1. The
342 sensitivity analysis showed similar results with wide uniform priors on the mean
343 and dispersion, here we only present the main results. Table 1 shows the results
344 for the five flocks which the molecular data indicated anthelmintic resistance.
345 The approximate CI cannot be computed for flock 37 using the FECRT, since
346 all the post-treatment FECs are zero. Because the standard FECRT method
347 does not take the paired structure into account, the approximate CI is wider in
348 general compares to the quasi-Poisson regression and the Bayesian models. The
349 Bayesian models are able to obtain an interval estimate even when the reduction
350 is 100%. The posterior mode estimate for the Bayesian model without zero-

351 inflation is similar to the FECRT, however the zero-inflated Bayesian model gave
 352 slightly different estimates. In particular, the posterior mode for the reduction in
 353 flock 33 is 76.8% using our proposed model, compare to 82.2% and 81.3% in the
 354 FECRT and PoGa(mode). Indeed, the mean reduction calculated using Eq. (1)
 355 is 82.2%, however this completely ignores the paired structure. The actual mean
 356 pairwise reduction for flock 33 is 73.1%, hence our proposed ZIPoGa model
 357 provide a more sensible result in this case. For flock 37, the Bayesian models
 358 classify it as suspected resistance due to its lower confidence limit. Since no
 359 parasite eggs were detected in 7 out of 13 sheep before treatment, the uncertainty
 360 in the treatment efficacy is high. Hence the interval estimate is much wider,
 361 which is only captured by the zero-inflation model. The other classification
 362 results stay the same.

Fig. 5: Estimated reduction in mean FECs and its 95% HPD interval for the 39 flocks that were sampled both before and after treated with BZ. Using the WAAVP guideline for the decision of anthelmintic resistance, the intervals in solid black lines belong to flocks with no anthelmintic resistance, intervals in dashed lines belong to flocks with suspected resistance and intervals in solid gray lines belong to flocks with resistance. The flock numbers that were flagged as resistant using molecular data are colored in grey.

363 Fig. 5 shows the estimated reductions and its 95% HPD intervals for all 39
 364 flocks considered in the case study. There are several flocks that are flagged
 365 as suspected resistance even though there were no eggs present in the post-
 366 treatment FECs. For example, flock 35 has 15 sheep, all of which had zero
 367 post-treatment FECs. However, 10 out of 15 sheep had zero pre-treatment
 368 counts, those could be the unexposed individuals that should not contribute
 369 to the estimation of treatment efficacy. This is captured by the zero-inflated
 370 model, hence the HPD credible interval for this flock is wide.

371 6. Discussion

372 In this paper we propose zero-inflated Bayesian hierarchical models for es-
 373 timating the reduction in FECs. The models capture the additional sources

374 of variability in the data, and allow for extra zero counts that are frequently
375 observed in practice due to unexposed animals. The simulation results suggest
376 that the zero-inflated Bayesian hierarchical models are robust methods to es-
377 timate the reduction, in both unpaired and paired designs. They consistently
378 provide small bias and good coverage in all the simulated scenarios even though
379 we did not simulate exactly according to our model specification. The case
380 study further illustrated the advantages of our proposed model, which can ac-
381 curately model the paired structure and provide an interval estimate where the
382 conventional method cannot. The extra uncertainty in reduction introduced by
383 the zero counts was only reflected in the proposed zero-inflation model.

384 An advantage of the Bayesian approach is that it does not only provide
385 the reduction estimate and the credible interval, but also it offers density dis-
386 tributions of the model parameters. Denwood et al. (2010) pointed out that
387 Bayesian methods allow for probabilistic classification on the efficacy, in terms
388 of the probability that a true reduction is below a given threshold. According to
389 the WAAVP guidelines, there are three possible decision outcomes on resistance
390 status, namely “yes”, “suspected” and “no”. Such trichotomy outcome should
391 be interpreted with caution, especially at the decision boundaries. We illustrate
392 the probabilistic view using flock number 37 and 39. Fig. 6 shows the posterior
393 marginal density of the reduction parameter $(1 - \delta)$ from the proposed model.
394 Coles et al. (2006) stated that a reduction greater than 95% is considered as
395 beneficial, hence we use this as the threshold. The shaded area in each case
396 corresponds to the probability that the reduction in mean FECs is less than
397 95%, i.e. the probability that anthelmintic resistance is present using a 95%
398 reduction as the threshold. Based on the posterior marginal distribution, the
399 probability that the resistance is present in flock 37 is 0.42, indicating moderate
400 evidence for resistance. For flock 39, the probability is 0.94 which suggests a
401 very strong evidence that the resistance is present.

Fig. 6: The marginal posterior density for the reduction $(1 - \delta)$ for flock 37 and 39. The shaded area represents the density mass for reduction less than 95%.

