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Using seasonal-trend decomposition based on loess (STL) to explore temporal patterns of pneumonic lesions in finishing pigs slaughtered in England, 2005–2011

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Abstract: Enzootic pneumonia (EP) is responsible for considerable economic losses in pig production. This study analyses temporal variations of pneumonic lesions present in slaughtered finishing pigs utilising a novel analytical tool – STL decomposition. Using data collected over a 6-year period starting in July 2005, time-series analyses were conducted to identify trend and the presence of seasonal variations to support industry led measures to monitor and control this important respiratory disease. In England, the BPEX Pig Health Scheme monitors the occurrence of EP in slaughtered finished pigs by identifying its gross pathology, enzootic pneumonia-like (EP-like) lesions. For visual analytics, the monthly prevalence for EP-like lesions was modelled using STL, a seasonal-trend decomposition method based on locally-weighted regression. A binomial generalised linear mixed-effects model (GLMM), accounting for clustering at batch level, was used to test the significance of the trend and seasonality. A mean of 12,370 pigs was assessed per month across 12 pig abattoirs over the study period. A trend toward reduction in prevalence of EP-like lesions during the first 3 years of BPHS, followed by an increasing trend, was identified with STL. This feature was consistent with the presence of a statistically significant positive quadratic term (“U” shape) as identified using the GLMM inference model. November and December appeared in the STL explorations as higher seasonal peaks of the occurrence of EP-like lesions. These 2 months had a significantly higher risk of this disease (OR = 1.38, 95% CI: 1.24–1.54 and OR = 1.4, 95% CI: 1.25–1.58, respectively, with July taken as baseline). The results were reported back to the pig industry as part of the national monitoring investigations.

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**9Using seasonal-trend decomposition based on loess (STL) to
10explore temporal patterns of pneumonic lesions in finishing
11pigs slaughtered in England, 2005-2011.**

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331. Abstract.

34Enzootic pneumonia (EP) is responsible for considerable economic
35losses in pig production. This study analyses temporal variations of
36pneumonic lesions present in slaughtered finishing pigs utilising a
37novel analytical tool - STL decomposition. Using data collected over a
38six-year period starting in July 2005, time-series analyses were
39conducted to identify trend and the presence of seasonal variations to
40support industry led measures to monitor and control this important
41respiratory disease. In England, the BPEX Pig Health Scheme monitors
42the occurrence of EP in slaughtered finished pigs by identifying its
43gross pathology, enzootic pneumonia-like (EP-like) lesions. For visual
44analytics, the monthly prevalence for EP-like lesions was modelled
45using STL, a seasonal-trend decomposition method based on locally-
46weighted regression. A binomial generalised linear mixed-effects
47model (GLMM), accounting for clustering at batch level, was used to
48test the significance of the trend and seasonality. A mean of 12,370
49pigs was assessed per month across 12 pig abattoirs over the study
50period. A trend toward reduction in prevalence of EP-like lesions during
51the first three years of BPHS, followed by an increasing trend, was
52identified with STL. This feature was consistent with the presence of a

53statistically significant positive quadratic term (“U” shape) as identified
54using the GLMM inference model. November and December appeared
55in the STL explorations as higher seasonal peaks of the occurrence of
56EP-like lesions. These two months had a significantly higher risk of this
57disease (OR = 1.38, 95% CI: 1.24 - 1.54 and OR = 1.4, 95% CI: 1.25 -
581.58, respectively, with July taken as baseline). The results were
59reported back to the pig industry as part of the national monitoring
60investigations.

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62Key words: pneumonia; pig-information systems; time-series analysis;
63seasonal dynamics

64

652. Introduction.

66Respiratory disorders are regarded as the most serious diseases in
67modern swine production world-wide (Sorensen et al., 2006).
68Particularly in Great Britain, enzootic pneumonia-like (EP-like) lesions
69have been reported as the most prevalent respiratory condition
70detected through pig abattoir monitoring (Sanchez-Vazquez et al.,
712010a). Although EP-like lesions are not pathognomonic for a particular
72pathogen (Sibila et al., 2009), *Mycoplasma hyopneumoniae* is usually
73involved in this pathology (Sorensen et al., 2006; Meyns et al., 2011).
74Substantial economic losses have been attributed to this infection
75including reduced feed efficiency, reduced daily weight gain and

76increased production costs due to medication (Straw et al., 1989;
77Thacker, 2006). Since 2005 the BPEX Pig Health Scheme (BPHS) has
78monitored the occurrence of respiratory gross pathology in pigs
79slaughtered in England's main pig abattoirs. On a regular basis, swine
80veterinarians carry out detailed post-mortem examinations in parallel
81to the routine official food-safety meat inspections. BPHS offers
82consistent monitoring of the occurrence of EP-like lesions, which is
83used by the pig industry to evaluate the behaviour of national trends
84and to promote strategies leading to health recommendations aimed
85at addressing increasing trends, or to confirm favourable situations
86when the level of a disease is diminishing.

