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Farmer's Attitude towards Disease Outbreak – Reactionary or Precautionary: A Case of Livestock Farmers in the Grootfontein Region of Namibia

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Abstract
Farmer's attitude towards disease outbreak was investigated with the aim of determining whether they can be classified as being reactionary or precautionary. They are more reactionary than precautionary if the level of mortality triggers more rapid positive reaction than the level of vaccine and vice versa. Using an aggregate clinical veterinary record from 2009 to 2015, the farmers' response to diseases were classified as *"poor", "fair"* and *"good"* and an ordered logit outcome model was fit. The result shows that the threat of mortality and the level of vaccine do not increase the likelihood of reporting on time. Farmers who vaccinated their livestock are less likely to report disease incidence on time compared to those who did not vaccinate. This is because their decision is influenced by the level of precaution they have previously embarked on. Consequently, they tend to embark on a wait-and-see attitude hoping the livestock will recover. On average, there is 28.74% probability that farmers' classified as "*poor*" will report clinical cases within 15 to 90 days. Similarly, farmers in the category classified as *"fair"* and *"good"* have 17.96% and 53.29% probabilities of reporting fairly and promptly respectively. The result shows that for a unit increase in mortality and the level of the vaccine, it is less likely that farmers' will report disease incidence within 1-5 days of onset. A more conspicuous presence of the veterinarian and extension services in the study area is recommended to facilitate training and reduced transaction cost faced by livestock farmers. Policy intervention is needed to reduce transaction cost and the stigma attached to farm quarantine and forced closures.
Keywords: Veterinary, ordered logit, reactionary, precautionary, mortality.

1. Introduction

Animal disease outbreaks present significant costs and risks to affected farmers, regions or countries especially if the disease is transboundary. According to Food and Agricultural Organization FAO (2016), transboundary animal disease (TAD) represents a big threat to national income, a potential drain on national budget, and an impediment to international trade. The economic impact of TAD on the economies of the developing countries could be enormous. For example, a country such as Namibia that generates large revenue from livestock exports, this could cause serious challenges as a result of an embargo on export by major trading partners, stricter livestock movement, and quarantine measures. In 2012, the total economic impact of future transboundary animal disease outbreak was estimated at N$6.8 billion (Thomson and Venter, 2012). On the other hand, there could be a spill-over effect of livestock disease outbreak to other sectors such as tourism and related industries (Rich, 2005). At the farm level, livestock diseases result in losses due to premature death and livestock degradation due to reduced live weight gain and market value. In most cases sub-clinical conditions reduce feed conversion rates and inhibit livestock development and productivity. On a large scale, disease conditions grossly affect productivity (Hawkins and Morris, 1978), resulting in welfare loss and increased food insecurity. An important question to be answered is how best can these challenges be mitigated?

One of the key ways is to adopt farm-level good animal health management and disease control measures which is a major challenge facing the sector. Livestock producers continually face decisions regarding the best management practices, effective and optimal disease control mechanism. The usual trade-off is either to prevent the disease from occurring or adopt a control measure when the disease incidence does occur. Adopting an *ex-ante* precautionary measure ensures resilience in the face of uncertainty and livestock health risk. Typical precautionary measures include: undergoing livestock vaccination exercise, testing, screening, isolation and culling of infected livestock. A typical *ex-post* control measure when infections do occur would be to urgently seek opportunities to mitigate impacts such as livestock treatment via veterinary services, extension personnel and other private or public service units. Early recognition and reporting of a disease condition increase the probability of a rapid and effective treatment and the chances of reducing mortality. In practice, it is observed that the situation is different especially in most rural communities. Clinical cases are not reported promptly, sometimes; farmers' report only when their livestock starts to die, in some occasions, clinical reports are made after a prolonged period say, three months, resulting in the loss of animals, in most cases, to preventable and curable diseases.

In lieu of these facts, this study seeks to explore the underlying option that best describes livestock farmer's attitude towards disease outbreak. The objective is to investigate farmer's attitude towards disease outbreak in the Grootfontein region of Namibia to determine whether they can be regarded as precautionary or reactionary. Do they (famers) respond to disease outbreak promptly as they should at the onset or is their response influenced by the increasing level of livestock mortality or the level of precaution they have undertaken especially through vaccination? The aim of the paper is to estimate the relationship between farmer's *response* (outcome variable) to disease outbreak and a set of independent variables (covariates) comprising; the number of *mortality* incurred and the *vaccination* record of the farmers using aggregate farm-level data from 2009 to 2015 compiled by the Department of Veterinary Service (DVS) in Grootfontein. Farmers' *response* is categorized into *poor*, *fair* and *good* according to the time lapse between the disease outbreak and the time it was reported to the DVS. This type of formulation involving the ordering of outcomes requires an outcome-based decision model. Therefore, an ordered logistic outcome-based choice model was used to estimate the probability of observing an outcome based on certain estimated ancillary (threshold) parameters or cut-points.

The North-East region of Grootfontein was chosen for this study because; it is a major agriculture and livestock production hub. With an average annual rainfall of 500mm, there is an extensive livestock farming activity and to a smaller extent, the production of maize, peanuts, sorghum, cotton, sunflower and various types of animal fodder. Breeding cattle and weaners are mainly produced in Grootfontein. Weaners are usually sold to speculators, ox-farmers and occasionally to the export market in South Africa. There are about 568 commercial farms in the Grootfontein district ranging from smallholdings of 25 ha to large cattle farms of more than 7,000 ha. The average extensive cattle farms normally range from 3,000 to 5,000 ha. According to the Namibian Statistical Agency (2012), there are about 159,049 livestock numbers in Grootfontein: Cattle number was 122,881 representing 77% of total livestock numbers; others are Sheep 21,558 (14%) and Goats 14,608 (9%). The farming community in the district is serviced by two government-owned experimental farms, a well-established agricultural extension office, and a veterinary office. These institutions play an active role in livestock disease surveillance, management, and control but whether these principles, surveillance, management and control are adopted by farmers is not know with certainty. The paper provides several important contributions to this effect. It highlights the need for more extension and veterinary services especially with regards to training, information dissemination, improvement of the general animal health management practices and strengthening policy on best practices.

The rest of the paper is structured as follows: Section 2 discusses the role of institution and stakeholders in disease surveillance, management, and control. This is followed by the conceptual framework underlying the study in section 3. In section 4, the model used to specify the concept is presented. Section 5 discusses data and method of estimation. Empirical results and discussions are presented in section 6. Concluding remarks and recommendations are made in section 7.

