Challenges for Mexican sheep production in the era of precision livestock farming and artificial intelligence

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Challenges for Mexican sheep production in the era of precision livestock farming and artificial intelligence

Abstract

This narrative review discusses high-precision technologies applied to sheep production, with an emphasis on the use of computer vision and machine learning. It also reviews recent studies conducted in Mexico that have applied machine learning techniques to predict sheep body composition and image analysis methods to estimate body weight. These efforts have led to significant advances in the use of artificial intelligence models, such as You Only Look Once and Segment Anything, for monitoring and optimizing sheep production. In today's interconnected world, decisions made in one context can immediately affect surrounding systems. Therefore, it is essential to consider individual animal welfare as a key factor in decision-making within production units, contributing to overall welfare. This article highlights emerging high-precision technologies in sheep farming, particularly those involving computer vision and machine learning.

Keywords: Sheep farming; Precision farming; Machine learning; Computer vision; Livestock monitoring.

Study contribution

Sheep farming is a key activity for many rural communities in Mexico, providing meat, milk, and wool. However, the sector faces significant challenges in improving productivity and efficiency. This narrative review explores the integration and advancements of machine learning, computer vision, and artificial intelligence (AI) in precision livestock farming techniques, focusing on research conducted by our group within Mexican sheep production systems. The studies discussed highlight how AI-driven models can enhance decision-making and operational efficiency through automated monitoring, weight estimation, and carcass composition prediction. These findings have the potential to support improvements in productivity and contribute to the modernization of Mexican sheep farming. Additionally, they may offer a sustainable framework for the future integration of emerging technologies.

Introduction

Sheep farming, although modest within Mexico's overall agricultural production, is essential for many farming families, as it provides meat, milk, and wool. This sector contributes significantly to the economy and culture of various regions of the country. In 2023, sheep meat production reached 68 451 tonnes, with states such as the State of Mexico, Hidalgo, and Veracruz standing out as the main producers.[(1)] In Mexico, sheep production systems include crosses and purebreds of both wool and hair breeds. A significant proportion of the country's sheep are also genetically 'criollos', which are not defined by a specific breed. Wool breeds include the Suffolk, Hampshire, Rambouillet and Dorset. In the tropical regions of Mexico, the most used sheep breeds are hair breeds, including Pelibuey, Blackbelly, Katahdin and Dorper. Production systems in tropical Mexico contribute around 25 % of sheep meat production based on hair breeds. Moreover, over the last decade, the Pelifolk sheep has become notable for its adaptability and resilience as a 100 % Mexican breed.[(1)]

Sheep farming offers multiple benefits, such as high adaptability, low technological requirements, and efficient land use. Sheep provide high-quality meat, milk for dairy products, and wool for the textile industry.(1) In Mexico, 95 % of sheep production is used for barbacoa, an emblematic dish. Introduced by the Spanish, sheep farming has adapted to local conditions and is now present in all states, contributing to food security. In 2023, national sheep meat production reached 68 451 tonnes, marking an increase of 1.8 % over the previous year and exceeding the 10-year average. With a growing market ranging from rural producers to experts in genetic improvement, sheep farming represents not only an investment in the present but also in the future of Mexican communities and gastronomy. Sheep farming is an important part of the livestock industry in Mexico. Although modest in terms of national production, it plays a crucial role in the lives of many farming families. Sheep farming not only contributes to the supply of meat, wool, and milk, but also serves as an economic and cultural mainstay in various regions of the country.(2)

Precision livestock farming (PLF) is a concept that has gained considerable interest in recent years due to its potential role in the development of sustainable livestock production systems.(3) PLF is a modern approach that uses advanced technologies to optimize animal production and improve sustainability.(3, 4) It is based on the collection and analysis of real-time data on animal welfare, health, feeding, and resource management.(4) In the sheep sector, it has been identified that there is a need to promote the development and application of national precision livestock technologies for automated monitoring of animal health and production status, and to facilitate the tasks of personnel.(1) It is also pointed out that, to improve the productivity of Mexican sheep production systems, the actors involved in the production chain, government authorities, and academic and research institutions must work together to understand and integrate three main elements and their complexities, which in turn are interrelated: the animal, social, and productive systems. We now live in an interconnected world, where decisions made in one situation immediately affect those around us. Therefore, we must continue to consider the concept of individual welfare as a link in the chain for decision-making in production units and to improve global welfare. This article explores new high-precision technologies applied to sheep production in Mexico, highlighting the use of computer vision and machine learning.

