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Economic evaluation of antimicrobial usage surveillance in livestock

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Summary

There is increased pressure by governments and industry to develop national surveillance programmes to evaluate antimicrobial usage (AMU) in animals. This article presents a methodological approach to cost-effectiveness analysis of such programmes.

Seven objectives are proposed for AMU surveillance in animals: quantifying use, finding trends, detecting hotspots, identifying risk factors, encouraging research, evaluating the impact of policies and diseases, and demonstrating compliance with regulations. Achieving these objectives would assist in making decisions about potential interventions, help to generate trust, incentivise the reduction of AMU and decrease the risk of antimicrobial resistance.

The cost-effectiveness of each objective can be found by dividing the cost of the programme by the performance indicators of the surveillance required to meet the objective concerned. The precision and accuracy of surveillance outputs are suggested here as useful performance indicators. Precision depends on the level of surveillance coverage (SC) and surveillance representativeness (SR). Accuracy is influenced by the quality of farm records and SR. The authors argue that there is an increase in marginal cost for each unit increase of SC, SR and data quality. This is caused by the increasing difficulty of recruiting farmers due to potential barriers such as staff capacity, capital availability, computing literacy and availability, and geographical differences, among other factors. A simulation model was conducted to test the approach, using the quantification of AMU as the primary objective, and to provide evidence of the application of the law of diminishing returns.

Cost-effectiveness analysis can be used to support decisions on the level of coverage, representativeness and data quality required in such AMU programmes.

Keywords

Antimicrobial usage – Cost-effectiveness analysis – Data collection – Data precision – Data quality – Livestock – National surveillance system.

Introduction

The increased use of antimicrobials is recognised as the main driver for the selection and spread of antimicrobial resistance (AMR) in bacteria that affect humans and animals [1]. Monitoring antimicrobial usage (AMU) through active surveillance programmes is being implemented or is under consideration in most high-income countries. Setting AMU targets for animal farming is seen as one of the optimum strategies for reducing use. However, in European countries, data on AMU are often inferred from antimicrobial sales to pharmacies, wholesalers and veterinarians. Although this method provides nearly maximum coverage, it produces low-resolution data that do not reflect accurate usage. This is because many farmers have a considerable amount of autonomy over treatment decisions [2, 3]. Furthermore, sales data are not yet being validated against prescriptions.

In addition, on-farm records, required under legislation in the European Union and United Kingdom (UK), should provide the most accurate, high-quality data. However, the format of these records is not standardised and varies greatly (paper or electronic), creating considerable challenges for collating farm-level data on AMU. It has been recognised that central digitalisation of AMU is needed for efficient surveillance [4]. The Centers for Disease Control and Prevention guidelines on surveillance programmes, along with the World Health Organization, state that the cost of such programmes should not be estimated alone, but judged relative to the effectiveness that these programmes can bring [5, 6].

Cost-effectiveness analysis (CEA) is a tool that has been applied extensively in animal health, production and welfare to evaluate interventions in economic terms [7]. It has been proposed as a useful technique to evaluate disease surveillance in animals [8]. The aim of this study is to present a cost-effectiveness approach to the development of a digital national centralised surveillance programme on AMU.

Setting objectives for a national antimicrobial usage surveillance programme for livestock production

According to the World Organisation for Animal Health, the objectives of AMU surveillance programmes are to:

- provide an indication of trends over time
- assess the potential impacts of AMR (and ensure a targeted response)
- help to manage risks by evaluating the effectiveness of interventions [9].

The objectives of an AMU monitoring programme implemented in the Netherlands included setting annual targets for AMU and benchmarking for farmers and veterinarians (identifying high users or prescribers) [10].

In Table I, seven objectives are proposed for the establishment of an AMU surveillance programme in animals. The capacity of the programme to achieve these objectives needs to be considered at the design stage. Farmers could benefit in several ways.

- Through benchmarking, individual farmers can compare their use of antimicrobials to that of other similar farmers and set targets for their own use.
- The detection of AMU hotspots (i.e. identifying areas or individual producers associated with large quantities of AMUs) will allow the establishment of targeted investigations and control measures to protect the farming community.
- The outputs of the surveillance programme can be used to provide evidence of compliance, help generate trust and facilitate access to profitable markets.
- The programme can incentivise the reduction of AMU and decrease the risks of AMR and its economic consequences.

