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Precision livestock farming as a useful tool to reduce environmental impact of the farms

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The livestock industry has numerous and diverse impacts on the environment. Everyday farming practices, combined with continuous real-time monitoring of animal parameters, can have a significant impact on the assessment of animal welfare and health, and hence on the environment, which are current topics of public interest. Animal husbandry and the environment are two concepts that are constantly intertwined. This paper reviews and analyses the environmental impact of current livestock management practices and highlights the critical role of Precision livestock farming (PLF) in ensuring the effective application of existing and new information on farms as a potential guideline to reduce the problems and risks of environmental impact. Strategies and methods to reduce environmental risk situations are being explored. Solutions are proposed with an emphasis on PLF as a useful monitoring tool in this regard. For risk analysis of agricultural sites, quantitative models are proposed. These formal models are based on the portfolio theory.

Keywords: environmental impact, PLF, IoT, livestock management, mitigation strategies, risk analysis.

INTRODUCTION

The increasing consumption of food of animal origin in recent years has necessitated an increase in its production on farms. On the one hand, this leads to the creation of a greater number of farms with large herds. On the other hand, this can lead to a number of risks, including sudden changes in the By applying information technologies such as software (cloud computing, artificial intelligence) and hardware (sensors, computers, and smartphones) in livestock farming, it is possible to automatically monitor and control environmental, physiological, and behavioral variables, ensuring the productivity and well-being of livestock in relation to the environment without any disturbance or manipulation. A major challenge in the livestock sector is how the environmental impact of the sector should be resolved. Food production accounts for 26% of global greenhouse gas emissions [1]. The Intergovernmental Panel on Climate Change (IPCC) guidelines, which focus on farm activities, state that agriculture is responsible for over 10% of greenhouse gas emissions in the EU, with the majority of these emissions coming from the livestock sector. According to [2], more than 90% of NH_3, 37% of CH_4 and 65% of N_2O in the atmosphere come from the livestock sector. This sector uses up to 30% of total land and 8 to 15% of water resources. A major contribution to reducing environmental impact would be to manage livestock production so that the performance of animals is closer to their genetic potential - less feed use, less manure and higher productivity. Keeping farmers competitive is a challenge and animal productivity is a key factor.

Digitalisation provides an opportunity to increase the competitiveness of the agricultural sector. The entry of information and communication technologies (ICT) into livestock farming and the increasing use of the Internet of Things (IoT) are opening up a new era of connectivity, in which things, people and animals are part of an exchange of data networks, leading to a new philosophy of the agricultural sector.

A number of authors [3-6] identify Precision livestock farming (PLF) as a valuable tool for reducing the environmental impact of livestock production. With PLF, farmers can ensure the good health and welfare of their animals, achieving good productive and reproductive outcomes, and reducing the environmental impact per unit of animal product. The main objective of PLF is to make livestock farming more economically, socially, and environmentally sustainable. This can be achieved through observation, behavioral interpretation, and where possible, individual animal control. Daily farming practices combined with continuous real-time monitoring of animal parameters can have a significant impact on reducing the problems and

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risks associated with environmental impacts. More research is needed to better analyze and assess the actual potential of PLF as a guideline for reducing environmental impacts.

This paper reviews and analyses the environmental impact of current livestock management practices and highlights the critical role of PLF in ensuring the effective application of existing and new information on farms as a potential guideline to reduce the problems and risks of environmental impact. Strategies and methods to reduce environmental risk situations are being explored. Quantitative models are proposed for the risk analysis of agricultural sites. These formal models are applied from portfolio theory. This provides a basis for applying this theory to farm management decisions. The aim is to maximize return and minimize risk. By minimizing economic risk, potential losses in livestock production can be reduced. This would reduce the problems and risks associated with environmental impacts.

Environmental effects

Livestock farming is a key factor for sustainable agricultural production. They contribute to food security, nutrition, poverty reduction, and economic growth. By adopting best practices, the sector can reduce its impact on the environment and become more efficient in its use of resources.

The livestock sector is an important user of natural resources and has a significant impact on the environment, including air quality, global climate, land, soil quality, water quality, and biodiversity (Figure 1).