Advanced technologies

Over the past few years, livestock data collection has evolved with advances in sensor technology and integration with the Internet of Things (IoT).[5] This technology allows data to be collected and transferred to the cloud, facilitating data storage and processing. The combination of IoT and sensors has given rise to the concept of big data, which is driving the modernization of agriculture.[5]

This has given rise to precision agriculture, which aims to increase food production and animal welfare sustainably. Current technologies include sensors that monitor growth, milk and egg production, animal behaviour, and the microenvironment in real-time, among many other applications. In addition, devices are being developed to transmit data wirelessly and in real-time to optimize livestock management.[6]

In addition, image processing technologies have developed rapidly and can be reliably used to quantitatively characterize the size, shape, and density of organisms or objects.[7, 8] Many fields, such as human and veterinary medicine and forensic science, currently employ digital image analysis. This technology is also used in animal science to predict carcass characteristics and the composition of meat products.[8] Similarly, these image analysis techniques have been widely used in animal science for body composition prediction, carcass classification, and assessment of meat quality traits in livestock.[9, 10] Using these non-invasive and non-destructive techniques (including X-ray, computed tomography, magnetic resonance imaging, ultrasound, and spectroscopy), which avoid carcass dissection (destroying or tearing) or chemical analysis, has become increasingly interesting for the meat industry.[9, 10]

Over the past few decades, image processing techniques have developed considerably due to their ability to characterize physical properties such as size, shape, colour, and texture in digital images. Image processing techniques have long been used in the food industry. They have been applied as a non-destructive quality assessment method for various food products.[11]

On the other hand, the determination of live weight (LW) in livestock using image analysis is an emerging area of research. It is possible to automatically measure the dimensions of an animal's images and use prediction equations to establish the relationship between them and LW.[12–14] In this context, AI offers several technologies that, through precision management, data-driven decision-making, early disease detection, and environmental monitoring, can improve both the quantity and quality of ruminant production in Latin America.[15] Challenges include its high cost, complexity, data requirements, risk of technological displacement, ethical and social implications, and regulatory and legal frameworks for the use of AI in Latin American ruminant production.

More research is needed to fully understand the potential impacts of AI in the ruminant sector, including assessing the economic benefits, ethical considerations, and long-term effects on the sector and surrounding communities.[15] **Figure 1** illustrates a schematic of a high-tech sheep production unit, integrating precision technologies such as drones, sensors, and automated animal management systems.