If such surveillance is successful in reducing AMU and controlling risk hotspots, consumers and society will benefit through:

- better public health protection, as the risk of AMR is reduced
- an increase of trust and confidence in animal products
- improved economic development, associated with more efficient farm systems.

In Denmark and the Netherlands, such programmes have generated evidence on the association between AMU and AMR, leading to significant policy changes, including the ban of antibiotic growth promoters in 2006 [10, 11, 12].

Table I

Proposed objectives of a national antimicrobial usage surveillance programme in livestock

Objective	Reason: to
Quantify antimicrobial usage	Generate awareness of the magnitude of usage Allow comparison with other countries or regions Provide benchmarking data for farmers to set objectives Allow the setting of targets for reduction in use
Detect trends and patterns	Understand whether usage is increasing or decreasing Detect seasonal variations in usage and the magnitude of variance Assess efficacy of policies or interventions
Detect hotspots	Identify areas with significantly higher usage of antimicrobials Identify farmers and veterinarians who are high or very high users or prescribers Identify sudden localised increases in usage due to disease outbreaks (real-time surveillance required)
Identify risk factors	Determine the possible causes for antimicrobial usage Identify systems that are more likely to have increased usage
Facilitate research	Investigate associations with antimicrobial resistance trends or emergence Understand links with animal and human health
Evaluate impact	Determine effectiveness of policies or interventions Allow a determination to be made of the disease impact
Allow compliance	Enable the demonstration of compliance with industry targets Assess the level of compliance against quality assurance standards Generate trust and facilitate trade

Surveillance coverage and representativeness

Surveillance coverage is defined as 'the proportion of the population of interest (target population) that is included in the surveillance activity' [13]. Bertino defined representativeness as 'the degree of capacity of the sample to exhibit the characteristics of the parent (target) population' [14]. Lack of coverage will affect the precision of AMU estimates by the programme. Lack of representativeness can lead to errors in the accuracy of AMU estimates. Both will jeopardise the capacity of the programme to assess the magnitude of AMU and evaluate trends and the effectiveness of interventions.

To minimise these errors, it is essential to have knowledge of the factors influencing AMU and their spread among the population (i.e. have a good understanding of the population structure). Some of the factors that can potentially influence AMU and record-keeping by farmers, among others, are:

- geographical region
- season
- production system
- herd size
- farmer's computing literacy
- information technology (IT) capacity (e.g. the presence of computers on farms and Internet services)
- the type of contract supplier (e.g. companies that buy livestock from farms have different requirements for AMU-associated data collection and use)
- age and experience of the farmer.

The importance of these factors varies, depending on the country. Many will influence disease prevalence, as different regions have various farm densities, climates and even policy environments that facilitate or reduce disease spread. Van Boeckel *et al.* show how AMU varies between countries and production systems [15]. Curone *et al.* provide evidence that Holstein Friesian cattle are more susceptible to diseases such as mastitis than local breeds [16]. This characteristic will also have an impact on AMU. Menéndez González *et al.* found that 32% of small Swiss dairy farms used paper records, representing a substantial obstacle to electronic surveillance [17].

The structure of the target farm population can then be described, based on the distribution of farms among these factors: i.e. by categorising the farm population into different strata ($x \rightarrow x_1, x_2, ..., x_n$). Measuring the level of representativeness becomes a useful indicator for subsequent CEA of the surveillance and to understand the quality of the sample (Figure 1). Several authors have provided suggestions of representative indexes, such as Bertino [14].

Data quality

Data quality can be defined as the capacity of the data to accurately reflect actual antimicrobial usage on farms. The quality of data is determined by the amount of missing and incorrect data. 'Missing data' refers to the proportion of treatments that have not been recorded in the system. 'Incorrect data' relates to the proportion of treatments recorded incorrectly, either because numbers were entered erroneously or because the wrong antimicrobial was recorded. Both types of error have different impacts on the accuracy of the final AMU measurement on the farm. Missing data underestimate the level of AMU. For example, a farm that has only recorded 80% of its treatments could result in a falsely reduced AMU. Incorrect data can increase or decrease the estimate, particularly if these data are associated with systematic errors (as opposed to random errors). Consequently, some of these errors will be more important than others, and further research is needed to understand the magnitude of such errors and the reasons for them. Both types of error can be used to estimate the proportion of total treatments recorded and recorded correctly (γ), in equation 1.