2. Disease surveillance, management and control.

Like many livestock exporting countries, livestock plays an important role in the life of many farmers in Namibia. Livestock production is the backbone of the 70% rural economy which depends on it for their sustenance. It is a major source of revenue for the Namibian economy. According to the Meat Board of Namibia (2014), export of red meat (mainly to the European Union and South Africa) amounts to N$160 million per year. However, cost constraint with regards to livestock diseases can cause significant economic losses thus an important course for a drastic measure to properly manage animal health and diseases outbreaks. Several institutions and stakeholders are responsible for animal health management including, public extension policies and advisory services. These include the Ministry of Agriculture, Water, and Forestry (MAWF); the Directorate of Agricultural Extension and Engineering Services (DAEAS); the Directorate of Veterinary Services (DVS). Others are public research and educational institutions such as National Agricultural Research Institute (NARI); Agricultural Research and Development Institute (ARDI); Directorate of Research and Training (DART); the Universities and Polytechnics.

The Directorate of Extension and Engineering Services (DEES) provides agricultural extension services to farmers, agro-industry, and other stakeholders in the form of information dissemination, advisory and training services. In the bid to decentralize information, extension offices are located in the districts. They disseminate information to farmers during farmer's days, training sections and workshops. The Directorate of Veterinary Services (DVS) amongst others promotes optimal animal health, production efficiency, and improved reproduction rates. This is done to ensure that Namibian livestock and livestock products enjoy the secure access to local and foreign markets. The DVS control the movement of animals and therefore, control the spread of disease. They also issue permits for importing animals into Namibia and control the certification of animals and animal products for export from Namibia. They provide laboratory services through the central veterinary laboratory services in Windhoek, which deals with testing samples for signs of diseases. In case of a suspected notifiable disease on any farm, the DVS are authorised to put farming activity under quarantine. They are authorized by law to order the mass slaughter of infected animals. In severe cases, they can close or suspend farming operation on a farm.

According to World Organization for Animal Health, (2010), Namibia red meat production and livestock products provide 85 – 90% of the national agricultural income. The country is uniquely placed to sustain an improved marketing potential and comparative advantage for the industry through the traceability and Famers Assured Namibian Meat system. This results in the creation of high-value livestock export products that are destined to the European Union and South Africa markets. The aim of the DVS in collaboration with the Meat Board of Namibia is to ensure this market relation is sustained. Therefore, the two entities have a major responsibility in the areas of animal disease surveillance, control, prevention, animal health-related extension as well as veterinary public health. The Meat Board of Namibia manages the Famers Assured Namibian Meat (FANMEAT) and the Namibian Livestock Identification and Traceability (NAMLITS) systems. These two systems ensure livestock welfare standards (Directorate of Veterinary Services, 2012).

Disease control and strategy is based on two disease zoning system namely; the Northern Veterinary Cordon Fence (NVCF) and the Southern Veterinary Cordon Fence (SVCF). This system is primarily established regarding Foot and Mouth Diseases (FMD) and other contagious diseases. Disease control and prevention is carried out through a system of livestock movement controls and vaccination against the major diseases such as: the FMD, Contagious Bovine Pleuropneumonia (CBPP), and Anthrax. In the Northern communal areas, the major diseases are controlled and prevented through a mass annual vaccination campaign by the government. Cattle are vaccinated against Anthrax in Tsumkwe area, FMD in the whole of the infected zone while CBPP vaccinations cover the entire Northern Communal Areas (NCA). The vaccines and the whole campaign is funded by the government and is administered free (DVS, 2012). The major diseases are Anthrax (cattle) and Brucellosis in heifers and small stock. It is compulsory that every farmer vaccinates against Anthrax and Brucellosis annually. Other concerned diseases in the SVCF are the Black quarter, Botulism, Rabies, Lumpy Skin disease (LSD), Bovine Malignant Catarrhal Fever, Sheep scab/mange and Pulpy Kidney in small stock. These diseases are less contagious than the former hence, farmers have an option whether to vaccinate or not. The major livestock kept in the Northern Communal areas (NCA's) are cattle, sheep, goats, donkeys, horses and pigs. However, the vaccination programmes concentrate only on cattle because it is less resistant to diseases and there is a high severity of cattle diseases compared to other animals. These measures tighten animal disease surveillance in the region. But to all effects, there is a concern about laxity in farmers 'reporting of clinical cases the nature of which is being investigated in this paper.

3. The ordered choice model

In the Northern Communal Area (NCA), it is mandatory to vaccinate livestock because the services are provided free nevertheless, not all farmers vaccinate their livestock, and in the advent of a disease outbreak, their response differs from farmer to farmer. Their response is categorised as "*good"* for those who respond promptly, "*fair"* for those who respond a few weeks after an outbreak, and "*poor"* for those who response a few months later say, two to three months. In this instance, the outcome variable referred to as "response," is ordered. The aim is to model the relationship between this outcome variable and a set of covariates consisting of; the number of livestock lost (*mortality*) and the vaccination record of the farmers (*vaccine*). Because this analysis involves an ordinal categorical dependent variable and it is about making a choice; an ordered choice outcome model is preferred. When a dependent variable is measured on an ordinal scale, the question arises as to which outcome-based model is the best fit. In the case of the hypothesized relationship stated above, various options can be exercised as follows (See Williams, 2015): (a) the farmer's response can be dichotomized to measure two outcomes, early versus late reporting - using a binary outcome technique; (b) It can be spaced equidistant, and treated as a continuous variable - using ordinary least square technique; (c) it can be modelled by ignoring the ordinal nature of the variable and treating it as nominal - using a multinomial logit or probit technique; (d) It can be treated like it was measured on a true ordinal scale and analysed using stereotyped logistic model techniques, and (e) it can be treated as though it were measured on an ordinal scale characterised by some form of crude measurement of an underlying interval or ratio scale – using ordered logit or probit techniques.

According to Williams (2015), choosing the right modelling techniques requires careful judgement. Ordered choice model is more of a latent regression than just a formal discrete choice formulation (Marcus and Greene, 1985). Given the observed outcome variable y, the aim is to estimate an unobserved latent variable $y*$ for a more meaningful interpretation of the outcome-mean based on thresholds (cut-points). The thresholds are used to differentiate the adjacent levels of the response variable y. A threshold is defined as the points on the latent unobserved variable that results in the different observed values on $y = 1, 2 \ldots m$. According to [10], ordering must have some meaning in utility satisfaction space that is, there should be a natural underlying preference scale if it is assumed the model is driven by the behavioural rule of utility maximization. By using ordinary least square or multinomial regression, information about the ordering is discarded, instead many more parameters that are often insignificant are estimated (Williams, 2015). Because of this, a naturally occurring ordered outcome model characterised by some form of crude measurement of an underlying interval or ratio scale that is based on utility maximization is modelled using ordered model techniques.