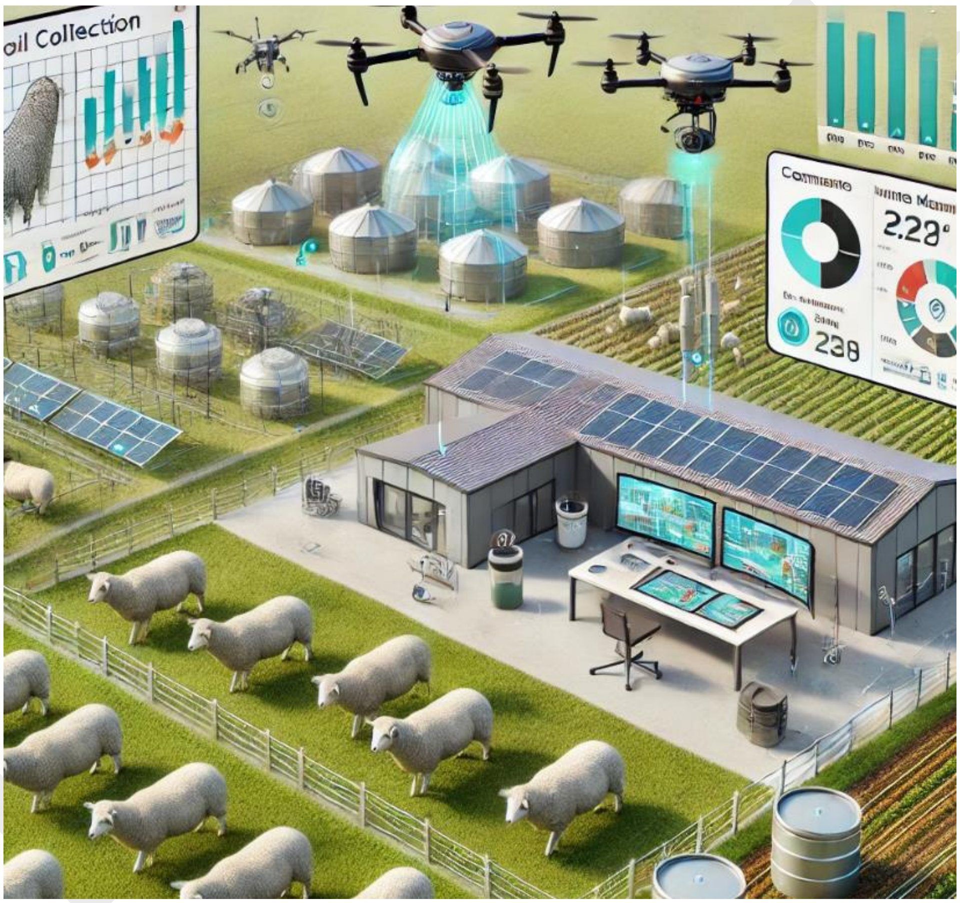

Figure 1. Schematic of a sheep production unit using high-precision technology such as drones, sensors, and technology-based animal management. This image was generated using artificial intelligence via Microsoft Copilot, which integrates DALL·E, an advanced image-generation model developed by OpenAI.

What is being done in Mexico?

In Mexico, several institutions from different states —such as Universidad Juárez Autónoma de Tabasco, Universidad Autónoma de Chihuahua, Universidad Autónoma de Yucatán, and Instituto Tecnológico de la Zona Maya— have started to join efforts to integrate new technologies in sheep production. The following are some of the studies and developments that have been carried out or are underway.

Machine learning and ultrasonic measurements

The accuracy and precision of carcass trait prediction in sheep can be improved using ultrasound measurements (**Table 1**). These tools can also assist selection programs and decision support systems in determining the optimal carcass endpoint, thereby improving the productivity of sheep production systems.[16, 17]

Table 1. Description of supervised learning techniques used in Mexican sheep production systems

Breed	Sex and physiological state	Objective	Independent variables	Methodology	R^2	Ref.
Blackbelly	Male lambs	Predict carcass tissue composition	Ultrasound measurements: subcutaneous fat thickness (SFT, cm), area (LDMA, cm^2), amplitude (ALDM, cm), and depth (DLDM, cm) of *longissimus thoracis*	Machine learning models: decision trees, random forests, support vector machines, and multi-layer perceptrons	$0.67 \leq R^2 \leq 0.76$	16
Blackbelly	Ewe lambs	Predict carcass tissue composition	Ultrasound measurements: SFT, LDMA, ALDM and DLDM	Multi-response multivariate adaptive regression splines algorithms	$0.65 \leq R^2 \leq 0.95$	17
Hair sheep lambs	Lambs	Predict carcass traits and tissue composition	Neck and shoulder traits	Multi-response multivariate adaptive regression splines algorithms	$0.94 \leq R^2 \leq 0.98$	21
Pelibuey	177 lambs, 97 females and 80 males aged 3–4	Evaluate the model performance in	Body condition score and hematological parameters	Support vector machines	0.97	25

	months, and 70 non-pregnant and non-lactating adult sheep aged 2–3 years	the classification of FAMACHA© scores				
Hair sheep breeds	Growing female and male	Body weight (BW)	Body measurements	Machine learning algorithms, classification and regression tree, and support vector machine regression algorithms	$0.94 \leq R^2 \leq 0.98$	27
Pelibuey	Growing male	BW	Biometric parameters of the animal obtained by computer vision tools	Metaheuristic algorithms: the genetic algorithm and Cuckoo search algorithm	0.79	28
			A biometric parameter acquisition system was developed using a Kinect as a sensor	Artificial neural network	0.88	29