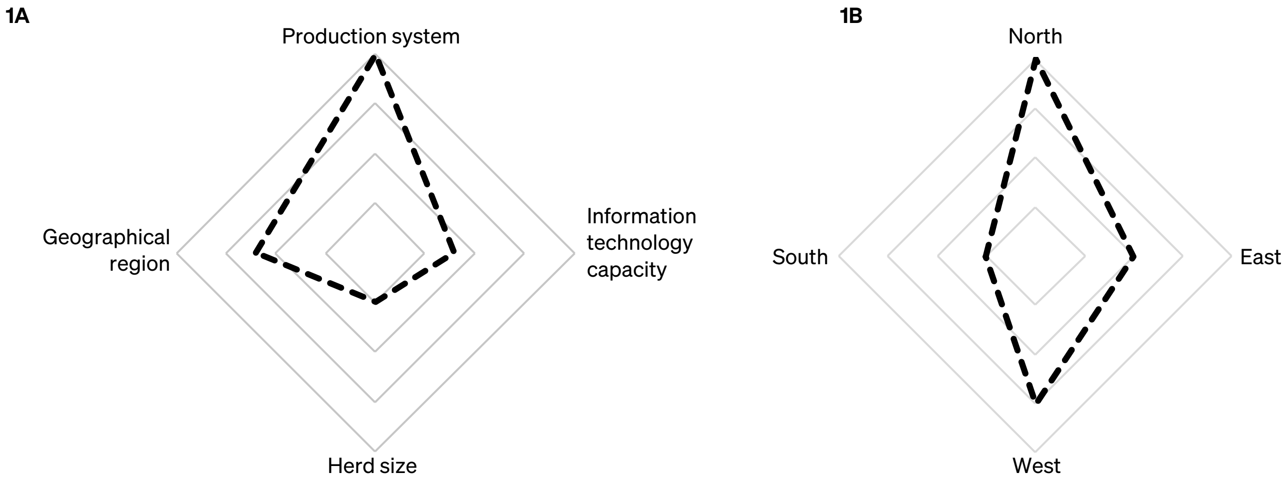

Figure 1

Example of a representativeness index of hypothetical antimicrobial usage surveillance in livestock within a country

Figure 1A shows the representativeness for different factors, while Figure 1B shows the representativeness of different strata within one factor (in this case, geographical region). In this example, the surveillance programme achieves good representation in information technology capacity and herd size but is potentially deficient in production systems and geographical regions. In terms of regions, the areas with poorer representativeness are the North and West

$$\gamma = [1\text{–}Proportion\ of\ treatment\ with\ missing\ data][1\text{–}Proportion\ of\ treatments\ with\ incorrect\ data] \quad (1)$$

For example, $\gamma = 0.9$ indicates that full data have been recorded correctly for 90% of treatments implemented on the farm.

Several studies have identified the potential under-reporting of AMU in medical records, including falsifying such records [18, 19, 20, 21]. A recent UK study found that on-farm records vary in quality and, as a result, veterinary sales data are currently the most reliable source of information on AMU [22]. A study of small Swiss dairy farms by Menéndez González *et al.* found that antibiotic name and dosage were often inaccurate, with under- and over-dosing frequently observed [17]. Trauffler *et al.* studied Austrian pig farms to discover that 14% of unrealistic drug amounts were present in farm records [23].

Calculation of the cost-effectiveness of an antimicrobial usage surveillance programme in livestock

For surveillance programmes, a CEA can be conducted for each of the objectives (i) of the surveillance, using an average cost-effectiveness ratio (ACER):

$$objective\ specific\ ACER_i = Ct / K_i \quad (2)$$

where Ct is the total cost of the surveillance and K indicates the performance of the programme for objective i. The incremental cost-effectiveness ratio (ICER) can also be calculated to assess the value of changes in key surveillance parameters, such as coverage and representativeness. Equation 3 illustrates the ICER for changes in surveillance coverage:

$$ICER = \frac{Ct_{10 + x\%\ coverage} - Ct_{x\ \%\ coverage}}{K_{at\ 10 + x\%\ coverage} - K_{at\ x\%\ coverage}} \quad (3)$$

In this case, ICER allows us to understand the increased cost of each additional unit of performance gained by increasing surveillance coverage by 10%. The ICER may represent a more useful approach to assist in decision-making on surveillance design.