87

88Understanding the temporal patterns of a disease is an essential step
89in learning about its epidemiology. Time-series analyses aim to provide
90a concise description of data correlated through time - serial
91correlation. Exploratory methods and graphical representations are
92integral to understanding the complexity of serially correlated data
93(Diggle, 1990). This is particularly true where the sample is equivalent
94to the population or a large sample size is available (where, for most
95practical purposes, the sample behaves approximately equal to the
96population), in which statistical inference is secondary in favour of
97descriptive methods. In this respect BPHS, with six years of consistent
98monitoring in English abattoirs, offers a unique opportunity to explore

99the temporal patterns of the occurrence of EP-like lesions. An
100exploratory method well-established in other fields is a seasonal-trend
101decomposition based on locally-weighted regression (loess) widely
102known as “STL” (Cleveland et al., 1990; Hafen et al., 2009). The STL
103method is straightforward to use, allows for flexibility in specifying the
104amount of variation in the trend and seasonal components of time-
105series, and produces robust estimates that are not distorted by
106transient outliers (Cleveland et al., 1990). In particular STL offers
107excellent data visualization - visual analytics - (Hafen et al., 2009). STL
108has been widely used in several disciplines including environmental
109science, ecology, epidemiology and public-health (Cleveland et al.,
1101990; Chaloupka, 2001; Silawan et al., 2008; Hafen et al., 2009).

111

112This study analyses the six year trend of BPHS EP-like lesions and
113identifies the presence of seasonal variations, thereby investigating
114the progress (if any) made by the industry in controlling this
115respiratory disease. This paper presents a time-series investigation
116executed in two steps: firstly, visual analytics through STL are utilised
117to explore the temporal structure of this respiratory pathology; and
118secondly, an inference model, generalised linear mixed model (GLMM),
119is used to statistically test the significance of the temporal attributes.
120This paper is also intended as a reminder of the importance of data
121exploration in time-series analyses, and therefore places a particular

122emphasis on describing the graphical exploratory process executed
123with STL.

124

1253. Material and Methods.

1263.1 Data source.

1273.1.1 BPEX Pig Health Scheme.

128BPHS has monitored the occurrence of EP-like lesions across the
129largest pig abattoirs in England since July 2005. Veterinarians assess
130every second pig in a batch (up to fifty pigs assessed) for gross
131pathology. The scheme feeds back benchmarked results from abattoir
132inspections to the participating producers (i.e. those paying a fee to be
133part of the scheme). The inspections, however, include all the batches
134submitted to the abattoir on the assessment days regardless of their
135BPHS membership status. More detailed information about BPHS can
136be found elsewhere (Sanchez-Vazquez et al., 2011).

137

1383.1.2 Study sample.

139This study used all (members and non-members) BPHS records
140available from the 12 abattoirs that participated in BPHS from July
1412005 to June 2011. The abattoirs are geographically wide-spread
142across England (see Fig. 1). A total of 890,654 pigs (from 20,874
143batches) has been assessed over this six-year period, submitted from

1441,541 herds. The study data are the combined set of pigs assessed by
145BPHS.

146

1473.1.3 The EP-like lesion.

148EP-like lesions are reported for the following gross pathology: a red-
149tan-grey discoloration, collapse, and rubbery firmness affecting
150cranioventral regions of the lungs in a lobular pattern (Caswell and
151Williams, 2007). The lungs of every pig inspected were given a score
152that represents the approximate percentage of the parenchyma
153consolidated on a scale from 0 to 55. Because the aim of this study
154was to investigate the occurrence of EP-like lesions, a positive case
155was defined as a pig affected with any degree of lesion (score >0) and
156a negative when lesions were absent (score =0). This criterion has
157been used before to investigate risk factors associated with EP-like
158lesions (Sanchez-Vazquez et al., 2010a).

159

1603.2 Modelling.

1613.2.1 Time-series data.

162The time-series was composed of monthly prevalence estimates,
163computed as the number of pigs affected with EP-like lesions, divided
164by the number of pigs assessed. The seasonal cycle was studied yearly
165(12 months), and for the seasonal cycle subseries comprised the set of

166 observations for a particular month across the six years (e.g. all the
167 values for July, all the values for August, and so on).

168

169 3.2.2 Visual analytics, STL.

170 STL was utilized to model the EP-like lesions time-series of monthly
171 prevalences. STL is a filtering procedure for decomposing a time-series
172 into additive components of variation (trend, seasonality and the
173 remainder) by the application of loess smoothing models (Cleveland et
174 al., 1990; Chaloupka, 2001). Six parameters determine the degree of
175 smoothing in the trend and seasonal components (Cleveland et al.,
176 1990):

- 177 • n_p - the number of observations in each seasonal cycle.
- 178 • n_i - the number of loess smoothing iterations to update the trend
179 and seasonal components (usually set to equal one or two).
- 180 • n_o - the number of robustness iterations. With a value of zero no
181 robustness iteration is applied whilst values of one or more apply
182 increasing robustness, particularly above 5. This parameter is
183 chosen in combination with n_i .
- 184 • n_l - the span of the loess window for each subseries; it is
185 recommended to use the next odd number to n_p .
- 186 • n_s - the span of loess window for seasonal extraction. Low values
187 (e.g. from 7 to 10) favour the use of local data while higher

188 figures pool values from the equivalent time of the year across
189 the time-series.

190 • n_t - the span of the loess window for trend extraction, typically
191 computed as $[1.5n_p/(1-1.5n_s^{-1})]$.