Machine learning models, such as decision trees, random forests, support vector machines, and multilayer perceptrons, were used to predict carcass tissue composition in Blackbelly sheep (**Table 1**). The most effective predictor of carcass bone, fat, and muscle content was the random forests model, with mean squared error of 0.31, 0.33, and 0.53; mean absolute error of 0.26, 0.29, and 0.53; and the coefficient of determination (R^2) of 0.67, 0.69, and 0.76, respectively. The results highlight the reliability of the use of live animal ultrasound measurements together with machine learning to determine carcass composition, which can improve profitability and efficiency in agricultural production.[16] The study used growing male lambs housed in controlled environments. Ultrasound technology was used to measure subcutaneous fat thickness and muscle area. The methodology used is shown in **Figure 2**. After slaughter, carcass components were assessed, and the predictive accuracy of the machine learning model was evaluated. These findings represent a significant advance in precision farming practices, suggesting that the use of appropriate statistical methods and machine learning algorithms can provide faster and more reliable assessments of tissue composition.

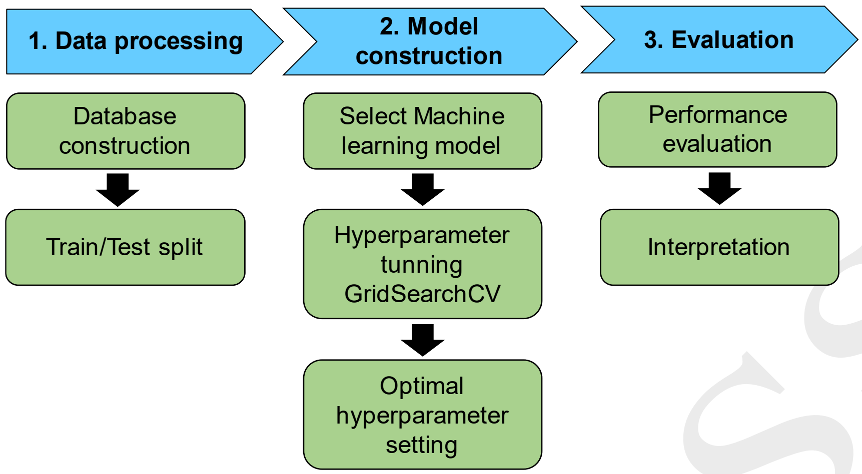

Figure 2. To evaluate machine learning models, 1. data needs to be processed, 2. models need to be built, and finally 3. evaluation needs to be performed.

On the other hand, the classical animal science approach to carcass tissue composition in sheep is based on the classical statistical approach (**Table 1**), namely multiple regression models, using live animals and ultrasound measurements as independent variables[(18, 19)] In this context, machine learning models proposed as an alternative to classical statistical approaches are data-driven learning algorithms that can be used to predict future scenarios from the pattern learned from the data.[(17, 20)] Compared to other statistical approaches, machine learning (ML) models can be used even when assumptions are common in commercial production data and desired by classical statistical methods.[(17, 20)]

In this context, animal producers who used ultrasound fat thickness and *longissimus thoracis* muscle characteristics, in combination with machine learning algorithms, to predict carcass tissue composition in Blackbelly lambs concluded that the