The overall costs of the programme can be calculated as in equation 4:

$$Ct = Co + Cf \quad (4)$$

where Co is the total cost incurred by the institution organising and implementing the surveillance. This could be a national or regional government or an industry board. On the other hand, Cf is the total cost incurred by the farmers participating in the surveillance programme. The performance indicator (K) is defined by the objectives set for the programme. This could be, for example, the power to identify trends in AMU, or the precision of AMU measurement at national, regional or farm levels.

Cost of the programme

Effective antimicrobials should be considered a public good, as society benefits from their proper use. Over-consumption of antimicrobials can also create negative externalities (that is, AMR). At the same time, farmers benefit from antimicrobials since they are seen as essential to control animal diseases and ensure efficient production. Hence, the assignment of costs of an AMU surveillance programme between the farming industry and the public purse requires careful consideration. In the Netherlands, surveillance programmes are implemented through public–private partnerships. In this section, the authors focus on the types of cost incurred when implementing such a surveillance programme [10].

The cost incurred by institutions organising and implementing the programme (Co) can be calculated as in equation 5:

$$Co = Start\ up\ costs + \sum_{t=1}^{tmax} \left(\frac{Fixed\ costs + variable\ costs}{(1+r)^t} \right) \quad (5)$$

The start-up costs are those expenses required before the programme begins. Variable costs and fixed costs are incurred on a yearly basis (t), with $tmax$ being the final year of the analysis. Some studies may concentrate on short-term analysis (e.g. if evaluating the cost-effectiveness of the surveillance programme in detecting trends) or longer term (e.g. if evaluating the impact of surveillance on the reduction of AMR and public health consequences). The costs should be discounted into the present value using the discount rate (r).

The types of costs are shown in Table II. The relevant start-up costs are the costs of developing an application interface that can extract data from the existing software used by farmers. In most countries, there is a wide range of data-recording software. A UK survey of dairy farms reported that eight different types of software were used by farmers to record AMU [24]. The number of farmers using each type of software will have an effect on the potential coverage of the surveillance.

The yearly fixed costs of the programme are a combination of the annual staff costs needed to run the programme, data storage costs and the costs of maintaining the equipment. Annual staff costs include the costs of extracting the data from farms and entering them into the centralised system,

Table II

Potential costs incurred in the development and implementation of a surveillance programme for antimicrobial usage surveillance in livestock

	Cost incurred by the organising institution	Cost incurred by farmers
Start-up costs	Cost of accessing the funding needed Cost of designing the programme Cost of employing experts to design and review the programme Cost of programme approval and validation Cost of equipment or technology (including developing an application interface to extract data from farmers) Cost of setting an enforcement mechanism*	Equipment (e.g. computers)**
Fixed costs	Permanent staff costs Cost of maintaining equipment Storage costs	Equipment maintenance** Recording software subscription** Internet access** Electricity**
Variable costs	Cost of training new farmers Cost of communicating results Cost of recruiting new farmers Cost of enforcement* Cost of incentivising data collection	Staff time (opportunity cost) Training costs

* Only applicable to compulsory programmes
** Only applicable to those farmers lacking such equipment costs before the programme

cleaning and analysing the data, and producing the relevant reports. If the programme is compulsory, staff costs needed to enforce the programme should be included. The yearly variable costs depend on the number of farmers participating in the surveillance programme each year against the number of farmers still needing to be recruited to achieve suitable coverage. The cost of training farmers may depend on their IT capacity. Those farmers who are already recording data electronically before the surveillance programme begins will require less training than those who record their information on paper and are not familiar with computers.

The cost of recruiting farmers will not be linear; there will be an increase in the marginal cost of recruiting each additional farmer. Initially, it will be relatively easy to recruit those farmers who are highly motivated, are readily accessible and have good IT capacity. After this, the effort to recruit new farmers will increasingly cost more, as farmers become more difficult to recruit and the costs of including them (e.g. training them to use computers) go up. This may affect the representativeness of the surveillance programme, as those who are not willing to participate are likely to have different AMU practices from those who readily take part. Figure 2 shows an example of the production function with the total costs for the organising institution, where the slope of the curve depends on the difficulty of recruiting farmers in a country. Yet, over time, once the country has reached the desired level of coverage, the costs will remain constant.