192The adequacy of the model fit was assessed by four graphical
193diagnostic methods: (1) the decomposition plot; (2) the trend-
194diagnostic plot; (3) the seasonal cycle subseries plot; and (4) the
195seasonal-diagnostic plot. Following Cleveland et al. (1990) and Jiang et
196al. (2010), a number of models were constructed using different
197parameter values and assessing the results against the diagnostic
198plots. Further information on the method and parameters can be found
199in the original paper describing the STL method (Cleveland et al.,
2001990). The need for data transformation was evaluated utilizing normal
201quantile plots of the residuals, ensuring its distribution is well
202approximated by the normal distribution (Hafen et al., 2009).
203Additionally, marginal residuals plots as described by Fraccaro et al.
204(2000) were investigated to identify any pattern that could be of
205concern.

206

2073.2.3 Statistical inference, GLM/GLMM.

208Batch EP-like lesions prevalence was modelled against time in monthly
209intervals. The ranges of season variables influencing the prevalence
210considered were monthly, quarterly and six-monthly. BPHS

211membership status and abattoir were also examined as covariates to
212account for their potential confounding effect. A simple binomial
213model, GLM, was used as a starting point; this evolved into a binomial
214generalised linear mixed-effects model (GLMM). In this latter model
215clustering at batch level, farm level, and both farm and batch were
216examined. Time was modelled as a polynomial function to allow for
217flexibility beyond a simple linear relationship, according to the findings
218observed in the visual analytics. The goodness of fit metric, Akaike's
219Information Criterion (AIC), was used for comparison among the
220different model structures and also to compare nested models through
221a stepwise selection process of covariates. The Wald tests were used
222to examine and present the significance (p value <0.05) of the
223variables retained in the final model, particularly for those with
224multiple categories (i.e. month, abattoir). Residual diagnostic plots
225were used to detect features of concern in the model and to identify
226the presence of potential outliers. The purpose of the inferential
227models was to confirm major trends picked up by STL and therefore
228only main effects were considered. All the analyses and graphs were
229performed using the R statistical software environment (R
230Development Core Team, 2009) using the libraries stats, epicalc and
231lme4.

232

2334. Results.

234The mean number of pigs assessed per month was 12,370 pigs (95%
235CI: 11,793 - 12,947), with a mean of 290 batches (95% CI: 276 - 304).
236Of those, the monthly mean number of pigs from BPHS members was
2377,086 pigs (95% CI: 6,692 - 7,480) with a mean of 159 batches (95%
238CI: 150 - 168). A total of 252,941 pigs (from 18,387 batches) was
239affected with EP-like lesions across the whole study period which
240represent 28.4% of the total pigs inspected (28.7% of the members
241and 27.9% of non-members).

242

2434.1 Results from the STL explorations.

244Three of the parameters, n_s , n_i and n_o , required tuning through the use
245of the graphical diagnostic methods. For n_s 7 months was chosen, for n_i
246and n_o a robust option was chosen being 1 and 5 respectively. The
247other three parameters were predefined following the
248recommendations from Cleveland et al. (1990), being $n_p=12$ months,
249 $n_l=13$ months and $n_t=23$ months.

250

251The STL fitted trend was observed in the decomposition plot (Fig. 2a) in
252comparison with the raw data. It shows a decline in prevalence
253between 2006 and 2008; falling from 34% of the pigs affected to 27%,
254after which it started to increase reaching 30% in June 2011. In the
255trend-diagnostic plot (Fig. 3a) the trend is compared with the

256 remainder, in graph (b) the two longest vertical lines in the remainder,
257 one in March 2006 and other in December 2007, appear as outliers.

258

259 The STL seasonal component observed in the decomposition plot (Fig.
260 2b) suggests an increase of EP-like lesions in November-December,
261 and a main drop in July. It also shows variation across years, with the
262 seasonality being more marked over the last three seasonal cycles for
263 most of the months. This interannual variation is more obvious in the
264 seasonal cycle subseries plot (Fig. 4), where particularly for July and
265 November, it is possible to appreciate the yearly seasonal values
266 becoming more distant from 0 on the last three seasonal cycles. The
267 seasonal diagnostic plot (Fig. 5) compares the fitted monthly values
268 within the cycle subseries for each year with the remainder. This
269 suggests the seasonal smoothing is robust to more outlying
270 observations such as March 2006 and December 2007.

271

272 4.2 Results from the GLM/GLMM testing.

273 The model allowing for clustering in the data at batch level was the
274 model that provided the best fit to the data. A quadratic term for trend
275 (measured in monthly intervals) gave a better fit to the data
276 ($AIC=76,129$) than a linear relationship ($AIC=76,237$). The results for
277 the final multivariable GLMM are presented in Table 1. The estimated
278 coefficient defining the quadratic term (16.37, 95% CI: 13.06 - 19.68)

279 indicates that the trend for EP-like lesions followed a “U” shape.
280 Compared to July (the month with the lowest prevalence acting as
281 baseline), November and December had a significantly higher risk of
282 EP-like lesions (OR = 1.38, 95% CI: 1.24 - 1.54 and OR = 1.4, 95% CI:
283 1.25 - 1.58, respectively). There were weak but significant differences
284 between members and non-members, with non-members having a
285 lower prevalence of EP-like lesions over the period studied, (OR = 0.94,
286 95% CI: 0.89 - 0.98). The inclusion of abattoir in the model improved
287 the model fit, indicating significant differences in the risk of EP-like
288 lesions between the different abattoirs compared to abattoir “A” that
289 was taken as the baseline. Exploratory analyses of the residuals
290 suggest that the chosen model was not inappropriate for the data.

