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Case Study 2

Sampling and surveillance in the grains industry

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Executive Summary

Effective sampling and surveillance strategies form an integral component of large agricultural industries such as the grains industry. Intensive fine scale sampling is essential for pest detection, integrated pest management and to ensure trade routes are secured, while surveillance over broad geographic regions ensures that biosecurity risks can be excluded, monitored, eradicated or contained. Significant research into techniques to maximise surveillance and fine scale sampling has been conducted in the grain industry. Primarily, the research has focussed on fine scale sampling strategies concentrating on 'within silo' detection however the need for effective surveillance strategies has been recognised. Interestingly, although surveillance and fine scale sampling has typically been considered independently, many techniques and concepts are common between the two fields. This review aims to consider the historical development of fine scale sampling and surveillance strategies and to identify methods that may be useful for both surveillance and fine scale sampling.

Introduction

Sampling programmes form an integral component of the grains production and supply industry (Subramanyam and Hagstrum 1996, Subramanyam *et al.* 1997, Elmouttie *et al.* 2010). Various types of sampling occur throughout the grain production and supply chain and are designed to measure parameters such as grain quality and the presence and abundance of pests (Subramanyam and Hagstrum 1996). From a pest management perspective sampling occurs throughout the production and supply chain to detect or estimate the abundance of pest species. However grain cultivation occurs over vast geographic areas, where climatic conditions can vary substantially, and this in turn can influence grain quality and the presence and abundance of pests. Because of this sampling programmes can differ significantly depending upon the objective of the programme and the specific characteristics of the geographic area where grain is being produced and stored (Hagstrum and Subramanyam 2006). One of the most significant drivers of the type of sampling programme adopted is the scale of the area being examined (Stephens 2001). For example, sampling strategies to maximise the detection of pests for an individual storage will differ from sampling programmes designed to detect pests for a geographic region (Cameron and Baldock 1998, Elmouttie *et al.* 2010).

As such, sampling programmes have typically been devised for two distinct scenarios that impact the grains industry. Sampling for the detection of pests within storages or shipments (herein defined as fine scale sampling) has historically been a primary focus and received significant attention in the literature (Hunter and Griffiths 1978, Hagstrum *et al.* 1985, Subramanyam and Harein 1990, Subramanyam *et al.* 1993, Hagstrum *et al.* 1997). Alternatively and more recently the need to develop broad scale surveillance methods for pests over larger landscapes has received attention (Taylor and Slattery 2008). Although broad scale surveillance and fine scale sampling poses similar conceptual challenges these issues have not previously been considered together. There are a number of reasons for this. In part, historical development of fine scale sampling strategies has typically been driven by trade related objectives rather than science and hence many sampling programmes have been developed in isolation (Jeffries 2000). Further, although surveillance is not a new concept, development of surveillance techniques within the grains industry is a relatively new and developing area (Taylor and Slattery 2008). This review aims to provide a synthesis and comparison of techniques used in surveillance and fine scale sampling across the grains industry and other areas identify the techniques from either sampling or surveillance which may be used to improve current methodologies.

Sampling within storages – fine scale sampling

Pest detection

Sampling within storages has received significant attention for a number of decades (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Subramanyam *et al.* 1997, Opit *et al.* 2009, Elmouttie *et al.* 2010). Initially sampling programmes were developed to secure trade routes by ensuring traded grain commodities were pest free (Jeffries 2000). As a result, sampling strategies were not designed on a robust statistical and biological basis but rather were often based on pragmatic considerations in the grains supply and distribution chain (Jeffries 2000).

As many early sampling strategies globally were designed to secure trade markets (*i.e.* demonstrating commodities were pest free) or to ensure incoming shipments met stated standards (Jeffries 2000) their primary focus was detection at a fixed threshold, typically zero live pests. However, as early sampling programmes were based on pragmatic and trade considerations rather than on a solid scientific basis, statistical justification of sampling techniques was often developed after sampling programmes were established (Hunter and Griffiths, 1978, Wilken 1991, Jeffries 2000). As such statistical sampling methods were often formulated based on assumptions made for convenience rather than being well justified, particularly in relation to pest biology and distribution (Jeffries 2000).