The costs incurred by individual farmers will differ, depending on population stratum and their first year of participation in the programme (as experience will reduce cost). Many of these costs will depend on the willingness of the farmer to pay for them. A low willingness to pay will have a significant impact on farmer participation and data quality if the full costs required by the programme are not met. In addition, some farmers may incur equipment and infrastructure costs to ensure that they have an adequate computer, subscriptions to recording software, a reliable electricity supply and good Internet connectivity on the farm. These represent the biggest barriers to AMU surveillance in low- and middle-income countries.

Calculating performance

Each objective will require its own measurement of performance. For example, performance can be measured based on the capacity to prevent AMR, or the number of lives saved (human or animal), or improvements in quality of life due to the avoidance of treatment failure in both humans and animals. In this paper, however, the authors focus on the surveillance objective of quantifying AMU at the national level, which can be used to set targets, to detect trends or as benchmarking for farmers. For this, precision and accuracy can represent performance, as the more precise and accurate the estimation, the better one can demonstrate changes in AMU and the efficacy of policies or interventions.

To measure these performance indicators, one can start by measuring the AMU per kg at farm level for the i^{th} farm in the j^{th} stratum. This is denoted this as c_{ij}, and it is calculated as in equation 6:

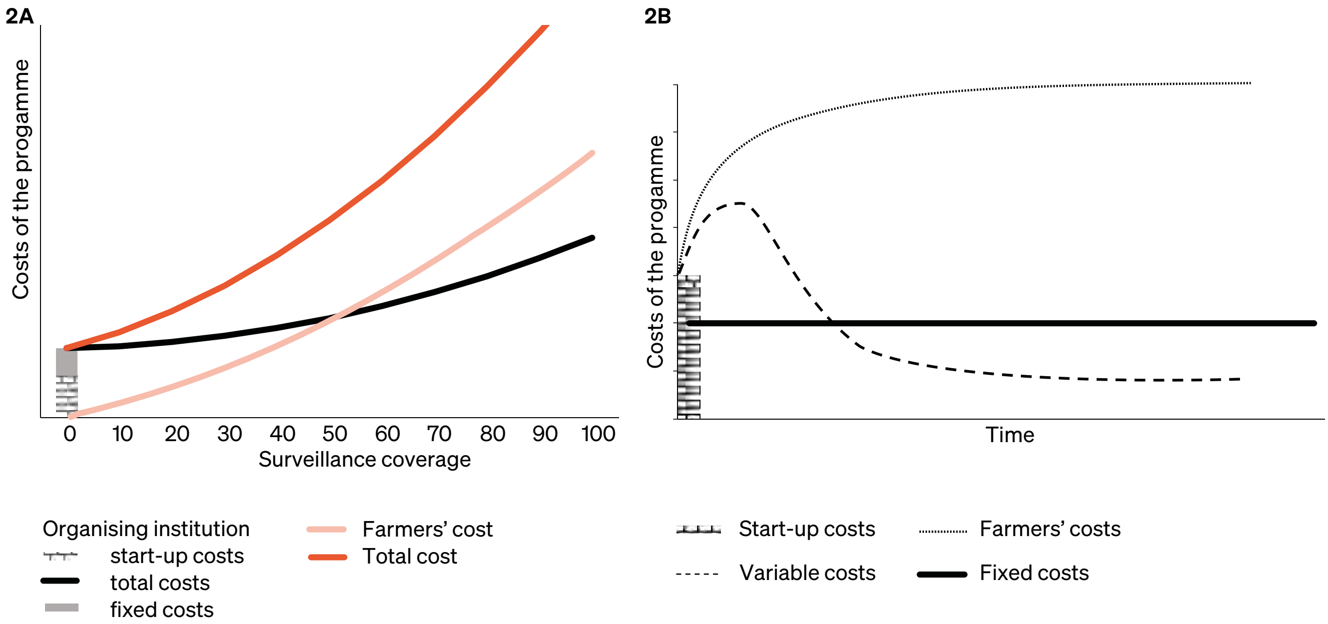

Figure 2

Example of the costs of a national surveillance antimicrobial usage programme in livestock