- A growth in meat consumption worldwide, leads to an increase of waste by livestock systems that pose dangers to the environment.
- Another impact of livestock farming on soil is the environmental pollution by antibiotics. Antibiotics are often used in the farming industry as veterinary drugs and growth promoters for therapeutic purposes.
- Livestock farming impacts on air through the emissions of ammonia (NH_3) and Green House Gases (GHG), arising simultaneously from animal housing, yards, manure storage and treatment, and land spreading. According to [7], implementing PLF ventilation control systems in animal housing can be reduced NH_3 emissions by 60-65%.
- Field application of livestock manure supply nutrients and micro-elements useful to crop growth, but also elements that can accumulate in their tissues and enter in the food chain.

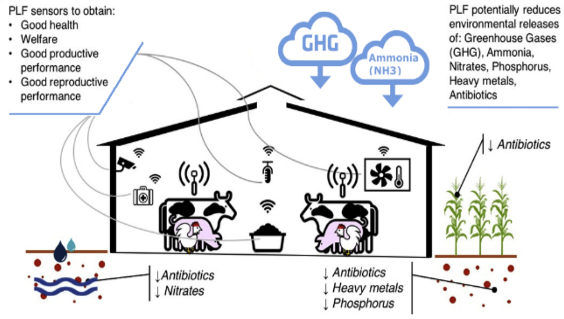

Figure 1. Effects of livestock farming on the environment [21]

Agriculture is responsible for the majority of global greenhouse gas emissions, according to the European Court of Auditors (ECA) [8].

Figure 2 shows the three main types of greenhouse gas emissions from agriculture, their main sources in the EU, and the share of these sources in total emissions from agriculture, which represent about 13% of total EU-27 greenhouse gas emissions (including an additional 2.7% from land use emissions and greenhouse gas removals from arable land and permanent grassland). Additional emissions not included in Figure 2 arise from the use of fuels for machinery and heating buildings, accounting for about 2% of total EU-27 emissions.

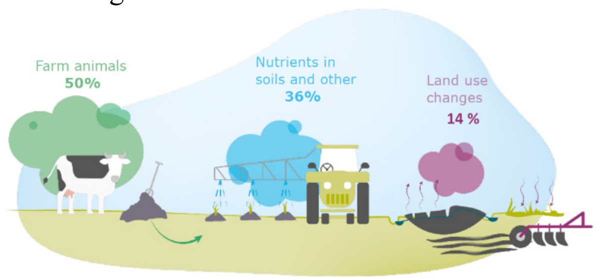

Figure 2. Main greenhouse gas emissions sources (CO_2 equiv.) Source: ECA based on the EU-27 GHG inventories in 2018 (EEA greenhouse gases, European Environment Agency (EEA)), [8]

Mainly methane (CH_4) from:

- Digestion of cattle and sheep feed.
- Storage of cattle and pig manure.

Mainly nitrous oxide (N_2O) from:

- Application of chemical fertilizers.
- Manure applied by farmers or deposited by grazing cattle.

Mainly carbon dioxide (CO_2) from:

- Treatment of drained organic soils (peatlands).
- Carbon sequestration on grassland and arable land.

Figure 3 shows the share of EU-27 emissions in 2020 (% of total kt (kilo tonnes) along gas), including the three main types of GHG. According to the statistics, the emissions of N_2O (CO_2eq) in 2020 are 166,830 kt (43.6%), of CO_2 - 9,722 kt (2.5%), of CH_4 (CO_2eq) - 205,897 kt (53.8%).

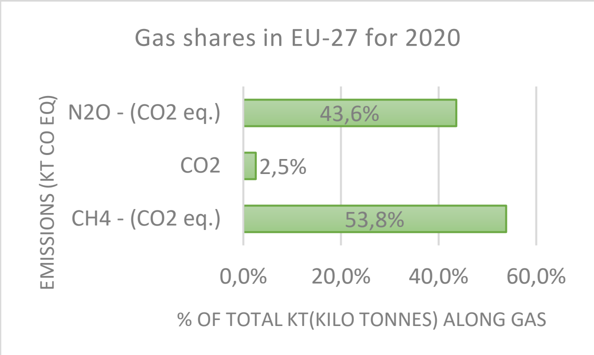

Figure 3. Gas shares in EU-27 for 2020. (Source: EEA greenhouse gases)

Trends in the EU from 2000 to 2020 for the three types of GHG emissions are shown in Figure 4.