This type of model has been widely used in the literature to model decision outcomes in the field of economics; sociology, psychology etc. For example, Greene and Henscher (2009) analysed factors affecting the assignment of naval recruits into jobs that were ordered as "Medium skilled", "Highly skilled" and "Nuclear qualified" in the USA. It has been applied to model educational attainment to see if the effects of father schooling and son's schooling differs between whites and non-whites (Winship and Mare, 1984). The effect of father's schooling on son's schooling is larger for whites and for sons of highly educated fathers than non-white sons. Long (1997) model the support for a warmer and secured relationship between mother and child for mothers who are working and those who do not work, where outcome categories are "Strongly disagree", "Disagree", "Agree" and "Strongly agree". Support was found to decreases with respondent's age, gender and race. Cameron and Trivedi (2005) model health status that are self-assessed as "Poor", "Fair", "Good "or "Excellent". The probability of excellent health was found to decrease as people age or have more disease and increases with income.

Using logistic distribution; the study estimate the probability of observing a *"poor"*, *"fair"* or *"good"* response conditional on a set of covariates. Though the application of ordinal outcome model in the literature is wide, it application in agricultural economics, especially focusing on farmer's attitude to livestock diseases outbreak is not known by the authors. Moreover, no known study of this type has been conducted in Namibia therefore; the study will be insightful for policy purposes for effectual livestock disease management and control.

4. Model specification

The ordered model is estimated by first exploring the relationship between y and y^*. The continuous latent variable y^* has threshold levels or cut-points, k. The value on y depends on whether or not a particular threshold is crossed. Given observed $y = 1, 2 \ldots m$, let $m = 3$ represent the three levels of the variable, *"response"*, y takes the value:

$$y_i = 1 \ \ if \ \ k_0 \le y_i^* \le k_1$$
$$y_i = 2 \ \ if \ \ k_1 \le y_i^* \le k_2$$
$$y_i = 3 \ if \ \ y_i^* \ge k_3 \ldots\ldots (1)$$

In ordered logit model, an underlying score is estimated as a linear function of the independent variables and a set of cut-points or ancillary parameters. The probability of observing outcome i corresponds to the probability that the estimated linear function, plus random error is within the range of cut-points estimated for the outcome. Therefore, the probability of a given observation for ordered logit is given as:

$$p_{ij} = \Pr(y_j = i) = \Pr(k_{i-1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \ldots + \beta_k x_{kj} + \mu_j \le k_i), \ldots\ldots (2)$$

where, μ_j is a random error term assumed to be standardized logistic distribution with mean zero and variance of $\pi^2/3$ (Greene and Henscher, 2009 and Stata, 2014). The μ_j is also assumed independent or uncorrelated with the set of exogenous covariates, $x_1, x_2 \ldots\ldots x_{kj}$. The $\beta_1, \beta_2, \ldots \beta_k$ as well as the thresholds (cut-points), $k_1, k_2, \ldots k_{m-1}$ are parameters to be estimated. The m is the number of possible outcomes, whereas, $k_0 = -\infty$ and $k_m = +\infty$ define the bounds for the entire real line specification. According to the modelling framework for ordered logit / probit techniques, the actual label of m taken by y is not relevant, because larger values are assumed to correspond to higher outcomes. The coefficients and the cut-points are estimated using maximum likelihood estimation techniques with no intercepts. The intercept term is not included because its effect is assumed to be absorbed into the cut-points (Long, 1997; Long and Freese, 2001; Greene and Henscher, 2009). The log likelihood function is expressed as:

$$\ln L = \sum_{j=1}^{N} \omega_j \sum_{i-1}^{k} \mathrm{I}_i(y_j) \ln p_{ij} \ldots\ldots (3)$$

Where ω_j is an optional weight and

$$\mathrm{I}_i(y_j) = \begin{cases} 1, \text{ if } y_j = 1 \\ 0, \text{ otherwise} \end{cases} \quad \text{(4)}$$

The unobserved variable y^* corresponds to the equation:

$$y_i^* = \sum_{k=1}^{k} \beta_k x_{ki} + \mu_i = z_i + \mu_i \quad \text{(5)}$$

Where

$$z = \sum_{k-1}^{k} \beta_k x_{ki} + \mu_i = E(y_i^*) \quad \text{(6)}$$

Alternative way to express equation (2) is

$$P(y_i > j) = \frac{\exp(x_i\beta - k_j)}{1 + [\exp(x_i\beta - k_j)]}, \; j = 1, 2, \ldots m-1, \quad \text{(7)}$$

which implies,

$$P(y_i = 1) = 1 - \frac{\exp(x_i\beta - k_1)}{1 + [\exp(x_i\beta - k_1)]} \quad \text{(8)}$$

$$P(y_i = j) = \frac{\exp(x_i\beta - k_{j-1})}{1 + [\exp(x_i\beta - k_{j-1})]} - \frac{\exp(x_i\beta - k_j)}{1 + [\exp(x_i\beta - k_j)]}, \; j = 1, 2, \ldots m-1 \quad \text{(9)}$$

$$P(y_i = m) = \frac{\exp(x_i\beta - k_{m-1})}{1 + [\exp(x_i\beta - k_{m-1})]} \quad \text{(10)}$$

As $m = 3$, which corresponds to the three outcomes: *"poor", "fair"* and *"good*", the above equations simplifies to:

$$P(y = 1) = \frac{1}{1 + \exp(z_i - k_1)} \quad \text{(11)}$$

$$P(y = 2) = \frac{1}{1 + \exp(z_i - k_2)} - \frac{1}{1 + \exp(z_i - k_1)} \quad \text{(12)}$$

$$P(y = 3) = 1 - \frac{1}{1 + \exp(z_i - k_2)} \quad \text{(13)}$$

5. Data and methodology

Data used in the study is a cross-sectional aggregate livestock disease record compiled during the years 2009 to 2015 by the Directorate of Veterinary Services (DVS) in Grootfontein district. The data consist of a record of: (a) the number of clinical cases reported to the DVS per year, (b) the onset of the disease, (c) the time of report, (d) mortality, (e) pre-vaccination record, (f) type of disease diagnosed, (g) and name of the farm.

The number of clinical cases reported per year varies from seven in 2009 to thirty-three in 2011. Overall, the number of reported cases in the district during the sample period was 167. This number consists of the total number of farmers recorded on the register (though with different disease profiles) who reported that their animal was sick. Appendix Figure A1 shows that the most prevalent cases are Anaplasmosis, Pasteurellosis, Pulpy kidney and Heartwater; others are Helminthiasis, Coccidiosis, Urea and Plant poisoning. The mortality rate of the most prevalent cases is shown in Appendix Figure A2. The figure shows that 22% of the mortality during the sample period was caused by Helminthiasis, 16% by Urea poisoning, 13% by Pasteurellosis, and 11% by Anaplasmosis. Others are rabies (3%), Pulpy kidney (3%), Heartwater (3%) and Coccidiosis (5%). The most affect areas are shown in Appendix Figure A3. Disease severity was highest in Jamkaub (13%), followed by Okamahundju (11%), others are Mooibome (6%), Okshoof (6%) and Fairview (7%).