Figure 2A shows the costs incurred by the organising institution and by farmers, depending on surveillance coverage. Figure 2B shows the evolution of costs over time

$$c_{ij} = \frac{\sum_q^k (ab_{iq})}{n_{ij}} \tag{6}$$

where ab_{iq} is the quantity of AMU for the q^{th} treatment $(q_1, q_2, \ldots, q_k)$, and n_{ij} denotes the herd size (in kg) for the i^{th} herd in stratum j. The equation can be corrected to account for missing data, as follows:

$$c_{ij\ corrected} = \frac{c_{ij}}{[1\text{–Proportion of treatments with missing data}]} \tag{7}$$

Equation 7 assumes that the treatments not entered have the same AMU distribution as those entered. If incorrect data are assumed to have been caused by a random error (e.g. a typing mistake), then they may not require correction. Yet, further research to understand the nature and distribution of data quality is essential. Based on this, the average AMU per kg (c) at each stratum and national level can be estimated.

Performance can then be calculated based on the magnitude of the range of c, so the precision of the final estimate is reflected by the size of the standard error (Eq. 8). Performance can also be measured based on the accuracy of the final estimate. This is the difference between c with no missing data and perfect sample representativeness and c with missing data and/or imperfect sample representativeness, as shown in equation 9:

$$K_{precision} = SE\ (c) \tag{8}$$

$$K_{accuracy} = c_{Missing\ data\ \neq\ 0\ and/or\ imperfect\ R} - c_{Missing\ data\ =\ 0\ \&\ perfect\ R} \tag{9}$$

where R denotes representativeness of the sample in the programme. It is possible to correct for the accuracy of the AMU measurement of surveillance with low representativeness by calculating the weighted mean (weights based on the proportion of farms in the population within each stratum). This will, however, increase standard errors in the final measurement and reduce the precision of the estimate.

Simulation of cost-effectiveness of antimicrobial usage surveillance for a country

To illustrate the methodology, the authors simulated the population of dairy farmers within a country. The simulation generated a population of 8,040 farms dispersed through four different regions. Only one stratum type (geographical) was used, for the sake of simplicity. The distribution of AMU from 40 English and Welsh farms, based on data from farm records [17], was used to establish usage on all farms in this simulation. The true average AMU per kg was 19.81 mg/kg (standard deviation = 7.48). Figure 3 shows the level

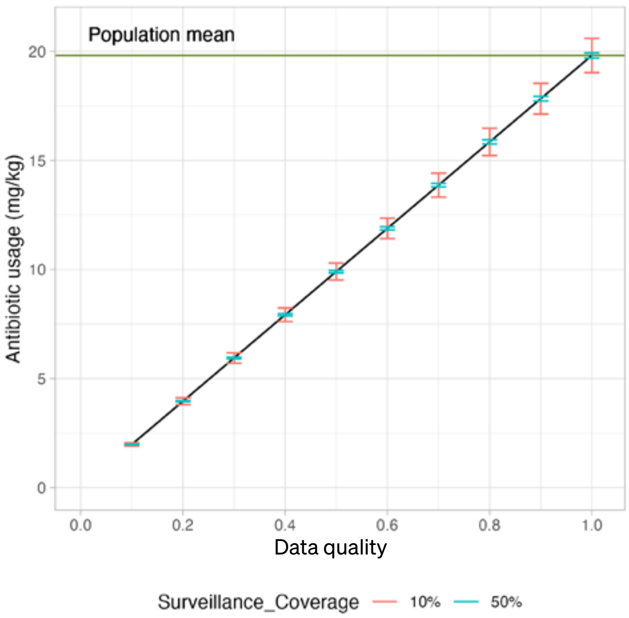

Figure 3

Estimate of mean antimicrobial usage from a national surveillance programme on the dairy farms of a hypothetical country, with 10% and 50% farm coverage, depending on the data quality of farm records