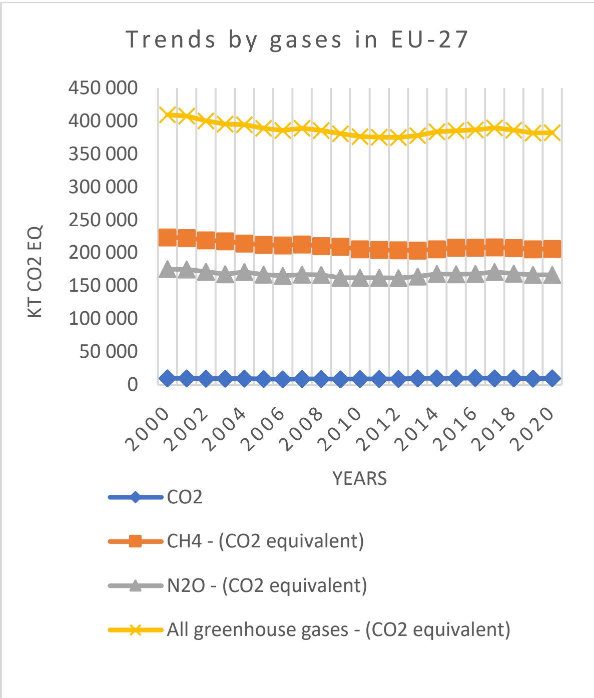

Figure 4. Trends by gases in EU-27 from 2000 to 2020, (Source: EEA greenhouse gases)

Some land use practices provide opportunities to reduce emissions and remove carbon dioxide (CO_2) from the atmosphere by storing carbon in the soil or in biomass (plants and trees). These practices include the restoration of drained peatlands or afforestation.

Emissions from the livestock sector, which mainly come from livestock farming, account for about half of the agricultural emissions and have remained stable since 2010.

Figure 5 shows the evolution of greenhouse gas emissions over the period 2000-2020. Between 2000 and 2010, they decreased mainly due to a decrease in fertiliser use and the number of farm animals. After 2010, emissions stopped falling.

According to the Intergovernmental Panel on Climate Change (IPCC, 2020), emissions of all greenhouse gases in the EU-27 from livestock, road transport, and public electricity and heat sectors are on a declining trend towards 2020. This trend is particularly pronounced in the energy sector, especially in the public electricity and heat sector (from 1,222,897 gigatonnes of CO_2 equivalent (CO_2eq) in 2003 to 655,620 tonnes of CO_2eq in 2020) (Figure 6). This indicates that more serious attention needs to be paid to so-called "green energy".

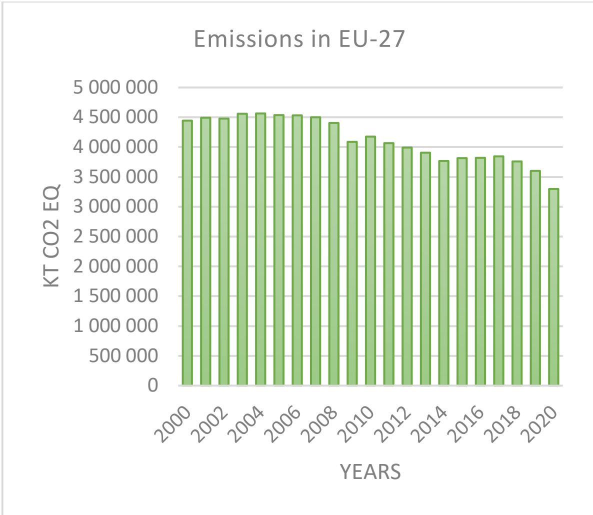

Figure 5. GHG emissions from agriculture in the EU-27 since 2000. (Total emissions (UNFCCC)) (Source: EEA greenhouse gases)

The research in [9] is aimed at investigating biogas production technologies, evaluating feedstocks and products, carefully investigating and evaluating all possible feedstock and product flows, and assessing the environmental impact of this activity. Based on the study, an optimisation model using Mixed Integer Linear Programming (MILP) was developed to determine potential locations and optimal parameters as well as transport flows of existing and potential activities.