291

2925. Discussion.

293 This study has utilised the STL methodology to robustly identify the six
294 year trend and seasonal pattern for EP-like lesions in finishing pigs in
295 England. The data source was the BPEX Pig Health Scheme, which
296 offered a large sample size of consistent abattoir monitoring providing
297 a suitable opportunity to explore temporal patterns. By utilising STL,
298 this paper maintains transparency in the explorations to identify the
299 sources of variation in the time-series (i.e. the trend, the seasonality
300 and a remainder). Both STL and GLMM results are consistent; thus, the

301inferential statistical testing assisted in confirming the findings from
302the exploratory process.

303

3045.1 The trend and seasonality.

305The GLMM identified a significant quadratic trend, which was described
306by STL as a decline in the occurrence of EP-like lesions between 2006
307and 2008 (the first three years of BPHS), followed by a period of
308increasing prevalence. The occurrence of EP-like lesions results in
309important economic losses for the industry, particularly due to the
310worsening in feed efficiency and mean daily gain as a result of pigs
311being affected by EP (Straw et al., 1989; Straw et al., 1990). The initial
312prevalence reduction detected could, in principle, be attributed to the
313impact of the scheme on the overall health of the pig units.
314Veterinarians reacted to the feedback received for the prevalence of
315EP-like lesions, implementing measures to reduce it. These measures
316were conceivably extended to BPHS non-member herds, as has been
317discussed before (Sanchez-Vazquez et al., 2011). Moreover, non-
318members appear to have maintained a slightly lower level of disease
319than members. This apparently paradoxical situation could be also
320explained by the reluctance of some breeding units to join the scheme
321since they have their own abattoir monitoring system for respiratory
322diseases, and such herds are normally in good health and EP free. The
323reason behind the increasing trend over the last three years (which

324also corresponded to a more marked seasonal pattern) is unclear, but
325it could reflect a relaxation in the use of *M. hyopneumoniae* vaccines.
326The results from this study were fed back to the industry board, whose
327role it is to inform field veterinarians and producers of the current
328situation.

329

330This STL investigation chose a small value to define the span of loess
331window seasonal extraction to allow for flexibility in the seasonality
332explorations for each year, rather than pooling the values for the same
333month across years, which could have potentially distorted the
334patterns (Hafen et al., 2009). The STL and GLMM results show the
335prevalence of EP-like lesions increasing at the end of the year
336(November and December) and declining in summer (July), a trend
337particularly obvious over the last three years. This pattern is consistent
338with that reported in most of the previous studies (Elbers et al., 1992;
339Stark, 2000) and that which has been observed in the syndromic
340surveillance of English growers and weaners (NADIS, 2008). Given that
341the life-span of EP lesions is at least two months, and that it could be
342detected as early as two weeks after infection (Caswell and Williams,
3432007), the November-December peaks may be reflecting farm
344challenges occurring across the whole autumn (from September to
345December). Done (1991) explained how housed pigs may have poorer
346air quality due to reduced housing ventilation over colder months in

347the trade off for maintaining the indoor temperatures; a practice which
348may lead to an increase in the incidence of pneumonia.

349

3505.2 STL in the context of time-series analyses techniques.

351Time-series analyses, particularly those focussed on seasonal-trend
352decomposition, are scarce in the veterinary literature. Three of the
353most typical methodologies for which examples in the veterinary field
354can be found are: (1) moving average (MA) models (Arc Moretti et al.,
3552010), (2) generalised additive models (GAM) (Jore et al., 2010), and
356(3) linear regression (and its generalizations (GLM)) (Ward, 2002). MA
357is probably the simplest statistical technique available for decomposing
358time-series, and among these three techniques, is the only one directly
359comparable to STL as they are both filtering procedures. In MA, the
360filtered value is the averaged results within a predefined slide time-
361window producing a series of subsets with averaged values. In STL, the
362loess iterations are regulated by predefined parameters allowing the
363model to account for several factors (e.g. robustness, smoothing),
364offering more flexibility than MA models and providing a better fit to
365the data. The GLM and GAM belong to a different group of analytic
366techniques than STL. Those are inference models which allow the
367possibility of testing the statistical significance of the time components
368and accounting for different covariates. Change point models
369(Christensen and Rudemo, 1996) and Kalman filter (de Mol et al., 1999)

370are also examples of other methods utilised in the veterinary field to
371explore changes in time-series. These models are not designed to
372decompose time-series but are more focussed on optimising the
373detection of significant changes in the occurrence of an event of
374interest.

375

376STL is presented here as an analytical tool for veterinary
377epidemiologists when tackling time-series explorations, being (i) a
378valid alternative to MA, (ii) a complementary method to GLM and GAM
379inference analyses, and (iii) a way to obtain temporal parameters that
380can be used to inform change-point and Kalman filter models. STL
381methodology produces robust outputs that provide a good fit to the
382data, maintains the transparency across the time-series decomposition
383(by examining the different diagnostic plots devised to work with this
384technique), and, what is perhaps its main strength, is ready and
385accessible for non-specialist analysts by utilising, for example,
386statistical packages that incorporate code to support the use of this
387methodology (e.g. STL function in R (R Development Core Team,
3882009)). STL methodology was originally presented for count data but it
389has also been proved suitable to model binomial data in occurrence of
390disease as proportions (Bollag et al., 2005; Silawan et al., 2008), as has
391been presented in this paper.