The horizontal line shows the true mean in the population

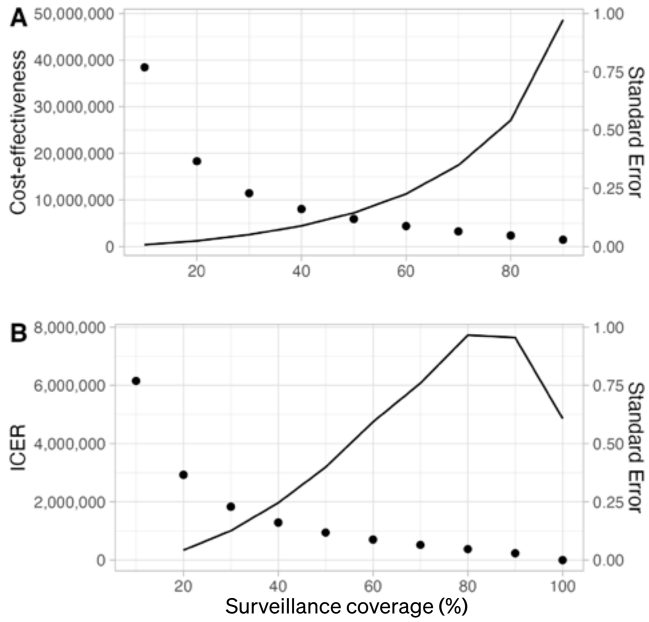

Figure 4

Average cost-effectiveness ratio (Figure 4A) and incremental cost-effectiveness ratio (ICER) (Figure 4B) of a surveillance programme on antimicrobial usage on the dairy farms of an hypothetical country, with different levels of surveillance

The dots represent the standard deviation

of precision of the measurement of mean AMU per kg for 10% and 50% coverage, which are shown as the confidence intervals, based on the standard error. Figure 3 shows the changes in accuracy due to the reduction in data quality.

The costs of the surveillance for the organising institution and for the farmers were simulated, based on a function that reflects the increased marginal costs of increasing farmer participation in the programme. The cost-effectiveness of the programme was then calculated, using precision (the standard error) to measure performance.

If perfect representativeness and data quality are assumed, the cost-effectiveness of the programme according to coverage is presented in Figure 4. The analysis shows that, in this scenario, a small standard error of 0.8 is achieved with only 10% coverage, with a small cost per unit of standard error. This standard error reduces significantly as coverage increases, while the cost increases substantially after 40%, 60% and 80% coverage, reflecting the law of diminishing returns. Surveillance designers can use this to know the increased cost of the programme per unit of precision gain, and decide the most economically acceptable level of coverage needed.

The authors argue that increasing the representativeness and data quality will represent an increased cost to the surveillance programme and to farmers, and thus affect the programme's cost-effectiveness. This means that, for the same level of coverage, a perfect representative sample will have smaller standard errors than a cheaper, non-representative sample. A similar effect will occur with data quality, as increasing data quality will require training, incentives and regular validation, and hence also increase programme costs. When designing AMU surveillance programmes, researchers should take into account the acceptable level of representativeness and data quality, since these are important factors in the programme's final cost effectiveness.

Conclusions

The design of national surveillance programmes requires multiple decisions that have important economic costs and performance consequences. A CEA can inform policy-makers about the potential trade-offs between increasing expenditure on surveillance and the consequent gain in programme performance. Whether a given increase in performance is desired or useful will also depend on the programme manager. Grosbois *et al.* suggest that the CEA should also assess the cost associated with the probability that the information generated by the programme may lead to inappropriate interventions or no interventions at all [25].

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Évaluation économique de la surveillance exercée sur l'utilisation d'agents antimicrobiens chez les animaux d'élevage

P. Alarcon, C.L. Strang, Y.M. Chang & M. Tak

Résumé

Les gouvernements tout comme le secteur de l'élevage exercent une pression croissante pour que des programmes nationaux de surveillance soient élaborés afin d'évaluer l'utilisation d'agents antimicrobiens (UAM) chez les animaux. Cet article présente une approche méthodologique permettant de réaliser l'analyse coût-efficacité de ces programmes. Sept objectifs sont proposés pour la surveillance de l'UAM chez les animaux : quantifier cette utilisation, relever les tendances, détecter les situations d'utilisation intensive, déceler les facteurs de risque, encourager la recherche, évaluer l'impact des politiques et des maladies et démontrer la conformité avec les réglementations. La réalisation de ces objectifs de surveillance permettra de prendre des décisions éclairées sur les interventions à mener, contribuera à mettre en place un climat de confiance, encouragera à réduire l'UAM et atténuera le risque d'apparition d'antibiorésistances.