However, the adoption of existing best practices and technologies in animal nutrition, health, and husbandry, as well as improved manure management, can make the global livestock sector more sustainable and reduce greenhouse gas emissions by up to 30%. In addition, carbon sequestration in biomass and pasture soils can significantly offset emissions from livestock production.

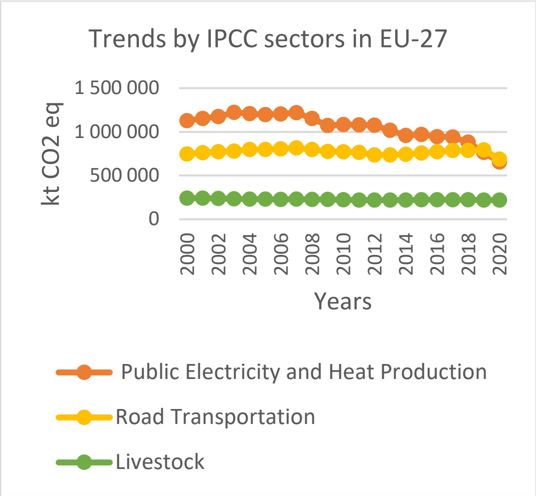

Figure 6. Trends by IPCC sectors in EU-27 since 2000. (Source: EEA greenhouse gases)

Mitigation strategies and methods

To address all of these issues, livestock systems and related agricultural activities need to move towards more sustainable practices.

The concept of sustainability applied to agricultural/livestock systems means that production levels are maintained within the capacity of the ecosystem that supports them.

The livestock sector is therefore in a difficult position, having to maintain high levels of production while at the same time improving its environmental performance.

Several sustainable development goals considered important and relevant to livestock production are shown in Figure 7.

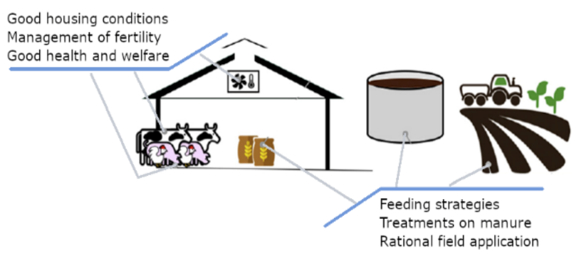

Figure 7. Mitigation strategies adopted in livestock farming [21]

These include fertility management, good health and welfare, good housing conditions, feeding strategies, rational field application, manure treatment.

According to [10, 11], an important step in the development of biotechnological process models is parameter identification by solving inverse problems. In [12, 13], an approach for parameter identification of multi-parameter models is proposed. This approach has been tested for the modelling of fermentation systems. The results obtained show a reduction in the model error variance at each successive hierarchical level.

Therefore, in the face of resource scarcity and with a view to reducing greenhouse gas emissions, the sector must maximise efficiency in production, animal welfare and profitability for farmers using practices and technologies that reduce environmental impact.

According to [14], in order for livestock production to cope with the impacts of climate change, several mitigation strategies need to be adopted. Mitigation potentials can be grouped into three main categories: 1) intensification and related structural changes in the livestock system; 2) technical and management interventions; and 3) moderate demand for animal products [15]. The last category is less realistic due to the increasing global demand for animal products [16].

In recent years, considerable research effort has gone into developing methods and strategies to mitigate and reduce the environmental impact of agricultural practices. There is no mention in the literature of PLF technology specifically designed to reduce the environmental impact of livestock production. However, the use of PLF to support management strategies can reduce the environmental impact of farms. There are a number of issues that need to be addressed in this sector, such as monitoring animal health and welfare, reducing environmental impact and ensuring process productivity. PLF aims to provide farmers with a real-time monitoring and management system. This is fundamentally different from other approaches that attempt to monitor animal welfare, such as using human experts to assess animal-based indicators. These methods do not improve the life of the animal being monitored. It is much better to identify a problem while the animal is being reared and take immediate management action.

PLF allows the biological responses of animals to be continuously monitored, modelled and controlled. The continuous monitoring of PLF allows the farmer to intervene as soon as animals show the first signs of poor welfare or health [17]. Thus, good production outcomes based on animal health and welfare achieved through PLF can reduce the environmental impact of livestock production [18]. In other words, by optimising livestock performance, PLF indirectly reduces environmental impacts.