Sampling for management

As production and storages developed and management strategies became more sophisticated the need for more advanced sampling strategies to work in unison with management strategies was recognised (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Hagstrum *et al.* 1988, Subramanyam *et al.* 1993). In contrast to early sampling strategies, newer sampling programmes were recognised as a tool that could be used in to improve management of grain storages rather than solely for the detection of pests to ensure commodity pest freedom for trade purposes (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Hagstrum *et al.* 1997). Fundamental to this change in mindset was the recognition that effective sampling programmes to maximise pest detection and estimate pest abundances needed to be based on understanding of how pests distributed within storages (Hagstrum *et al.* 1985). In turn this led to a consideration of how pest distribution would influence sampling statistics and sampling programmes and ultimately led to grain specific sampling programmes being developed for pests (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Hagstrum *et al.* 1997, Opit *et al.* 2009, Elmouttie *et al.* 2010).

Unlike sampling programmes developed solely for export or trade which assumed insect distribution to be homogenous for convenience (Hunter and Griffiths 1978, SCA Working party 1981, Wilken 1991, Jeffries 2000), newer sampling programmes attempted to describe spatial partitioning within grain masses and incorporate this into sampling statistics (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987). As such sampling statistics were not based on a single probability distribution, such as a binomial or Poisson, which assumed a spatial distribution, but rather were based on a statistical formulation which described how pests distributed through the grain mass (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Hagstrum *et al.* 1997). Taylor's power law (Taylor 1961) formed a fundamental basis of many of these sampling programmes and has been used in a number of studies to accurately describe the dispersion pattern of insects within storages (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Subramanyam *et al.* 1993, Hagstrum *et al.* 1997, Subramanyam *et al.* 1997). These approaches used Taylor's power law to incorporate sample to sample variation into sampling statistics. This was first considered by Hagstrum *et al.* (1985), who incorporated sample to sample variation into the double logarithmic model which accounts for "the logarithmic increase in sample units occupied by more than one insect with an increase in mean density" and the "logarithmic increase in the number of insects occupying the infested sample units" to maximise sampling efficiency.

More recently, Elmouttie *et al.* 2010 proposed an approach for sampling grain storages which unlike previous methodology, was not based on Taylor's power law. The approach explicitly considers that grain storages can be separated into two distinct components, infested and un-infested, and that within the infested portion of the lot the density of pests needs to be considered. The approach therefore considers the prevalence of pests within storages and the intensity of pests where they are located. A major benefit of this approach is that parameters are easily estimated as they have direct biological relevance and as such prior information may be able to be incorporated into the approach which would increase its utility.

Surveillance in grain production

Surveillance is more than just sampling to detect pests. By definition, surveillance is the process of collecting and recording data on pest occurrence and absence (FAO 2009). As such surveillance methods vary substantially depending on the system under consideration. Broadly, surveillance can be separated into two distinct categories, general surveillance, which utilises information gathered from range of sources or, specific survey surveillance, which utilises specific survey techniques to actively target a particular pest species (FAO 2009). Further surveillance techniques can be separated into active and passive surveillance depending on whether the data is actively collected (e.g. field surveys, sampling, trapping) or passively obtained through indirect activities (e.g. questionnaires, prior studies, government data bases) (Hellstrom 2008, Keen *et al.* 2008).

Detection surveys

Detection, pest or commodity surveys are used to collect data on the presence or absence of a pest or pests within a defined area. Typically these survey methods are designed to support claims of pest freedom (McMaugh 2005). In essence these types of survey techniques are the same as detection techniques used in fine scale sampling when sampling grain bulks, *i.e.* sampling to detect pests. However in surveillance, these techniques have broader application. For example, such techniques may also be utilised after an incursion of a known pest to demonstrate the success of an eradication programme, that is, verifying area pest freedom. In Western Australia for example, the four years of surveillance that was conducted for apple scrub post eradication illustrates the use of a detection survey for a verification program (Mckirdy *et al.* 2001).