Multi-response Multivariate Adaptive Regression Splines (MMARS) algorithm provides an accurate and efficient method for estimating total carcass fat, bone, and muscle.[17] The use of the MMARS algorithm is a valuable tool for analyzing important carcass trait parameters in hair lambs. It also enables a comprehensive understanding of carcass composition and carcass quality, allowing both aspects to be modeled simultaneously.[21] By incorporating various input variables—such as breed, age, body size, and other relevant factors—the MMARS algorithm can effectively estimate these carcass parameters in hair sheep lambs (**Table 1**). In terms of reliability and interpretability, this method offers significant advantages. It is a promising approach for evaluating carcass traits in hair sheep production, as well as for use in breeding programs, management decisions, and meat quality assessment.[17, 21] Furthermore, the algorithm is a valuable tool for livestock producers and processors, as it integrates data from multiple sources to accurately predict carcass parameters. It also offers a practical and cost-effective means of facilitating the efficient and accurate analysis of carcasses.[17, 21] Multi-algorithmic forecasting methods such as artificial neural networks, support vector machines (SVM), random forests, and decision trees are among the new ML tools increasingly being applied in animal science research.[21–24]

Recently, Torres-Chable et al.[25] demonstrated the potential of SVM technology in veterinary epidemiology and provided important information for future applications (**Table 1**). These results may support efforts to improve scientific strategies for managing parasitic infections. The current study on the prediction of FAMACHA© scores using support vector machines has shown that this method can be an effective tool in parasite load assessment. According to the results, the SVM model achieved high prediction accuracy, particularly for class 1 and class 3. The sensitivity and specificity rates for both classes reached almost perfect levels, and very few false positive predictions were recorded in these categories. The model performed slightly less effectively for class 2, and areas for improvement in this class were identified.

Its effective predictive ability indicates that it can be a powerful tool in disease detection and management based on FAMACHA© scores. In addition, the F1 score for FAMACHA© 1 was calculated as 0.956, FAMACHA© 2 as 0.956, and FAMACHA© 3 as 1.000. These results show that the model provides an excellent balance of sensitivity and specificity, especially in the FAMACHA© 3 class, indicating that the model performs flawlessly in distinguishing true positives and true negatives in this class.

Computer vision

Computer vision is a technology that has had a significant impact on the field of animal and veterinary science. It allows for non-invasive, real-time animal monitoring. This is possible thanks to advanced image and video analysis.[26]

In sheep selection and production, determining body weight is one of the most essential economic factors. Knowing the estimated body weight can help with decisions such as which breed to use for a particular type of production, for example, whether to prioritize wool or meat production. There are several reasons why estimating body weight in small ruminants is important. These include breeding, feeding, and disease management for optimal health and productivity.[27, 28] Accurate estimates ($R^2 \geq 0.95$) of body weight are important for assessing overall animal health, productivity, nutrition, and management.[28]

Using computer vision techniques, these studies aim to estimate the body weight of Pelibuey sheep from biometric parameters (**Table 1**). To measure these parameters, images captured by a Kinect® sensor were used. This approach for a reduced margin of error. **Figure 3** shows the Kinect® sensor image acquisition configuration and **Figure 4** shows the image processing used to obtain the biometric parameters.

Figure 3. Image acquisition setup.

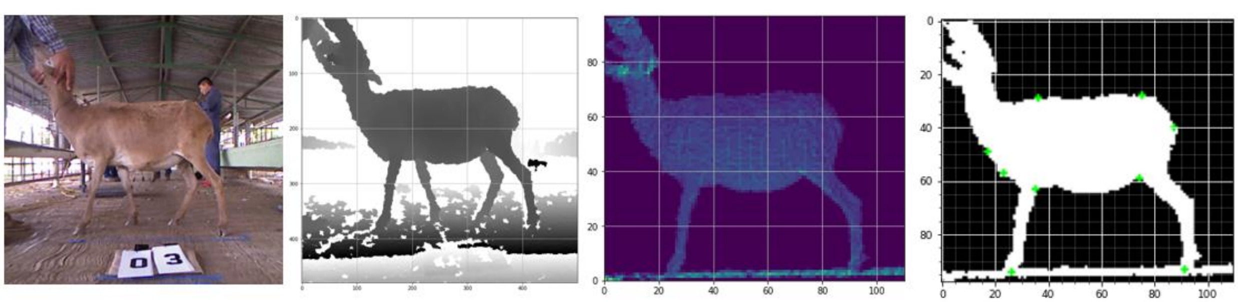

Figure 4. Processing images obtained by the Kinect® sensor.