Internet of Things (IoT)

PLF is helping to improve the efficiency of livestock farming through the use of advanced IoT technologies and methods. By implementing smart solutions, many benefits are achieved such as:

improved animal health and welfare, increased economic efficiency, more optimal use of resources, precise control of all necessary processes, reduced carbon footprint and environmental impact of farms. Some studies have focused on ventilation to improve indoor air quality [7], ammonia emission measurement procedures [19] and dust monitoring in agricultural buildings [20]. Thus, the application of PLF methods improves the overall management of livestock farms [21].

In [22], the authors describe how PLF technology can provide solutions by describing its basic principles and how it can be applied on a larger scale.

Figure 8 shows how IoT offers many opportunities for modern farms, such as the collection of large amounts of data, information on the individual condition of animals and easy response to their needs, monitoring and control of various parameters.

The signals are sent and processed in cloud data centers and the control signals are sent back to the farm.

The point of IoT is to connect multiple standalone devices (sensors and controllers) to a local network, cloud server or the Internet. This creates an automated intelligent system that uses the information gathered from the devices and helps manage them in a unified and efficient way. For example, the extension of IoT with W-IoT technology is widely used in modern livestock farming for animal health monitoring and early disease detection. This application is supported by real-time analysis of animal health data sent by sensors.

Expanding IoT has led to a significant increase in the amount of data generated. To address the issue of processing and storing all the requirements and constraints associated with smart agriculture, cloud computing, and big data provide numerous tools [23].

The authors of [24] review, analyse and compare eight farm management software (FMS) platforms. The comparison is made based on several key features that characterise a modern FMS platform designed to make livestock and crop production more profitable, efficient and secure.

FMS platforms help to manage and solve many tasks of varying complexity [25]. Various tools aim to make important decisions in a short time. Farming and livestock applications not only speed up the process. They also provide a well-informed background. This increases the chances that the solution will be correct. A great advantage of modern life is that the entire complexity of these operations can be automated and digitised [26].

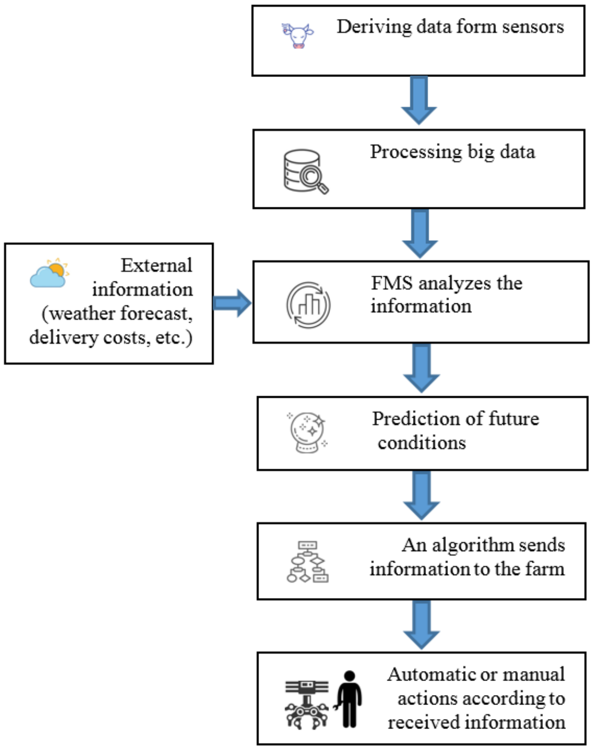

Figure 8. Application of IoT in Smart farming [22]

As a whole, there are three main applications of monitoring in precision farming: monitoring of livestock, monitoring of fields, and monitoring of greenhouse gases [27]. IoT allows farmers to monitor livestock using multiple sensors that monitor multiple animal variables such as heart rate, temperature and digestion. Field monitoring applications are designed to report on various conditions such as soil fertility, temperature, gas content, and the presence of disease in crops [28]. The use of IoT sensors and devices has also made it possible to remove some of the need for manual intervention. This has led to the development of intelligent greenhouses that can monitor and regulate various climatic parameters according to the needs of the plants [23].