The information on mortality shows the total number of death per reporter (farmer) before and after reporting. In some cases, after treatment, the animals might recover, in most cases, depending on the time of reporting, they animals die, resulting in a total recorded mortality of 264 during the sampled period. For the sake of this study, farmer's attitude towards reporting of these disease conditions was categorized into *"poor"* if they reported the incidence within fifteen to ninety days, *"fair"* if they reported within six to fourteen days and *"good'* if they reported within one to five days after the first symptom was noticed. To investigate the relationship between farmer's response and mortality, equation (2) was fit. The aim is to determine whether mortality influences farmer's choice. Based on ordered model techniques, the major issue is to determine the probability that a particular outcome will be observed. Another important covariates included in the model is the vaccination record. Since vaccination is compulsory in the NCA, the variable "vaccine" depends on whether mortality was caused by a pathogenic or a non-pathogenic organism. For the farmers who vaccinated and who encountered some levels of mortality caused by pathogenic organisms, the variable "vaccine" takes the value of one if they vaccinated, zero otherwise. A total of sixty-five farmers falls into this category.

6. Empirical results and discussions

The variables chosen for the outcome model are shown in Table 1. The variable "response" has three categories namely, *"poor", "fair"* and *"good"* which correspond to the censored outcomes of livestock clinical reporting. The variable "vaccine" is categorical as explained previously. Table 2 shows the frequency distribution of the data set. It can be seen that 48 out of 167 farmers have "poor" response towards reporting of clinical cases, corresponding to 48/167 = 0.2874 probability of reporting based on the data. On average, there is 28.74% probability that farmers in this category will report clinical cases within 15 to 90 days. Similarly, farmers in the category classified as *"fair"* and *"good"* have 17.96% and 53.29% probabilities of reporting fairly on time and promptly respectively. The vaccination record shows that about 61.08% the sampled farmers did not vaccinate their cattle, whereas, only 38.92% vaccination cases were observed. Using the ordered logit model, further predictions are made in the section that follows.

6.1 Choice of model estimate

Ordered logit was preferred in this study because it is simpler with less mathematical complications compared to ordered probit model nevertheless, results obtained with both models do not differ markedly (Long, 1997; Long and Freese, 2001; Cameron and Trivedi, 2005; Greene and Henscher, 2009). An ordered logit model is less flexible than other models because its estimates are based on one equation overall outcome levels of the response variable. To test for model adequacy, some tests have been recommended. For example, to ensure the ordered outcome is equidistant from each other, Brant (1990) test was used to test the assumption that the odd of observing one outcome to another is proportional. That is, the relationship between each pair of outcome groups is the same – the coefficients that describe the relationship between, say, "poor" versus "fair" and "good" is the same as the one that describes the relationship between fair and good and so on. The Brant (1990) proportional assumption test is shown in Table 3. The insignificance of the chi-squared statistics for each variable, mortality, and vaccine together with the overall test named "All" is an indication that the ordered logit proportional odds assumptions are met. This assumption is often referred to as the parallel regression model whereby ordered logits are assumed to have the same slope across all categories but with different intercepts that are estimated simultaneously. In addition to this test, a joint test of the parallel assumption was also performed as shown in Table 3. The null hypothesis is that the location parameters of the slope coefficients are the same across the dependent variable. Like the Brant (1990) test, a significant test statistics provides evidence that the parallel regression assumption has been violated. It can be seen that all the different test statistics show that the assumption was not violated. This is an indication that the ordering of the dependent variable is appropriate otherwise; a different modelling approach should be considered such as multinomial or generalized ordered logit models.

Nevertheless, it is observed that the Brant (1990) test often over-rejects the null hypothesis of parallel regression assumption and may not be accurate all the time especially with small sample (Long and Freese, 2001), therefore, for comparison with ordered logit, other models such as, ordered probit, ordinary least square (OLS), multinomial logit were estimated. The results are shown in Table 4. The result shows that the estimate obtained with ordered probit did not differ much with ordered logit. The result obtained with OLS and multinomial logit are mixed. While the OLS results seem to be spurious with lack of association (low R^2 and highly significant coefficients), the multinomial logit result has some insignificant parameters. Further comparison was made with the information criteria estimated for each model. The Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) estimates chose the logit model as the best fit for the data therefore, further interpretation of the relation between the outcome variable and the covariates are made considering the logit model.

Table 4 reports a description of the observed data on the outcomes (*"poor", "fair"* and *"good"*), the likelihood iteration results, diagnostic statistics, and some measures of goodness-of-fit. Estimation was by maximum likelihood technique that undergoes an iteration process. Iteration starts from zero or log-likelihood of no model -167.363 and increases until the difference between successful iterations were small. Convergence was achieved after three iterations with a maximum log-likelihood of –160.212. According to Long (1997), interpretations of the ordered logit results depends on whether the concern of the researcher is on the interpretability of the latent variables, then the latent can be re-scaled and interpreted by computing y-standardized and fully standardized coefficients. Otherwise, if the observed categories are of utmost importance, regardless of whether the latent variable is reasonable, the model can be interpreted in terms of predicted probabilities, partial and discrete change in probabilities and odds ratios. The latter was preferred.

With regards to log-odds, the signs for the coefficient for "mortality" and "vaccine" are negative, an indication of a negative relationship with the dependent variable, "Response". The result shows that mortality does not increase the likelihood of farmers reporting disease condition of their livestock on time. On the other hand, the likelihood of moving from lower to higher outcomes decreases for those farmers who vaccinated than those who did not vaccinate. This implies that if the levels of vaccine increases, farmers are less likely to respond promptly to diseases outbreak, they seem to become complacent and adopt a wait-and-see attitude hoping the livestock will recover. In this instance, a one unit increase in mortality would not diminish their expectation, leading to a decrease in the log-odds of reporting it. This can be attributed to the following reasons: farmers' often try to avoid transaction costs such as, (a) the transport cost of transporting the animal to the veterinary office, (b) the cost of inviting the veterinarian to the farms because veterinary service is at their own cost and (c) the cost of prescribed medicine. Sometimes farmers do not report on time because they have not vaccinated the animal, thus they wait until they vaccinate before reporting to the veterinarian. The reason for this is that, if they veterinarian discovers that they did not vaccinate, their farm will be closed. In some occasions, when their farm record is not up to date, they are afraid of reporting to the veterinary office. This is because their farm records must always be up-to-date, containing information such as, (a) animal movement to-and-fro the farm – a measure of animal traceability, (b) drug and vaccine records – for disease prevention and control, (c) feed supplement records - for animal nutrition and health, (d) record of farm worker's training – consisting of vaccination and record keeping for their development of animal health management system. In other words, there is a trade-off between risking a few more livestock (hoping they will recover) than lose the entire farm. In this regards, their attitude towards disease outbreak is rather driven more by expectation than by the immediate daring physical condition of the livestock.