Le ratio coût-efficacité de chaque objectif peut être déterminé en divisant le coût du programme par les indicateurs de performance de la surveillance requise pour chacun des objectifs examinés. Les auteurs considèrent que la précision et l'exactitude des résultats de la surveillance sont des indicateurs de performance utiles à cet effet. La précision dépend du niveau de couverture de la surveillance (CS) et de sa représentativité (RS). L'exactitude est fonction de la qualité des registres d'élevage et de la RS. D'après les auteurs, chaque accroissement unitaire de la CS, de la RS et de la qualité des données donne lieu à une augmentation du coût marginal. Celle-ci s'explique par la difficulté croissante de recruter des éleveurs pour cette activité, en raison d'obstacles tels que le manque d'effectifs, la disponibilité de capitaux, le manque de compétences et d'équipements informatiques et les différences géographiques, entre autres facteurs potentiels. Un modèle de simulation a été mis en œuvre pour tester cette approche à partir de l'objectif principal (la quantification de l'UAM), et pour apporter des éléments démontrant l'application de la loi des rendements décroissants dans ce domaine.

L'analyse coût-efficacité peut être utilisée pour étayer les décisions concernant la couverture, la représentativité et la qualité des données requises pour les programmes de surveillance de l'UAM.

Mots-clés

Analyse coût-efficacité – Animaux d'élevage – Collecte de données – Précision des données – Qualité des données – Système national de surveillance – Utilisation d'agents antimicrobiens.

Evaluación en clave económica de la vigilancia del uso de agentes antimicrobianos en el ganado

P. Alarcon, C.L. Strang, Y.M. Chang & M. Tak

Resumen

Los gobiernos y la industria vienen presionando cada vez más para la implantación de programas nacionales de vigilancia destinados a evaluar el uso de agentes antimicrobianos (UAM) en los animales. Los autores presentan una solución metodológica para analizar la relación costo-eficacia de tales programas.

En primer lugar proponen un conjunto de siete objetivos que deben cumplirse al vigilar el UAM en los animales: cuantificar el uso, detectar tendencias, localizar áreas de «gran intensidad» de uso, determinar los factores de riesgo, alentar la investigación, evaluar la repercusión de las políticas y las enfermedades y comprobar la observancia de los reglamentos. El logro de estos objetivos ayudaría a decidir sobre posibles intervenciones y a generar confianza, supondría un incentivo para reducir el UAM y atenuaría el riesgo de que surgieran resistencias a estos productos.

Para cada objetivo es posible determinar la relación costo-eficacia dividiendo el costo del programa por los indicadores de desempeño de la vigilancia requerida para cumplir el objetivo en cuestión. Los autores proponen utilizar la precisión y exactitud de los resultados de la vigilancia como útiles indicadores de desempeño. La precisión depende del nivel de cobertura y de representatividad de la vigilancia. En la exactitud, por su parte, influyen la calidad de los archivos de las explotaciones pecuarias y la representatividad de la vigilancia. Los autores postulan que cada aumento unitario de la cobertura y la representatividad de la vigilancia y de la calidad de los datos se acompaña de un aumento correspondiente del costo marginal. Ello se explica por la creciente dificultad que presenta la participación de ganaderos en el proceso, debida a su vez a posibles barreras en aspectos como la dotación de personal, el capital disponible, los conocimientos en informática y el acceso a ordenadores o las diferencias geográficas, entre otros factores.

Para ensayar el método y probar que se aplica el principio de los rendimientos decrecientes, los autores emplearon un modelo de simulación, utilizando como principal objetivo la cuantificación del UAM.

El análisis de la relación costo-eficacia puede ser utilizado como herramienta auxiliar para tomar decisiones sobre el nivel de cobertura, representatividad y calidad de los datos que se necesita en este tipo de programas de vigilancia del UAM.

Palabras clave

Análisis de la relación costo-eficacia – Calidad de los datos – Ganado – Precisión de los datos – Recogida de datos – Sistema nacional de vigilancia – Uso de agentes antimicrobianos.

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