Big Data

The vast amount of information produced and collected every day is processed and analysed using Big Data, which is beyond the capabilities of traditional techniques. Big Data serves as the basis for advanced technological and statistical tools that analyse huge amounts of data and extrapolate information. Big Data makes it possible to handle and use this ever-growing amount of data quickly and easily [29].

A key feature of Big Data is that it can be used to extract a huge amount of values, which requires the use of complex analytical methods.

Data processing covers a wide range of applications. These include image or video processing, decision support systems, and data loading and collection. Depending on the system requirements, any functionality that can work simultaneously to provide other services can be integrated.

On-farms risk management

Farm management is one of the most important resources in farm operations. Farm management determines how farm life is organised, how resources are allocated and how activities are carried out. It deals with different strategies and methods to keep a farm productive, sustainable, resilient and profitable. This would reduce the problems and risks associated with environmental impacts.

Decision making is the core activity of management. All decisions have certain outcomes or consequences [30]. In many situations, however, the outcome of a decision cannot be predicted.

Management strategies and sources of risk at agricultural sites are described and analysed in [31]. A comprehensive analysis of risk types and their assessment is given in [32]. Research and recommendations for risk management in agriculture are the focus of resource-based farm management [33, 34]. The management of farms aims at sustainable development and predictable results in their operation [35, 36]. The application of PLF technologies makes it possible to manage agricultural sites with quantitative assessments and the application of logical and formal models. This is a prerequisite for achieving optimal results in farm management, maximising production and income and minimising costs. Quantification approaches are recommended and applied in farm management [35] and environmental tasks [37]. The management of agriculture is aimed at the prospective development of production and economic performance [38-40]. The management is evaluated in an integral form by means of economic criteria [41]. Various criteria can be used to quantify the economic situation of a farm and its development. These criteria quantify the variables and parameters of its exploitation. The main issue is to provide a quantitative assessment of the components that result from the activities of the management of the farm. Such types of criteria, variables and parameters in management are discussed in detail in [42]. An important policy to follow when making production and financial decisions is to manage farms through risk aversion [43].

Sustainable management generally focuses on minimising risk and maximising return from the management of production and economic activities. All activities that the farmer is expected to manage are shown in Figure 9 and include:

1) Planning (doing scenario analyses);
2) Organization (resource allocation);
3) Monitoring (data collection/acquisition);
4) Controlling (comparison of actual and targeted key performance indicators (KPIs);
5) Identification of optimization opportunities (maximising profit and minimising risk).

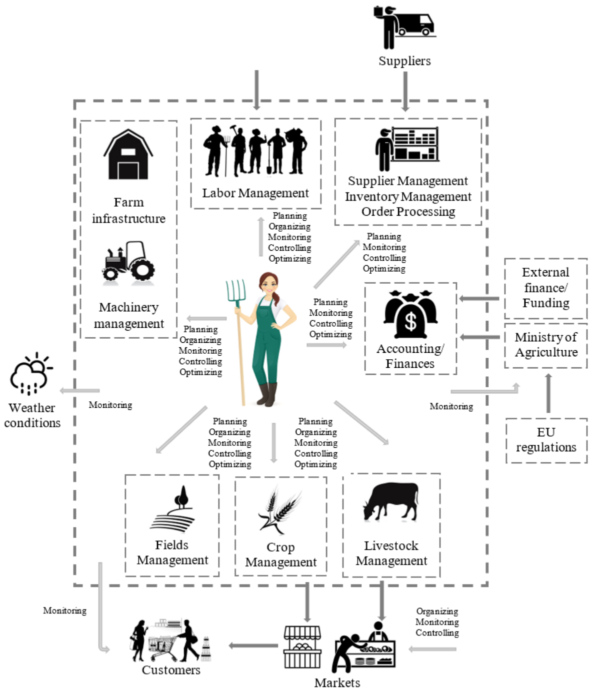

Figure 9. Farm management activities [22]

By minimising economic risk, potential losses in livestock production can be reduced and these are the guiding criteria for planning future resource allocation. The new point added in this study is the intelligent quantification of the functionality of the farm in order to reduce risk and at the same time analytically determine the best trade-off between return and risk.