392

393 Another typical objective when fitting models to time-series data is the
394 prediction of future values. Jiang et al. (2010) compared STL with other
395 widely-used methodologies to produce forecasting models with the
396 presence of seasonal variation, seasonal autoregressive integrated
397 moving average (SARIMA) and dynamic harmonic regression (DHR),
398 concluding that the three methods are effective for time-series
399 analysis.

400

401 5.3 Large scale monitoring schemes.

402 This paper is an extended example of the analyses that are periodically
403 performed on the BPHS data to explore the time components of the
404 different lesions investigated through the scheme. BPHS abattoir
405 records have been considered to provide reliable trends (Stark and
406 Nevel, 2009) and this system of detailed post-mortem inspection is
407 presumed to have good sensitivity and specificity. A similar inspection
408 system, also focused on a limited number of organs and pigs, was
409 found to have good classification characteristics (Enoe et al., 2003).
410 The presence of operator bias affecting the gross pathology
411 classification over time cannot be ruled out; this is unlikely to happen,
412 however, as BPHS organises training and refresher days for the
413 veterinarians and conducts internal comparisons on the same pigs
414 assessed by different veterinarians, aiming to maintain assessor
415 consistency over time. On the whole, any imperfection in the scoring in

416this investigation could be considered randomly distributed over time
417and it would have been reflected in our study as statistical noise
418allocated in the remainder. The difference in prevalence of EP-like
419lesions observed across the abattoirs is likely to represent genuine
420differences across farm (clusters/geographical areas) due to the
421uneven distribution of specific respiratory pathogens or the effect of
422health strategies implemented by the different pig groups and
423veterinary practices (Sanchez-Vazquez et al., 2010a). In a previous
424investigation (Sanchez-Vazquez et al., 2010b), it was observed that
425BPHS participating abattoirs appeared to capture the pig shipments
426from neighbourhood farms.

427

428The BPHS offers a very large sample size – an average of 12,370 pigs
429per month were assessed – and in this scenario, statistical inference is
430secondary in favour of descriptive methods. The larger the sample size
431the closer the sample will be to the population and the more likely it is
432to find statistically significant results in the inference models. This
433situation is demonstrated in this paper, where the temporal features
434extracted by visual analytics are consistent with those from the
435inference model, after accounting for the effect of other potential
436confounding covariates. The study population was those pig herds
437assessed over time by BPHS. However, these findings could confidently
438be extrapolated to the English commercial pig finishing units (i.e. the

439reference population), as the BPHS assessments are likely to be highly
440representative of the monthly cross-sectional disease prevalence
441occurring in these pig units.

442

4436. Conclusion.

444The evolution of EP-like lesions between July 2005 and June 2011
445followed a “U” shape, with the initial reduction occurring during the
446first three years. The occurrence of this respiratory condition shows a
447seasonal pattern with the lowest level observed in July and peaks
448occurring in November and December. STL has a clear application in
449veterinary population medicine, particularly on national diseases
450monitoring, and it can be used in conjunction with inference models.
451This work shows an example of the utility of abattoir health schemes
452based on detailed post-mortem inspection as a large-scale health
453monitoring tool.

454

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457reviewed the manuscript, for his contribution with technical expertise
458on pig production. We are also grateful for the comments on the
459results of this study from Derek Armstrong (BPEX) and other pig
460experts participating in the BPHS steering group.

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512Figure 1. Map of Great Britain showing England shaded, with dots
513representing the location of the 12 abattoirs included in the study.

514

515Figure 2. Decomposition plot of the prevalence of pigs affected with
516EP-like lesions in 12 English abattoirs (2005-2011), STL method. This
517plot assists evaluation of the trend, seasonality and remainder against
518the raw data. In the graph (a), the dots represent the monthly time-
519series for the proportion of pigs affected with EP-like lesions and the
520line is the STL fitted trend. The graph (b) is the STL seasonal pattern
521per 12 months. The values on 0 indicate no seasonal variation, as 0
522represents an inflection point across the STL extracted trend; anything
523over 0 indicates increasing seasonal pattern (i.e. above trend) in the
524proportion of EP-like lesions and below 0 indicates decrease (i.e. below
525trend). The graph (c) represents the remainder after the trend and the
526seasonal pattern have been fitted to the time-series values. The sum of
527the trend, the seasonal pattern and the remainder equals exactly the
528time-series (dots in the panel (a)). The units in the vertical axis
529represent the proportion of pigs affected with EP-like lesions.

530

531Figure 3. Trend-diagnostic plot of the prevalence of pigs affected with
532EP-like lesions in 12 English abattoirs (2005-2011), STL method. This
533plot assists to assess the fit of the trend to the data, which evaluates
534how much variation in the data other than seasonality goes into the
535trend and how much goes into the remainder - particularly useful for
536investigating the effect of the outliers on the trend. In panel (a) the
537points represent the STL fitted trend plus the remainder and the line is
538the STL trend. The panel (b) represents the remainder. The units in the

539vertical axis represent the proportion of pigs affected with EP-like
540lesions.

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542Figure 4. Seasonal cycle subseries plot of the prevalence of pigs
543affected with EP-like lesions in 12 English abattoirs (2005-2011), STL
544method. This plot assists in assessing dispersion of each value of the
545cycle subseries against their mean; thus providing an assessment of
546the historical seasonal pattern as well as the temporal behaviour of
547each monthly subseries. Each cycle subseries is graphed separately
548against years (from 2005 to 2011); the month for each cycle subseries
549being indicated by its initial in the horizontal axis. The horizontal line is
550the mean of the STL fitted monthly values for each cycle subseries
551(values from Figure 2 graph (b)). The fitted values (ends of vertical
552lines) in relation to the mean show the pattern of the interannual
553variation of the monthly subseries. The units in the vertical axis
554represent the proportion of pigs affected with EP-like lesions.