402 Another advantage of the Bayesian hierarchical models is its flexibility in
403 model formulation. In this paper we have assumed the reduction in FECs is the
404 same for every animal, as one can expect the efficacy of anthelmintic treatment
405 across animals are similar within a resistant community. However each animal
406 can experience different efficacy due to different metabolism or drug availability
407 (Cabaret and Berrag, 2004), one can adjust the model to introduce animal-
408 specific reductions. Sufficient data are required to ensure the convergence of
409 the model. In the case study, if researchers are interested in assessing the an-
410 thelmintic resistance in the Swedish sheep population in general, a hierarchical
411 meta-analysis model over all the flocks can be formulated. The corresponding
412 model parameters from each flock would follow the same distributions, for exam-
413 ple, the parameter μ from each flock together follows a normal distribution with
414 some population mean. This can be particular useful if one wishes to consider
415 some national treatment schemes applied to the entire sheep population.

416 The proposed Bayesian models are implemented using efficient MCMC al-
417 gorithm in the “eggCounts” package (Wang and Paul, 2016) in R. A website
418 application that features all the basic functionalities of the package is available
419 at <http://t.uzh.ch/D1> (Furrer et al., 2016), it has a easy-to-use interface and
420 is designed for practitioners who do not have sufficient R knowledge.

421 Currently, the models assume the counts belong to the same species of par-
422 asites. However if there is a mixture of parasite species with different infection
423 level, one expects a multi-modal distribution from the counts. Additionally if
424 there is a different reduction for each species of the mixture, then the reduc-
425 tion parameter also follows a multi-modal distribution. Instead of a gamma
426 distribution in Eq. (3)–(5), a mixture of Gamma distribution with an additional
427 weight parameter for each component of the mixture could be used. Different
428 possibilities of reduction from each species need to be carefully considered in
429 the presence of mixture.

430 With the proposed models in mind, one can also design more efficient sam-
431 pling process in order to obtain the estimated FEC reduction with sufficient
432 statistical power. The sample size and the analytical sensitivity are the two

433 important factors involved in a study design. The CIs are expected to be nar-
434 rower for larger sample size and higher analytical sensitivity. The minimum
435 sample size required for a reliable estimation of the reduction and the influence
436 of analytical sensitivity can be further investigated for the zero-inflated Bayesian
437 hierarchical models.

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573 **Figure captions**

574 Fig. 1 Boxplots of the estimated FECs reduction in the unpaired design,
 575 using FECRT with approximated CI (FECRT); the hierarchical model without
 576 zero-inflation (Wang and Paul, 2016) and using the posterior median of $(1 -$
 577 $\bar{Y}_i^C / \bar{Y}_i^T)$ as the point estimate (PoGa(median)); the hierarchical model without
 578 zero-inflation (Wang and Paul, 2016) and using the posterior mode of $(1 - \delta)$
 579 as the point estimate (PoGa(mode)); our proposed zero-inflated hierarchical
 580 model for the unpaired design (ZIPoGa); and parametric bootstrap (pBoot).
 581 The horizontal line indicates zero bias.

582 Fig. 2 Barplots of the coverage probability of the 95% CIs, or HPD credible
 583 intervals for the FECs reduction in the unpaired design. The error bars are
 584 calculated based on the 95% binomial confidence interval. The horizontal line
 585 indicates 95% coverage. The methods are the same as described in Fig. 1.

586 Fig. 3 Boxplots of the estimated FECs reduction in the paired design, us-
 587 ing FECRT with approximated CI (FECRT); the hierarchical model with-
 588 out zero-inflation (Paul et al., 2014) and using the posterior median as the
 589 point estimate (PoGa(median)); the hierarchical model without zero-inflation
 590 (Paul et al., 2014) and using the posterior mode as the point estimate (PoGa(mode));
 591 our proposed zero-inflated hierarchical model for the paired design (ZIPoGa);
 592 and quasi-Poisson regression (qPois). The horizontal line indicates zero bias.

593 Fig. 4 Barplots of the coverage probability of the 95% CIs, or HPD credible
 594 intervals in the case of Bayesian models, for the FECs reduction in the paired
 595 design. The error bars are calculated based on the 95% binomial confidence
 596 interval. The horizontal line indicates 95% coverage. The methods are the
 597 same as described in Fig. 3.

598 Fig. 5 Estimated reduction in mean FECs and its 95% HPD interval for the
 599 39 flocks that were sampled both before and after treated with BZ. Using the
 600 WAAVP guideline for the decision of anthelmintic resistance, the intervals in
 601 solid black lines belong to flocks with no anthelmintic resistance, intervals in
 602 dashed lines belong to flocks with suspected resistance and intervals in solid

603 gray lines belong to flocks with resistance. The flock numbers that were flagged
604 as resistant using molecular data are colored in grey.

605 Fig. 6 The marginal posterior density for the reduction ($1-\delta$) for flock 37 and
606 39. The shaded area represents the density mass for reduction less than 95%.