The analytical formalisation of management decisions in the farm can be done by using relations from modern portfolio theory. The latter derives models that simultaneously consider the requirements for increasing the portfolio return and reducing the portfolio risk. The formalisation and quantification of risk indicators are successfully applied in portfolio theory [44-47]. Risk has a stochastic nature and its management must take this random behaviour into account [48, 49]. The statistical characteristics of a stochastic variable $R_i(t)$ change its values mainly in the diapason $[E_i-\sigma_i, E_i+\sigma_i]$, where the value E is the average level of the stochastic variable for a given period. Therefore, if the risk σ_i has a small value, the range around the mean E_i will be small and the real value of the stochastic variable $Ri(t)$ will be close to the mean E_i. This will benefit the quantification of the real value and its prediction for the case of decision making in farm management. In the opposite case, if the risk σ_i is a large value, it means that the real value of the stochastic parameter can vary in a wide range around the mean E_i, and the value $R_i(t)$ can be considered to be higher or lower than the estimated mean E_i. This case is not favourable for the management of the farm, since it is determined that there is a significant risk in the use of this variable in management. The real level of this parameter $R_i(t)$ can be in the range $[E_i-\sigma_i, E_i+\sigma_i]$, which in the case of high risk σ_i can be significantly different from the mean E_i.

The formal analytical relations for describing the mean value and the risk of a stochastic variable are performed with linear and quadratic relations. For a set of N random variables $R_i(t)$, their values are recorded in a discrete set of sequences of n values in time,

$$R_1 = [R_1^{(1)}, R_1^{(2)}, \ldots, R_1^{(n)}]$$
$$\ldots\ldots \qquad (1)$$
$$R_N = [R_N^{(1)}, R_N^{(2)}, \ldots, R_N^{(n)}].$$

These records make it possible to estimate the mean value E_i of the N variables for this time interval $1 \div n$ and the corresponding deviations σ_i^2.

$$E_i = \frac{1}{n}\sum_{k=1}^{n} R_i^{(k)}$$
$$(2)$$
$$\sigma_i^2 = \frac{1}{n}\sum_{k=1}^{n} (E_i - R_i^{(k)})^2, i = 1 \ldots N.$$

In this way, the risk of the stochastic variable $R_i(t)$ is estimated numerically as the standard deviation σ_i.

Another form of risk quantification is provided by the inequality of probabilities, which is applied with the Value at Risk (VaR) parameter [50]. VaR quantifies the level of risk in terms of the maximum probable loss [47]. There is an attempt to apply the VaR form of risk to resource allocation [51, 52]. The quantification of risk in the formal definition of VaR is applied in supply chain networks [53]. The estimation and use of the VaR formalisation is accepted as a promising way to manage risk [51].

The formal representation of VaR is shown by the density function of the risk index, which represents the return and loss variable in farm management. The positive value of the portfolio return is the farm management profit and the negative value is the loss [54].

The formal models discussed are applied from portfolio theory. This provides a basis for applying this theory to farm management decision making. The aim is to maximise return and minimise risk. The application of elements of portfolio theory can be found in [48], where the components of the portfolio are applied to inventory policy. In particular, risk in the form of VaR is formalised in terms of probabilistic relations. Such a probabilistic form of risk is used in [55] for decision making in inventory control in farm management. In [53], the VaR parameter is used to quantify the risk in the allocation of resources on a farm.

CONCLUSION

The EU's role in mitigating climate change in agriculture is crucial, as it sets environmental standards and co-finances most Member States' agricultural spending.

Ongoing technological development and validation of theoretical aspects and prototypes are contributing to the creation of diagnostic tools for PLF that can detect on-farm problems without manipulating animals (non-contact and non-invasive data collection) or inducing stress, providing the opportunity for early detection of disease outbreaks. In this context, the benefits to farmers include improved decision making, increased interest in the sector among young farmers, and a positive impact on overcoming problems and gaps with the end user by transforming raw data into useful information that can currently only be obtained through expert analysis and interpretation.

This paper reviews and analyses the environmental impacts of current livestock management practices and highlights the critical role of PLF in ensuring the effective application of existing and new information on farms as a potential avenue for reducing environmental impact issues and risks. Strategies and methods to reduce environmental risk situations are considered. Solutions are proposed with an emphasis on PLF as a useful monitoring tool in this regard.

Quantitative risk analysis models based on portfolio theory are proposed. Subsequently, the research will focus on the application of these models to achieve optimal production and environmental performance by minimizing risk situations at agricultural sites.

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