Delimiting or monitoring surveys

Delimiting survey methods are designed to demonstrate the distribution of a pest within an area while monitoring surveys are designed to detect changes of pest density in a population within its distribution (McMaugh 2005). Delimiting surveys are most commonly utilised in the event of an incursion to determine where pests may be present across a landscape. Monitoring surveys in contrast are more commonly utilised to gather information on established pests and diseases. Although utilised at different stages of the pest incursion and establishment cycle both surveillance methods have particular relevance to biosecurity, as they provide a means to either establish the area of interest or concern and to determine the intensity of pests within areas of interest (McMaugh 2005).

Sampling and Surveillance to demonstrate Pest Freedom

Surveys to demonstrate pest freedom are becoming increasingly important over a number of industries (Cameron and Baldock 1998, Jeffries 2000). Changes in government regulation, a growing awareness of biosecurity, production of commodities and securing of agricultural trade links have all influenced pursuit for methodologies to ensure pest freedom (Cameron and Baldock 1998, Jeffries 2000). However, demonstrating that an area or consignment is unambiguously pest free is impossible unless 100% of the area or consignment is inspected. Over small areas this may be possible, however within large commodities or over large geographic areas a total census is not possible due to cost associated with sampling or surveying, the availability of man power, and time limitations (Stephens 2001). Thus demonstration of pest freedom is reliant on robust scientific survey methods based on an acceptable level of confidence to demonstrate freedom (FAO 2009).

Historically, pest freedom has been based on an absence of pest detections, with the evidence required to demonstrate freedom dependent on agreements between agencies or trading partners (Jorgonsen *et al.* 2003). This 'lack of evidence approach' used in surveillance is similar to early sampling protocols for grain storages, where pest freedom was demonstrated by sampling at pre-determined rate and if pests were not detected, the commodity was deemed pest free (Hunter and Griffiths 1978). In the International Standards for Phytosanitary Measures, the need for surveillance is discussed for the establishment, maintenance and verification of pest free areas, however no guidelines are provided on how surveillance should be conducted (FAO 2009). A lack of guidelines for sampling storages to display pest freedom is also evident, as although statistics for many early sampling strategies have been developed to justify entrenched sampling rates, these have typically been developed after sampling strategies have been established and based on assumptions for convenience (Jeffries 2000).

Evaluating Surveillance and Sampling systems

There are a number of qualitative and quantitative methodologies used to evaluate surveillance and sampling systems. The evaluation method chosen will vary for a number of reasons. In part the methodology selected will depend on the type of data that can be accessed, the areas or commodities being sampled, the availability of historical data, and the type of surveillance and sampling that can be conducted. The reason for the surveillance or sampling activity will also have a significant influence on the evaluation process, with more robust evaluations required for particular circumstances such as when establishing pest freedom or when evaluating a pest eradication programme.

Qualitative methodologies

Qualitative methodologies such as stakeholder questionnaires, expert opinion, fault trees and critical examination can be used in surveillance and fine scale sampling strategies (Jeffries 2000, Salmon *et al.* 2003a, Weinburg 2005). Although such techniques have not been widely adopted in Australia, stakeholder questioners may provide a useful tool to monitor pest incursions, and for early detection or demonstration of pest freedom within grain producing and storage regions at relatively low cost (Czaja and Blair 2005, Taylor and Slattery 2008). For example, surveillance for Khapra beetle *(Trogoderma granarium)*, a species not present in Australia, could be strengthened by using stakeholder knowledge monitor and demonstrate pest freedom over a broad area (Taylor and Slattery 2008). Furthermore although questionnaires are a qualitative approach, newer quantitative methods have been developed which can incorporate such data (Martin *et al.* 2005). Bayesian methods for example can be adapted to incorporate qualitative data into a quantitative framework (Gelman *et al.* 2003).

Fault tree analysis may also provide a useful methodology for risk analysis of biosecurity threats within the grains industry. The technique has been used to assess the threat of introducing marine species in ballast waters (Hayes 2002), and for animal health surveillance (Salman *et al.* 2003b). Fault tree analyses have received criticism for their focus on negative events however and as such, surveillance systems based on these methodologies are often criticised (Salmon *et al.* 2003b). Moreover, fault tree analyses do not provide quantifiable estimates of the probability that the target pest is absent or present below a specified prevalence.