Two methods were used. First, to optimize the coefficients and exponents of the biometric variables in the polynomial model, two metaheuristic algorithms were applied: the genetic algorithm and the Boogeyman search algorithm. Both algorithms showed similar performance, which indicates that the model can estimate the weight accurately from the measured parameters.[29] In the second method, these biometric parameters were fed into a neural network. The network was tested with different configurations to identify the most efficient one (**Table 1**). The results showed that the neural network-based model is highly competitive compared to traditional methods. However, its performance depends on the accuracy of the biometric data obtained.[30]

Manual measurements and those obtained by other computer vision-based methods showed a high correlation (≥ 0.95). This confirms the reliability of the approach. The models and measurement process can be integrated into an embedded system for practical applications. This research highlights the importance of computer vision techniques in livestock management, providing an accurate, automated alternative for monitoring sheep weight without relying on traditional methods.

Artificial intelligence-based technologies

The term “artificial intelligence” (AI) refers to a comprehensive range of technologies that enable machines to imitate human intelligence.[26] Computer vision technology can be complemented by models based on artificial intelligence, such as YOLO (You Only Look Once), a deep neural network model designed to detect objects in images in real-time.[31] Unlike other models that divide the image into regions and process each region separately, YOLO performs the prediction in a single pass. This allows multiple objects to be detected very quickly and accurately. One of the advantages of this model is that it only needs images that can be captured directly with a mobile phone to work. Estimation of biometric parameter measurements or individual object recognition are some of the applications. **Figure 5** shows an example of YOLO detection. Another technology is Segment Anything Model. This is an artificial intelligence model introduced by Meta in 2023 that focuses on identifying and segmenting elements in images and videos. Some examples of its use are that it can segment and count animals in each area.(31) It is also possible to estimate individual measurements of each specimen; for example, from aerial photographs, it is possible to estimate the dorsal area, which would allow weight estimation. In addition, computer vision is a technology that has had a big impact on the field of animal and veterinary science. It allows us to monitor animals in a way that is not invasive, and which happens in real time. This is possible thanks to advanced image and video analysis.(26)

Figure 5. You Only Look Once implementation (left) and Segment Anything Model implementation (right).

In the domain of animal science, artificial intelligence has become a prevalent tool, employed across a range of disciplines. The integration of AI has been instrumental in enhancing productivity, promoting animal welfare, and fostering sustainability.(26) The use of artificial intelligence in farming is valuable for predicting animal productivity and gaining insights into individual animals. It can also be used in breeding programs, especially when it comes to identifying which animals are best for the herd. It makes it easier to make decisions, create predictive models, and automate processes.(26, 32) This is a fast-growing area with a lot of potential, but there aren't enough qualified professionals in agricultural science.(32)

Final remarks

For many rural communities in Mexico, sheep farming plays a vital role in their economy and culture. As well as producing meat, milk, and wool, the sector has a direct impact on the country's food security. Sheep production can be modernized using advanced technologies such as the Internet of Things (IoT), machine learning, and computer vision. The implementation of innovative methods has significant potential to transform traditional sheep farming practices. This will allow for faster and more accurate assessments. This research highlights the importance of adopting new technologies in the sector. The adoption of these technologies can help producers increase their production system profitability and ensure a sustainable and prosperous future for sheep farming in Mexico. Finally, it is important to point out that currently, in the world and Mexico, there is no formal training program in artificial intelligence and precision livestock farming that offers the basics of these concepts to students related to the agricultural sector. This is a need that is becoming more pressing every day, and therefore universities technology, and research centers must pay attention.

Data availability

All relevant data are included in the document.

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Conflict of interest

The authors declare that there is no conflict of interest related to this manuscript.

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