For further interpretations of the result, the odds ratio was considered. The aim is to compare the proportion of the responses between outcome groups that are > or $\leq m$, where m is the level of variable, "response". Because of the proportional odds assumption, changes between one category and groups or between groups and one category are similar. According to the result in Table 5 col. 5, for a one unit increase in the level of vaccine administered, the odds of observing a "good" response versus a combined ("fair" plus "poor") responses decreases by 0.46 times other variable remaining constant. Similarly, for a one unit increase in vaccine application, the odds of observing a combined responses ('fair' plus 'poor") versus "good" decreases by 0.46 times. On the other hand, for a one unit increase in mortality, the odds of observing a "good" response versus a combined ("fair" plus "poor") responses decreases by 0.84 times. Similarly, for a one unit increase in mortality, the odds of observing a combined responses ('fair' plus 'poor") versus "good" decreases by 0.84 times other variables remaining constant. Odds ratios were also estimated in percentage terms. The odds of having a farmer that belong to the higher category of response are 15.7% lower if mortality increases. Also, the odds of farmers reporting on time are 53.3% lower if they vaccinated than if they did not vaccinate (Table 5 col. 8).

6.2 Goodness of fit

The goodness of fit for the ordered logit model was evaluated by comparing its log-likelihood value with that obtained with multinomial model. The Log-Likelihood Ratio test is calculated from the equation:

$LR = -2(\ln L_1 - \ln L_2)$, where, L_1 and L_2 are Log-likelihood for ordered logit and multinomial models respectively. Assuming the multinomial model estimates $p(k-1)$ additional parameters, the LR statistic is compared with $\chi^2(p(k-2)$,where, p is the number of independent variable excluding constant. A large value of $LR = -2(\ln L_1 - \ln L_2)$, is an indication of poor fit (Stata 2014). The computed LR statistic is approximately 98.33; the value is not too large as indicated therefore, the ordered model is considered to have good fit. Post regression hypothesis test was conducted with the tabulated Log-likelihood Ratio (LR) statistics in Table 4. The log-likelihood Ratio (LR) statistics of 12.7 tests the hypothesis that at least one of the coefficients in the model is statistically different from zero. The LR statistics is calculated as: LR =-2*(LL (Null model) - LL (fitted model)) = -2*((-167.363)-(-160.212)) = 14.3. The null hypothesis of zero coefficients is rejected at one per cent level of significance. Further test of significance is shown in Table 6. This is a Wald test of individual and joint significance. The result shows that the coefficients significantly contribute to the prediction of the model.

6.3 Estimating probabilities

Using equation 1, the value of the observed variable y is expressed as;

$$y_i = 1 \text{ if } y_i^* \text{ is } \leq -1.5393$$
$$y_i = 2 \text{ if } -1.5393 \leq y_i^* \leq -0.7011$$
$$y_i = 3 \text{ if } y_i^* \geq -0.7011 \quad \ldots\ldots (14)$$

To estimate the probability that an observation falls into Pr(y=1, 2…..m), the value of latent variable y_i^* must be estimated. If the estimated $y_i^* \leq -1.5393$, the observation of interest falls into outcome 1, and so on. The predicted probability for a selected number of farms is shown in Table 9. For example, farm Mangetti NDC had no vaccine record, on the 1st of July 2009, the farm reported abortion a month later with 7 mortalities. The probability that the farm falls into any of the categories is calculated as follows. First, a proxy variable z was calculated as shown in equations 5 and 6.

$$z_i = (-0.1702 * 7) + (-0.7621 * 0) = -1.1914 \quad \ldots\ldots (15)$$

Using equations 11 to 13, the probabilities for the three outcomes are calculated as:

$$P(y=1) = \frac{1}{1+\exp(-1.1914-(-1.5393))} = 0.4139 \quad \ldots\ldots (16)$$

$$P(y=2) = \frac{1}{1+\exp(-1.1914-(-0.7011))} - \frac{1}{1+\exp(-1.1914-(-1.5393))} = 0.2063 \quad \ldots\ldots (17)$$

$$P(y=3) = 1 - \frac{1}{1+\exp(-1.1914-(-0.7011))} = 0.3798 \quad \ldots\ldots (18)$$

Note that the estimated z differs slightly from the z calculated in equation (15); this is as a result of the unobserved error term μ shown in equations (5) and (6). The probabilities estimated for the first 15 farms are shown in Table 9

6.4 Average predicted probabilities

Using equations (15) to (18), the probability of the farms falling into a particular outcome was calculated. The average for the entire predicted outcome is given in Table 7. It can be seen that the average predicted probabilities for farms in the three outcome categories are 28.57%, 17.95% and '53.48% respectively. The probability that the outcome variable is equal to the first category ("Poor") given that other variables are at their mean is 28.57%, the probability for outcome 2 = "Fair" and 3 = "Good" are interpreted the same way. These probabilities correspond to the sample frequency distribution given in Table 2. This is an indication that the logit model has good predictive property.

6.5 Marginal effects

Marginal effects show the change in probability for a unit change in the predictors. For continuous variables this represents the instantaneous change given that the unit change may be small. For a binary variable, the change is from 0 to 1. Marginal effects are estimated at the mean of the predictors (MEM) and at the sample average (AME). The results for the marginal effects are shown in Table 8. It can be seen that the effects estimated at the mean are larger compared to the average effects, therefore interpretation is based on the MEM. The results show that a one unit change in mortality increases the probability that farmers will fall in the first category ("Poor") by 3.4 %. The change in probability of falling in the second ("fair") category for a unit change in mortality is 0.085% whereas, it is less likely that farmers will fall in the third category ("Good") for a unit increase in mortality. The result shows that the likelihood of achieving a higher response decreases from 3.4%, 0.085% to a negative value. This implies that, it is difficult for farmers to report disease outbreak between 1-5 days of onset. The reason for this has been given previously.

The result in Table 8 shows that farmers who vaccinated their livestock are less likely to report disease incidence on time compared to those who did not vaccinate. This is because a unit increase in the level of vaccine increases the probability of reporting "poorly" by 15.17% and the probability of a "fair" reporting by 3.8%. A unit increase in the level of vaccine decreases the probability of reporting within 1-5 days by 18.9%.

In comparison, the marginal effect of mortality on the probability of reporting poorly is 3.4% compared to 15.17% for vaccine. They are more likely to report poorly if they vaccinated their livestock than if mortality is rising. Also, the probability of fair reporting increases by 0.08.5% for a unit increase in mortality compared to 3.8% for one unit increase in vaccine. And lastly, the probability of falling in the third category ("good") decreases more rapidly for vaccine application (18.97%) than for mortality (4.24%). Therefore, based on the precinct of these results, it can be concluded that farmers' attitude is more precautionary than reactionary. The reason is that their decision is based mainly on the expectation that the livestock will not die because they vaccinated them therefore, they tend to react more to the level of precaution they have undertaken previously than to the level of mortality. If the level of precaution increases, it has more marginal impact for those who vaccinated than those who did not vaccinate and less impact on overall probabilities due to a change in the level of mortality. In other words, their reaction is a function of precaution.