Quantitative methodologies

For broad scale surveillance and fine scale sampling programmes, quantitative analyses are becoming increasingly important. The need for robust quantitative analysis in part is to provide a method to compare surveillance and sampling programmes and to determine whether the particular measures undertaken meet the stated objective of the programme (Stephens 2001). For example, statistical methods developed for sampling grain commodities are used to justify that a particular exporting countries commodities meet the standards prescribed at the time of sale (Jeffries 2000, Elmouttie *et al.* 2010). Unlike qualitative methods, quantitative methods are repeatable and more transparent. Quantitative methods also provide a robust defendable method to demonstrate issues such as pest freedom or eradication success.

Structured surveys have been the fundamental method for demonstrating pest freedom in fine scale sampling or broad scale surveillance. Structured surveys are commonly used in epidemiology to detect diseases within population. Using a structured survey the sensitivity of the survey confidence level (e.g. detection of a disease) given that the disease is present in the surveyed population, can be calculated at a particular design prevalence (i.e. proportion of the population with the disease; Cannon and Roe 1982).

There are a range of methods for calculating sampling intensity and confidence levels for structured surveys in many fields including, epidemiology (Cannon and Roe 1982, Cameron and Balddock 1998), acceptance sampling (Stephens 2001), ecology (Green and Young 1993) and pest management (Hunter and Griffiths 1978, Love *et al.* 1983). Common across all disciplines is that statistical methodologies are based on probability functions, typically the Poisson, binomial or hyper geometric functions. The probability function selected is chosen on the basis of how well it can describe the system being sampled. However as no statistical function perfectly describes a biological system approximations are made or inferred (Stephens 2001).

Although structured surveys can be statistically evaluated when designed correctly they are typically labour intensive and expensive particularly when demonstrating pest freedom for pests at low density. Further, statistical models which form the justification of structured surveys are often based on assumptions more for convenience rather than a sound biological basis (Jeffries 2000, Elmouttie *et al.* 2010). In addition data collected from non-structured survey and general surveillance are not easily included into analysis and thus pest freedom must be based solely on the structured survey methods.

Stochastic modelling and Scenario Trees

Unlike many statistical approaches developed for structured surveys (Love *et al.* 1983, Green and Young 1993, Stephens 2001) approaches based on stochastic modelling incorporate variability and uncertainty in model parameters using a probability distribution in place of fixed values (Audige *et al.* 2003). As such, outputs are described by a range of possible values rather than a fixed value (Vose 2008). This ability to incorporate variation and uncertainty has seen a number of stochastic modelling approaches being developed for surveillance systems in animal and plant health (Scott and Zummo 1995, Audige *et al.* 2001, Fischer *et al.* 2005) as biological variation in the form of uncertainty can be incorporated into models. Stochastic simulation models may also be used to evaluate surveillance systems for the demonstration of pest freedom and to compare the sensitivity of surveillance strategies.

Scenario trees are constructed to display all the possible scenarios that could occur in the system being analysed (Hoyland and Wallace 2001, Martin *et al.* 2007a, Hadorn *et al.* 2009). In this respect they are similar to fault trees as they map out the system, however they differ by displaying all possible scenarios not just potential faults (Salman *et al.* 2003b). Further, scenarios trees have probabilities assigned at each node of the tree allowing quantitative analysis of particular pathways to be assessed (Martin *et al.* 2007a, Salman *et al.* 2003b).

Scenario trees have been used as surveillance systems and to demonstrate freedom in animal health (Hueston and Yoe 2000, Martin *et al.* 2007a). A major advantage of scenario trees is that they are transparent, providing a clear description of the surveillance system and methods used (Stark 2003, Martin *et al.* 2007a). In addition, scenario trees may be combined with alternative methods such as stochastic modelling techniques to provide robust quantitative analysis of surveillance sensitivity (Stark 2003). Although used in broader surveillance systems stochastic modelling and scenario trees have not been used to demonstrate pest freedom in fine scale sampling programmes for detection such as those used in grain storages. In part, this relates to data outputs not being favoured by end users, as these methods do not provide a definitive answer, rather a range of potential scenarios and probabilities associated with each outcome. Additionally scenario trees can be time consuming to construct and data to estimate parameters may be limited.