555

556Figure 5. Seasonal-diagnostic plot of the prevalence of pigs affected
557with EP-like lesions in 12 English abattoirs (2005-2011), STL method.
558This plot assists in assessing loess regression fit to the month across
559each year, evaluating how much variation in the data other than trend
560goes into the seasonal component and how much into the remainder.
561This plot helps to assess how the presence of outliers or transitional
562values with aberrant behaviour influences the results of the seasonal
563component. Each box represents a monthly subseries starting with
564January in the top left and progressing from left to right and from the
565top to the bottom. The initial for each month is used to identify the
566month in each box. The dots represent the STL fitted monthly values
567within the cycle subseries for each year, plus the remainder. The lines
568represent the STL fitted monthly values within the cycle subseries for
569each year. The units in the vertical axis represent the proportion of
570pigs affected with EP-like lesions.

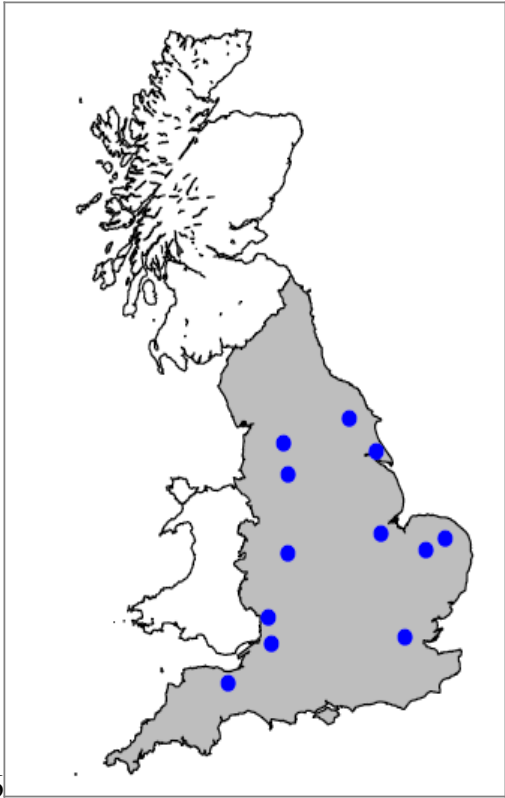
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572Figure 1.

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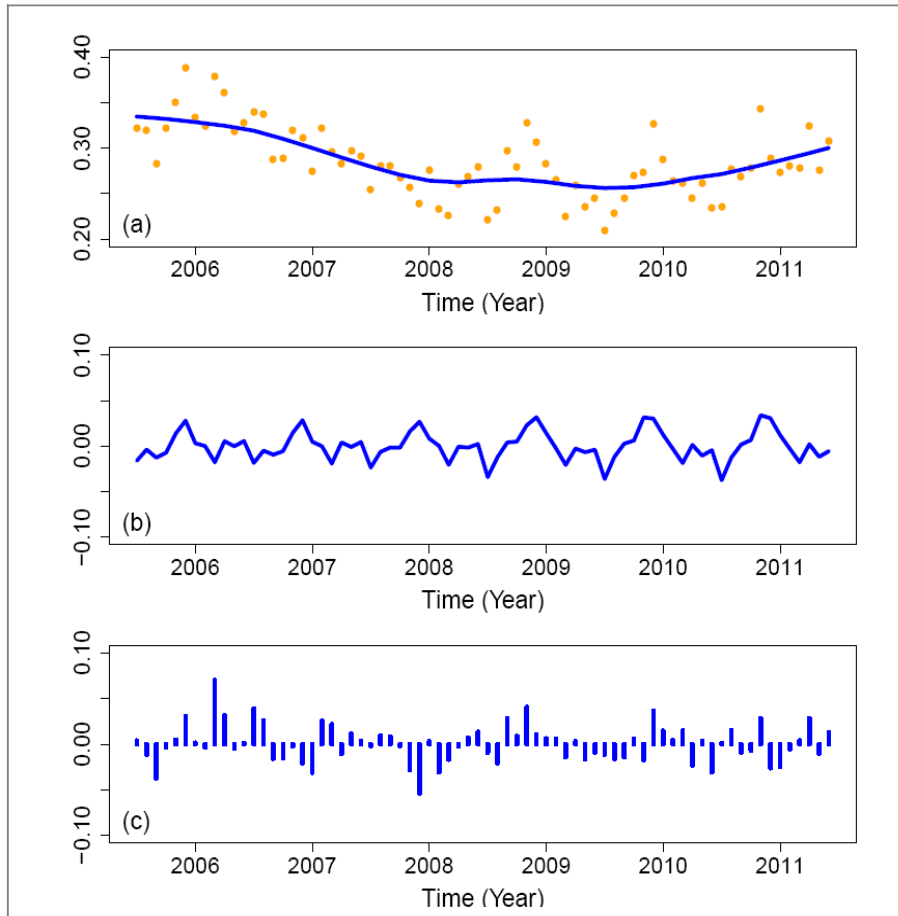
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587Figure 2.