7. Conclusions

Animal disease outbreaks pose a serious threat to the livestock industry especially in countries where livestock contribute immensely to the Gross National Income. The challenges can be mitigated with a good livestock disease surveillance and management programmes. This involves *ex-ante* precautionary and *ex-post* control measures. Precautionary measures include activities such as vaccination regimes, testing and screening exercises, others are early detection, isolation, and culling of infested animals. In terms of an outbreak, control measures involve early reporting and treatment of affected livestock. These activities are facilitated by relevant authorities amongst who is the Department of Veterinary Services (DVS), nevertheless, its effectiveness and success relies heavily on the roles farmers play. There is a concern that commitment at the farm level is lax. As a result, preventable losses are incurred because farmers' do not undertake adequate precaution and in the event of an outbreak, reporting the incidence occurs with considerable time lapse leading to high mortality.

Therefore, this study investigated how best to characterize farmers' behaviour towards the handling of livestock diseases - are they reactionary or precautionary? The aim is to investigate how sensitive they are towards disease outbreaks. Using an aggregate clinical record compiled by the DVS in Namibia, the study investigated the relationship between farmers' response and the level of mortality and vaccine. This was evaluated using an ordered logistic outcome model where framer's level of response were classified as *"poor'*, "*fair"* and *"good"*. The result shows that the threat of mortality and the level of vaccine do not increase the likelihood of reporting on time. Farmers who vaccinated their livestock are less likely to report disease incidence on time compared to those who did not vaccinate. On average, there is 28.74% probability that farmers' category classifies as "*poor*" will report clinical cases within 15 to 90 days. Similarly, farmers in the category classified as *"fair"* and *"good"* have 17.96% and 53.29% probabilities of reporting fairly and promptly respectively. For a unit increase in mortality and the level of vaccine, it is less likely that farmers' will report disease incidence within 1-5 days of onset. The reasons for this type farmers' attitude is attributable to the following: (a) Farmers who vaccinated adopt a wait-and-see attitude hoping the livestock will recover, (b) transaction cost may be a limiting factor, these includes, veterinary fee and cost of transporting livestock to the veterinary office and (c) farmers veterinary record may be in arrears, delay may be due to in-house clean up to avoid more costly consequences.

In the light of this, farmers' in the study region can be regarded as being more precautionary. They do not react more rapidly to the level of mortality rather; they react to the level of precaution they have undertaken previously. If they vaccinated they are less likely to react to changes in mortality than when they did not vaccinate. Therefore, their reaction is a function of their level of precaution. The recommended solution to this situation is as follows: (a) Adequate training is needed for easy recognition of fatal disease conditions; (b) The DVS offices must be conspicuously located in the remote areas to facilitate access to veterinary services; (c) Stringent veterinary regulations should be relaxed to reduce the stigma of closure or quarantine faced by the farmers; (d) veterinary services should be free of charge to reduce transaction cost. These recommendations have policy implications and should be considered with great urgency.

In conclusion, attention is drawn to the limitations of this study. The aggregate nature of the study obliterates some of the inherent characteristics in micro-farm level data. Therefore, it will be necessary to engage further study at the farm-level. Further investigations are needed to understand how factors that militate against early reporting determine how farmers are categorized. This will assist in developing an intervention policy towards livestock disease management and control.

Tables

Table 1 Descriptive statistics

Variable	Obs	Mean	Std.Dev	Min	Max
Response	167	2.2455	0.8745	1	3
Good	167	0.5329	0.5004	0	1
Fair	167	0.1796	0.3850	0	1
Poor	167	0.2874	0.4539	0	1
Mortality	167	1.5808	2.4796	0	15
Vaccine	167	0.3892	0.4890	0	1

Table 2 Frequency distribution

Variables	Frequency	Percentage	Cumulative
Response:			
Poor	48	28.74	28.74
Fair	30	17.96	46.71
Good	89	53.29	100
Vaccine:			
None	102	61.08	61.08
Given	65	38.92	100
Total	167	100	

Table 3 Test of proportionality of regression or the parallel regression assumption

Tests	Chi-square	P>chi2	Df
Brant (1990) Test of parallel regression:			
All	0.86	0.651	2
Mortility	0.85	0.355	1
Vaccine	0.01	0.941	1
Oparallel joint tests:			
Wolfe Gould (1998)	0.3500	0.839	2
Brant (1990)	0.8598	0.651	2
Score	0.4572	0.796	2
Likelihood ratio	0.5036	0.777	2
Wald	0.4597	0.795	2

Table 4 Parameter estimates with different models

Variables	Ordered Logit	Ordered Probit	Multi-nomial Logit	Ordinary Least Squares
Col.1	**Col.2**	**Col.4**	**Col.5**	Col.6
Response:				
Mortality	-0.1702*** (0.0070)	-0.0974*** (0.0070)		-0.0728*** (0.0070)
Vaccine	-0.7621** (0.0140)	-0.4541** (0.0160)		-0.3200** (0.0180)
Constant				2.4851*** (0.0000)
Threshold 1	-1.5393	-0.9242		
Threshold 2	-0.7011	-0.4175		
Poor:			Base	
Fair:				
Mortality			-0.0248 (0.7600)	
Vaccine			-0.3441 (0.4630)	
Constant			-0.2526 (0.4810)	
Good:				
Mortality			-0.2107** (0.0100)	
Vaccine			-0.8761** (0.0200)	
Constant			1.3034*** (0.0000)	
Log-Likelihood at zero LL(0)	-167.363	-167.3630	-167.363	
Log-Likelihood at Convergence LL(3)	-160.212	-160.4780	-159.955	
Likelihood-Ratio chi-square stat	14.3	-160.4779	14.2	
Probability > chi-square	0.0008	0.001	0.0051	
McFadden Pseudo-R^2	0.0427	0.0411	0.0443	
R^2				0.081
AIC	328.425	328.956	331.910	420.015
BIC	340.897	341.426	350.618	429.369
Number of Observation	167	167	167	167

The symbols ***, **, & * signify statistical significance at the 1%, 5% and 10% levels respectively. Figures in parenthesis are p-values.