Bayesian modelling

Bayesian approaches are growing in popularity in both surveillance and sampling systems due primarily to their ability to incorporate a range of data types. Expert opinion, qualitative data, prior knowledge alternative data types as well as uncertainty can be incorporated into Bayesian analysis making them extremely powerful (Gardner 2002, Wagner *et al.* 2003, McCarthy 2007). Bayesian methods have been used to incorporate information on disease status to demonstrate disease freedom in cattle (Audige *et al.* 2001) as well as in conjunction with scenario trees incorporating historical surveillance evidence (Martin *et al.* 2007a, Martin *et al.* 2007b). Methods have also been adapted for us in epidemiology to calculate disease prevalence, sample sizes and estimate test sensitivity and specificity (Gardner 2002, Branscum *et al.* 2004, Johnson *et al.* 2004, Branscum *et al.* 2005). As such Bayesian methods are applicable over a broad range of surveillance and sampling systems due to their flexibility, and may provide significant advances to surveillance and sampling systems within the grain production and storage systems due to the type of data which can be incorporated.

Combining broad scale surveillance and fine scale sampling systems in grains

Throughout this review a range of methodologies have been discussed, some designed specifically for surveillance, some designed for local area sampling and others designed for alternative uses which may be applicable to both surveillance and fine scale sampling. Of interest is that many of the methodologies used in broad scale surveillance and fine scale sampling are similar in concept (*i.e.* detection methods), however techniques have rarely crossed disciplines. In an industry as large as the grain industry, which involves the production, storage and export of grain over large geographic areas globally and issues of area freedom, broad scale surveillance and fine scale detection great advantage can be gained by exploring alternative techniques to achieve these goals across the industry.

In part, the separation between broad scale surveillance and fine scale sampling has been historical. Fine scale sampling techniques primarily arose as a response to poor hygiene in storages, to secure trade routes (Jeffries 2000). As such although structured surveys (sampling) have formed the basis to many sampling strategies, methodological development was *ad hoc* and based purely on practical restrictions rather than science (Jeffries 2000). Further, many of the statistical methodologies, although fundamentally similar to those used in surveillance today, were based on assumptions of a homogenous distribution of pests throughout the grain mass (Wilken 1991, Jeffries 2000), although insects have been shown to be heterogeneously distributed (Hagstrum *et al.* 1985).

In contrast, sampling methodologies developed throughout the 1980's and 1990's for use in grain storages have been developed primarily for Integrated Pest management (IPM) (Hagstrum *et al.* 1985, Lippert and Hagstrum 1987, Subramanyam *et al.* 1997, Hagstrum *et al.* 1997). Although statistically robust, methods are not focused on detection but rather on mean abundance estimation and as such have limited suitability for the demonstration of area freedom that is required in surveillance. Furthermore, parameter estimation of the methodologies is typically data intensive requiring extensive data to calibrate models and making them unsuitable for surveillance activities where data can be limited.

Surveillance methods for biosecurity in contrast are relatively new concept for the grains industry (Taylor and Slattery 2008). Methods to maximise surveillance successes and quantify surveillance strategies have been considered from a number of fields, including epidemiology, ecology and plant pathology. A number of methodologies developed for surveillance which could be used for surveillance systems in grains may also have application for fine scale sampling programmes in the grains industry. For example, stochastic scenario trees have been used extensively in surveillance but may also help in the development of cost effective fine scale sampling systems. Although structured sampling is undertaken in grain storages to detect pests, such methods do not incorporate varied risk throughout the production and storage network. Pest density in storages is known to fluctuate in relation to a number of factors including hygiene, storage type and climatic conditions (e.g. temperature and humidly; Hagstrum 1996, Rees 2004). It would be of great benefit to producers and storage managers if fine scale sampling programmes could account for the variation in pest density (risk) associated with such factors. Stochastic scenario trees, could provide a mechanism to incorporate risk relating to different regions, farms or even geographic areas to better inform and parameterise sampling models. Hadorn *et al.* (2009) demonstrated that stochastic scenario trees could be used to develop a cost effective surveillance system for Bluetongue virus, BTV (an insect borne viral disease of ruminants) in central Europe. Similarly to insect pests within storages which vary in density and distribution (Hagstrum *et al.* 1985), BTV is a vector borne viral disease that is present at different prevalences and intensities within a population over a geographic area. Hadorn *et al.* (2009) demonstrated that stochastic scenario trees could be used to better allocate surveillance resources where disease or pest prevalence and intensity varied, and therefore improve the cost effectiveness of surveillance and sampling systems.