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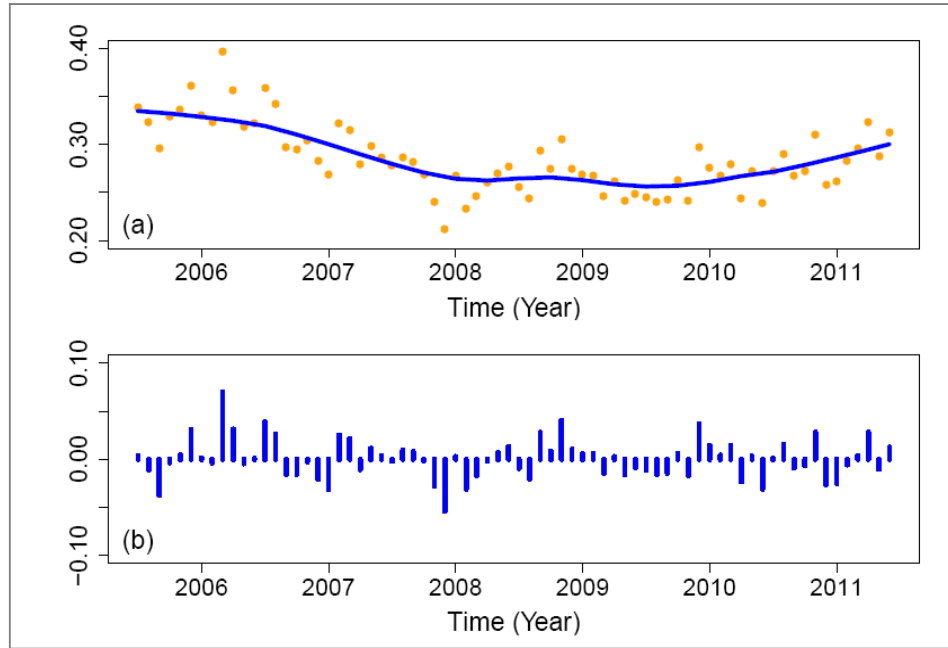
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599Figure 3.

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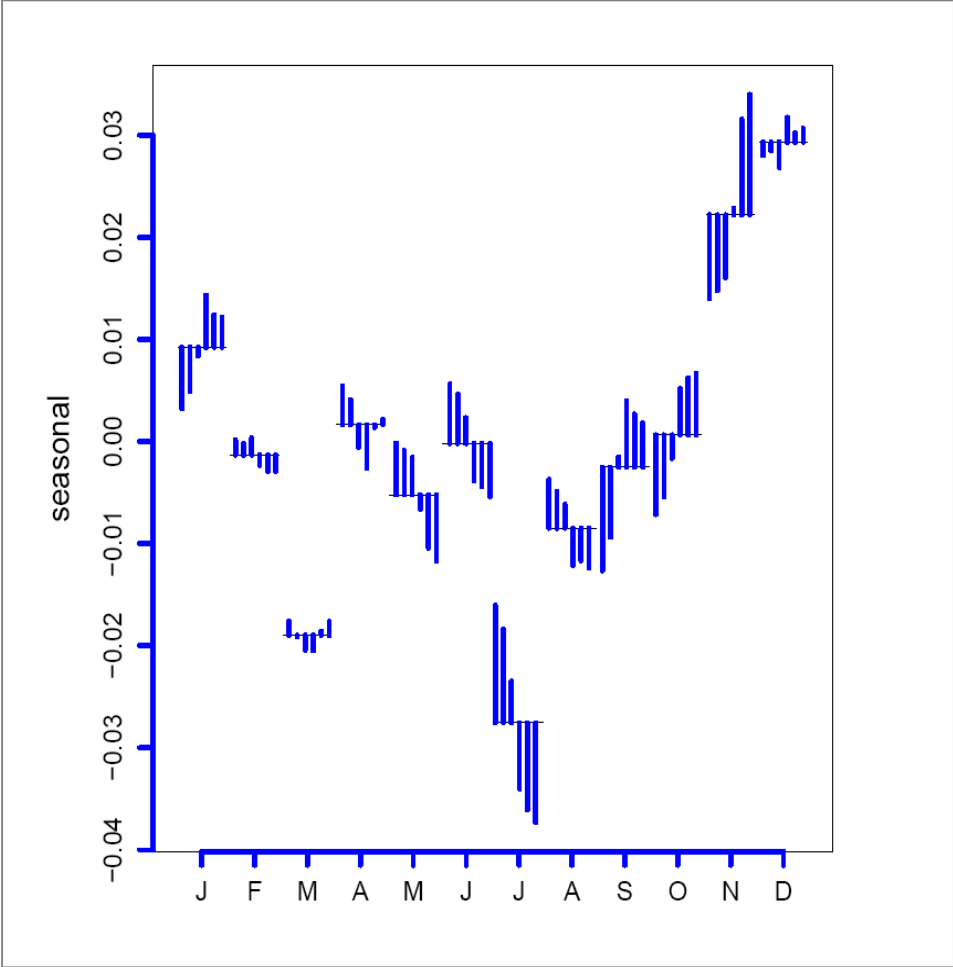
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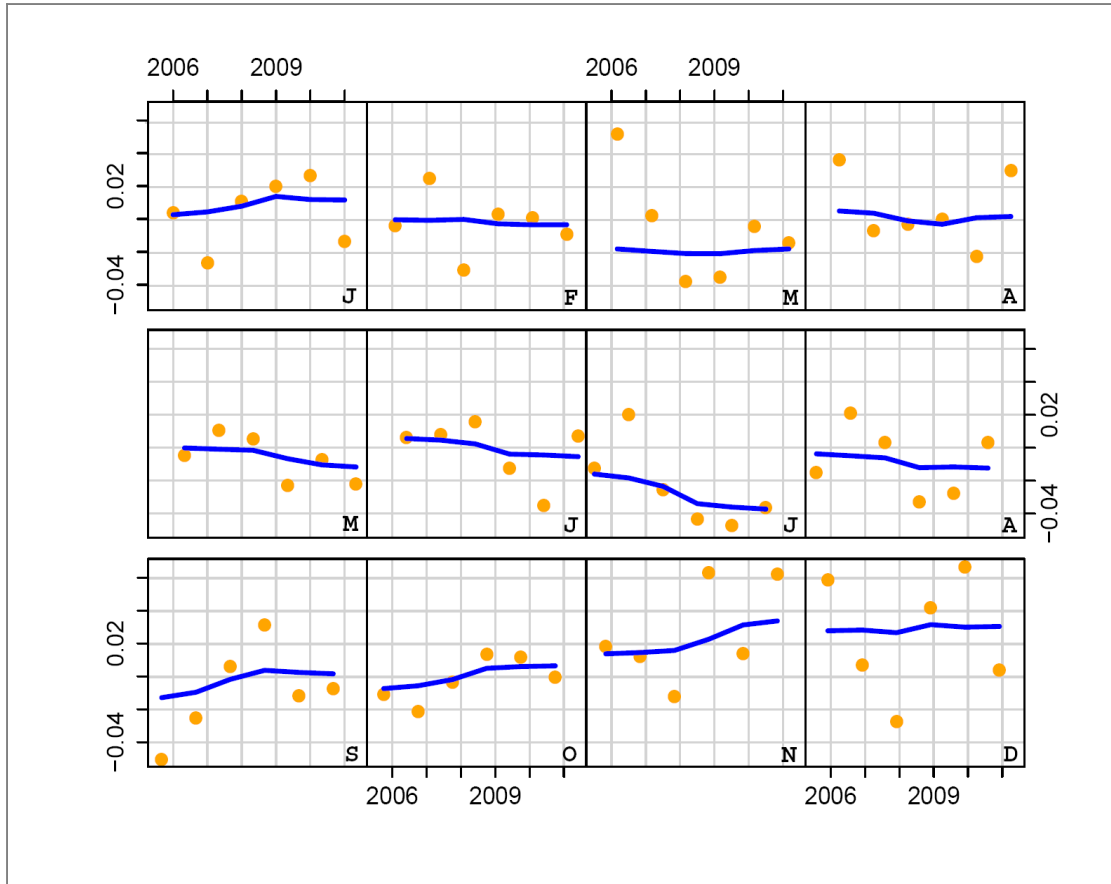
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633Figure 5.