Table 5 The Odds ratio for the probability of observing an outcome

Variables	b	z-stat	P>|z|	e^b	e^bStdX	SDofX	Percent	%StdX
Col.1	Col. 2	Col.3	Col. 4	Col. 5	Col. 6	Col.7	Col.8	Col.9
Units*:								
Mortality	-0.1702	-2.699	0.007	0.843	0.656	2.48		
Vaccine	-0.7621	-2.465	0.014	0.467	0.689	0.489		
Percentage*								
Mortality	-0.1702	-2.699	0.007			2.48	-15.7	-34.4
Vaccine	-0.7621	-2.465	0.014			0.489	-53.3	-31.1

**Odds ratio is measured in units and in percentage points: where b is the raw coefficient, z is the z-score for the z-test of b = 0, P>|z| is the p-value for the z-test, e^b is the factor change in odds for a unit increase in X, e^bStdX is a measure of the change in odds for a Std. Dev. increase in X, SDofX stands for standard deviation, Percent stands for the interpretation for the percentage change in odds for a unit increase in X while %StdX stands for percentage change in odds for a std. dev increase in X.*

Table 6 Wald test of coefficient significance*

Hypothesis:	χ^2	Probability > χ^2
Ho: Response(Mortality) = 0	7.72	0.0069
Ho: Response(Vaccine) = 0	6.08	0.0137
Ho: Response(Mortality=Vaccine) = 0	13.12	0.0014

**Note: Wald test is synonymous with homogeneity test.*

Table 7 Average predicted probabilities

Variable	Margin	Delta method Standard Error	z-stat	P-value
Outcome 1:				
Constant	0.2857	0.0334	8.5500	0.0000
Outcome 2:				
Constant	0.1795	0.0296	6.0600	0.0000
Outcome 3:				
Constant	0.5348	0.0371	14.4200	0.0000

Table 8 Marginal effects of predictors on estimated probabilities

Pr (Response = 1)**	**MEM**	**AME**
Variable	**Margin**	**Margin**
Outcome 1:		
Mortality	0.0339*** (0.0070)	0.0322*** (0.0040)
*Vaccine**	0.1517** (0.0140)	0.1443** (0.0100)
Outcome 2:		
Mortality	0.0085** (0.0420)	0.0071*** (0.0310)
Vaccine*	0.0380* (0.0550)	0.0317** (0.0250)
Outcome 3:		
Mortality	-0.0424*** (0.0070)	-0.0393*** (0.0040)
*Vaccine**	-0.1897** (0.0140)	-0.1760*** (0.0080)

*Note: MEM stands for Marginal effects at the mean, AME stands for average marginal effects. Figures in parenthesis are the p-values. The symbols ***, **, & *, stands for statistical significance at the 1%, 5% and 10% levels respectively.*

Table 9: Predicted outcome probabilities

Year	Farm	Disease	Mortality	Vaccine	Poor	Fair	Good	Prob (1)	Prob (2)	Prob (3)	Z
2009	Mangetti ndc	Abortion	7	None	1	0	0	0.4139	0.2063	0.3798	-1.1916
2009	Kududam	Ketosis	1	Given	1	0	0	0.3527	0.2048	0.4424	-0.9323
2009	Rietfontein	BVD*	5	Given	1	0	0	0.5185	0.1950	0.2866	-1.6132
2009	Otjondundu rest	Anaplasmosis	6	None	1	0	0	0.3733	0.2061	0.4206	-1.0213
2009	Maria brownn	Rabies	0	Given	1	0	0	0.3149	0.2003	0.4847	-0.7621
2009	Schwarzefelde	Lead poisoning	5	Given	1	0	0	0.5185	0.1950	0.2866	-1.6132
2009	Okambongora	Ketosis	1	None	1	0	0	0.2028	0.1676	0.6297	-0.1702
2010	Hoffnung	Pulpy kidney	5	None	1	0	0	0.3344	0.2030	0.4626	-0.8511
2010	Onde	Urolthiosis	0	None	1	0	0	0.1766	0.1549	0.6684	0.0000
2010	Homeland	Anaplasmosis	0	None	1	0	0	0.1766	0.1549	0.6684	0.0000
2010	Onde	Rabies	0	Given	1	0	0	0.3149	0.2003	0.4847	-0.7621
2010	Omega	Rabies	3	None	1	0	0	0.2633	0.1892	0.5475	-0.5107
2010	Omega	Rabies	0	Given	1	0	0	0.3149	0.2003	0.4847	-0.7621
2010	Sukkelsoek	Plant poisoning	2	Given	1	0	0	0.3925	0.2065	0.4010	-1.1026
2010	Bubus	Abcess	0	Given	1	0	0	0.3149	0.2003	0.4847	-0.7621

*BVD = Bovine Viral Diarrhoea

References

Brant, R., 1990, "Assessing proportionality in the proportional odds models for ordinal logistics regression". Biometrics. Vol. 46: 117-1178.

Cameron, A.C., Trivedi, P.K., 2005,"Macroeconometrics, Methods and Applications", Cambridge University Press, USA.

Directorate of Veterinary Services 2012, "Annual Report"

Food and Agriculture Organization, 2010, Guide lines: economic analysis of animal disease. ISSN 18100708.

Greene, W.H., and Henscher, D.A, 2009, "Modelling ordered choices". Department of Economics, Stern School of Business, New York University, New York, NY 10012.

Hawkins, C.D., and Morris, R.S., 1978, "Depression of productivity in sheep infected with *Fasciola hepatica*". Veterinary Parasitology 4: 341-357. 8.

Long, J.S., 1997, "Regression models for categorical and linear dependent variables. Advanced Quatitative Techniques in the Social Science Series". Sage publications, ISBN 0-8039-73748, USA.

Long, J.S., and Freese, J., 2001, "Regression models for categorical dependent variables using Stata". A Stata press publication, Stata corporation college station, Texas, USA.

Marcus, A, and Greene, W. H., 1985, "The determinants of rating assignment and performance", Working Paper, No. CRC528. Alexandria, VA, Center for Naval Analyses

Namibian Statistical Agency 2012, "Agricultural census".

Rich, K.M., 2005, "Spatial Models of Animal Disease Control in South America."University of Illinois at Urbana-Champaign. Unpublished Ph.D. dissertation.

Stata 13, 2014. "Documentation"

The Meat Board of Namibia 2014, http://www.nammic.com.na/

Thomson, G.R., and Venter, R., 2012, "Risk analysis on animal disease hazards associated with imports of animal commodities (Including live animals) and products into Namibia and consequences thereof". A study conducted on behalf of the Meat Board of Namibia

Williams, R., 2015, "Ordered Logit Models – Overview". University of Notre Dame. http:/www3.nd.edu/~rwilliam.

Winship, C and Mare, R.D., 1984, "Regression models with ordinal variables". American Sociological Review, Vol. 49:512-525.

World Organization for Animal Health 2010. http://www.oie.int/animal-health-in-the-world/update-on-avian-influenza/2010/.