Methodologies and current data collection practices from fine scale sampling may also be of benefit to surveillance strategies. Structured surveys which are currently standard practice in the grains storage network, both on farm and in bulk storages would have significant benefits in the development of state or nationwide surveillance systems. From a broad scale surveillance perspective although structured surveys provide a robust quantifiable method for determining pest freedom and eradication success, they are usually cost prohibitive due to the areas that need to be sampled or surveyed. The data collected from individual storages and bulk handling facilities however would be invaluable for surveillance. Furthermore, if industry could modify sampling systems into a uniform region or nationwide system broad scale surveillance could be improved substantially and relatively little cost, as activities are currently undertaken for pest management activities. Using such data from existing storages would also aid in demonstrating freedom of pests such as Khapra beetle from countries were it remains absent such as Australia.

Bayesian methods may provide the greatest gains to grains surveillance and fine scale sampling systems. Bayesian analysis provides a methodology to incorporate multiple forms of both surveillance and sampling data to improve predictive power and inform sampling models (Marcot *et al.* 2001). Across the grain industry, a range of data (qualitative and quantitative) is collected for surveillance purposes and pest management by government agencies, local land owners, industry professionals and research. Although the data is of value, it is often not utilised to its full potential, as data collection methods vary from region to region and between land owners, industry groups etc. As such, analysis for any one surveillance or sampling activity only uses a portion of the total available data. Bayesian techniques can allow for a range of data types to be incorporated into a single analysis (Marcot et a. 2001). Furthermore, Bayesian analysis can be used to incorporate expert opinion as prior information. For example, Bayesian belief networks have been used to incorporate range of data sources for the prediction of algal blooms (Hamilton *et al.* 2007), and fish and wildlife viability (Marcot *et al.* 2001). These studies illustrated the utility of these approaches as predictive tools where multiple data types are present. Similar to scenario trees, Bayesian techniques may also provide a means to incorporate alternative data types to inform parameter estimates of alternative sampling and surveillance approaches.

There are existing methodologies that could benefit from the incorporation of alternative data sources. Elmouttie *et al.* (2010) proposed a methodology for sampling grain storages which overcome the shortfalls of traditional techniques and in many respects is similar to techniques to demonstrate freedom in targeted surveys in epidemiology. The technique considers that both the prevalence and intensity of individual within an area has an influence on the probability of detection. However unlike techniques based on the hyper geometric or binomial functions (Cannon and Roe 1982, Cameron and Baldock 1998) the method proposed by Elmouttie *et al.* (2010) explicitly considers that pests may be heterogeneously distributed. The methodology proposed contains two parameters which need direct estimation, the prevalence of pests and their intensity. As these parameters are a direct translation of a biological occurrence the authors suggested that they may be estimated from a number of data sources. As such Bayesian methodology to incorporate multiple data forms with uncertainty may provide a valuable tool for sampling models for fine scale sampling and surveillance systems.

Conclusion

Sampling and surveillance systems form a major component of the grain supply, production and biosecurity system and their importance will continue to grow into future. A number of techniques designed to justify pest freedom in grain sampling and in surveillance are conceptually similar and hence coordination of strategies would benefit the grains industry. The development of techniques based on stochastic scenario trees and Bayesian analysis may provide a means to a) make sampling more cost effective by targeting sampling where most required and b) allow for alternative data sources to be incorporated into existing sampling plans and methodologies. An area where significant to both surveillance and fine scale sampling can be made is the use of all available data. System need to be developed such that sampling and surveillance strategies become intertwined and data is shared to maximise biosecurity and pest management outcomes.

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