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653 Table 1. Estimated coefficients for the linear and quadratic terms fitted
654 to the temporal trend and estimated odds ratios for the covariates in
655 the multivariable binomial generalized linear mixed-effects model for

656the prevalence of EP-like lesions in finishing pigs slaughtered in English
 657abattoirs accounting for clustering at batch level, 2005-2011.

658

Variable For random effects	Variance	Standard error of variance component		
Batch	2.42	1.56		

Variables For fixed effects	Level	Estimate / Odds ratio	95% confidence intervals	P- value
Trend	Linear term	-16.18 [‡]	-19.54, -12.82	<0.001
	Quadratic term	16.37 [‡]	13.06, 19.68	<0.001
Month	July (baseline)	1	-	-
	August	1.12 [‡]	1.01, 1.25	0.04
	September	1.14 [‡]	1.02, 1.27	0.017
	October	1.17 [‡]	1.05, 1.29	0.004
	November	1.38 [‡]	1.24, 1.54	<0.001
	December	1.4 [‡]	1.25, 1.58	<0.001
	January	1.28 [‡]	1.15, 1.43	<0.001
	February	1.27 [‡]	1.14, 1.42	<0.001
	March	1.16 [‡]	1.04, 1.3	0.007
	April	1.27 [‡]	1.14, 1.42	<0.001
	May	1.21 [‡]	1.08, 1.35	0.001
	June	1.19 [‡]	1.07, 1.33	0.002
Being a BPHS member	Member (baseline)	1 [‡]	-	-
	Non-member	0.94 [‡]	0.89, 0.98	0.005
Abattoir	A (baseline)	1	-	-
	B	0.98 [‡]	0.85, 1.14	0.818
	C	0.55 [‡]	0.51, 0.61	<0.001
	D	0.44 [‡]	0.35, 0.55	<0.001
	E	0.31 [‡]	0.27, 0.35	<0.001
	F	0.34 [‡]	0.31, 0.37	<0.001
	G	0.56 [‡]	0.51, 0.61	<0.001
	H	0.6 [‡]	0.53, 0.69	<0.001
	I	0.43 [‡]	0.37, 0.5	<0.001
	J	0.66 [‡]	0.59, 0.74	<0.001
	K	0.4 [‡]	0.36, 0.44	<0.001
	L	0.71 [‡]	0.64, 0.78	<0.001

659 Model based in a sample of 890,654 pigs from 20,874 batches.

660

661 ‡ Estimated coefficients for the linear and quadratic term (U shape) for EP
 662like lesion trend.

663 ¶ Odds ratios.