Appendices Figures

Appendix Figure A

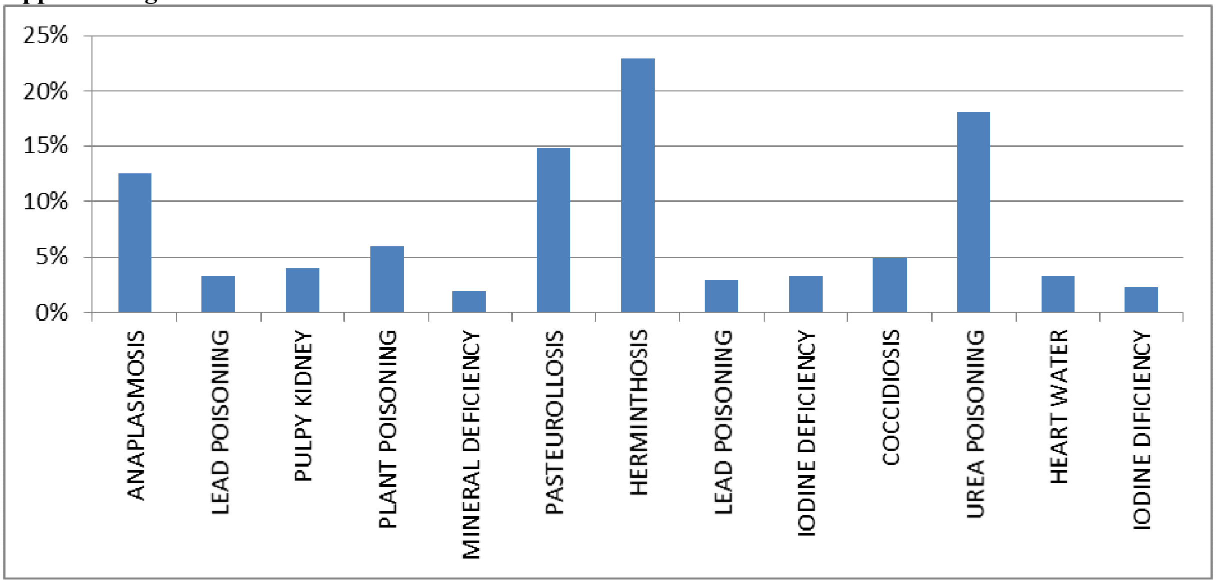

Figure A1: Frequency of disease occurrence. Source: Author's computation.

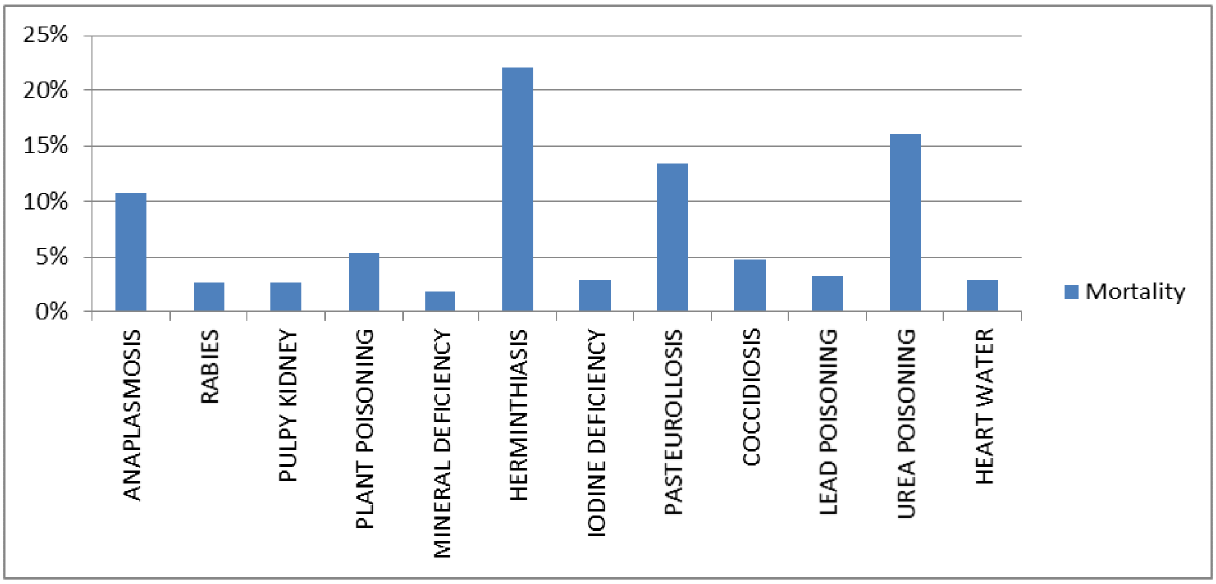

Figure A2: Mortality rate. Source: Author's computation

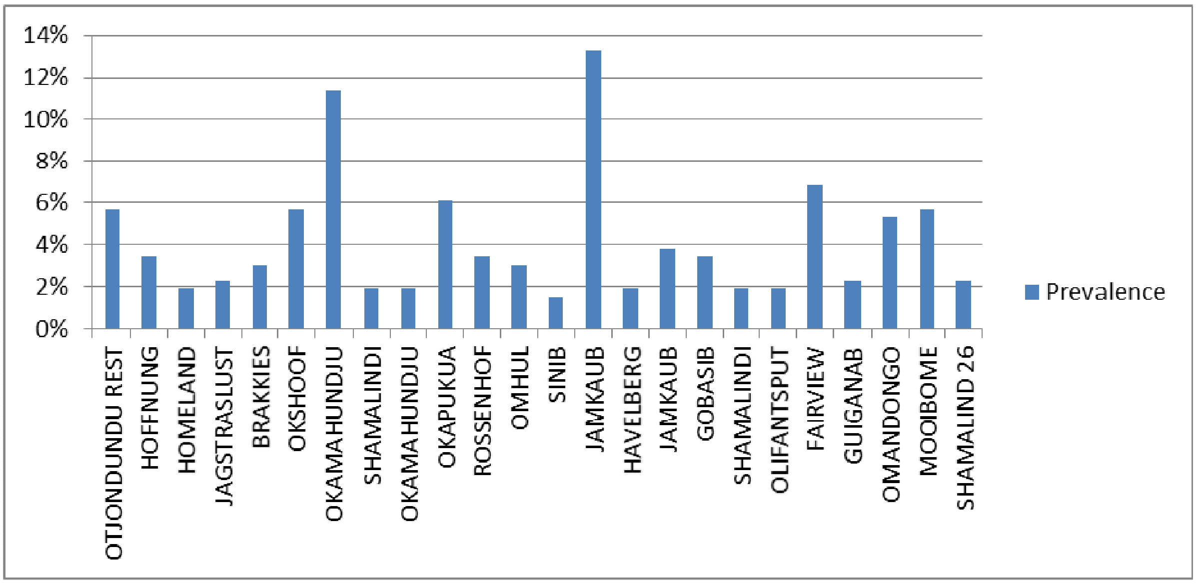

Figure A3: Disease prevalence rate per area. Source: Author’s computation