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Global trends and research frontiers on machine learning in sustainable animal production in times of climate change: Bibliometric analysis aimed at insights and orientations for the coming decades

Robson Mateus Freitas Silveira [a,c,*], Concepta Mcmanus [b], Iran José Oliveira da Siva [c]

[a] University of São Paulo (USP), "Luiz de Queiroz" Agriculture College (ESALQ), Department of Animal Science, 13418-900, Piracicaba, São Paulo State, Brazil
[b] Center for Nuclear Energy in Agriculture, University of São Paulo (CENA), 13418-900, Piracicaba, São Paulo State, Brazil
[c] University of São Paulo (USP), "Luiz de Queiroz" Agriculture College (ESALQ), Department of Biosystems Engineering, Environment Livestock Research Group (NUPEA), 13418-900, Piracicaba, São Paulo State, Brazil

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ABSTRACT

According to topics, such as climate change, global population, animal production and food security, it is important improving food production systems' sustainability and getting to know that using machine learning in sustainable animal production in times of climate change will be a useful tool to increase food production with guaranteed animal welfare by reducing carbon and water footprints. The present pioneering review provides a longitudinal perspective on the current state of academic research in the emerging machine learning field linked to sustainable animal production in times of climate change. The study will provide scholars and professionals with a holistic view of the current state of studies, opportunities and associated risks on this topic, and pathways for future research in this emerging and promising field. In total, 1082 documents published in the last 70 years, in Scopus Database, were selected for the study. The annual growth rate recorded for publications in this field reached 3.78% per year, with 31.52% international contribution and 22.2 citations per document. The main insights generated in the bibliometric analysis were (i) sustainable animal production changed from unidisciplinary science to multidisciplinary science linked to agricultural, environmental and engineering sciences, mainly to genetics and computing; (ii) the concept of sustainable animal production emerged from animal welfare and climate change concepts found in UN's 2030 Agenda; (iii) omics sciences, greenhouse gases, energy efficiency and animal welfare are the main keywords for bibliometric analyses in future studies related to sustainable animal production in the coming centuries; (iii) prediction and classification analyses, i.e., supervised machine learning models used as main tools in animal production; (iv) residual feed intake applied to measure sustainable feed efficiency in animal farming in the past and nowadays; and (v) The United States, China, Brazil and Australia are the main countries publishing studies on sustainability in animal production, but only China has been gaining prominence in publications in this field, in recent years, and it will turn this country into an emerging leader in future publications on this topic. The present study provides new insights that were not previously fully captured or assessed in other reviews. Finally, improving livestock production sustainability is particularly important, because a significant part of the projected increases in the global food demand is expected to come from livestock, and artificial intelligence will certainly help producers in decision-making processes, mainly in times of climate change.

1. Introduction

Recent studies discuss animal production sustainability, and this is a multifactorial concern given the paradox among climate change × the growing demand for animal-origin food × animal welfare and health × efficient use of natural resources × technological innovations × environmental issues associated with food production (Nacimento et al., 2024). These elements are a global issue, since sustainable animal

* Corresponding author. Department of Animal Science, "Luiz de Queiroz" Agriculture College (ESALQ), University of São Paulo (USP), 13418900, Piracicaba, São Paulo State, Brazil.
E-mail address: robsonmateusfs1994@gmail.com (R.M.F. Silveira).

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production is closely related to Sustainable Development Goals (SDGs) in UN's 2030 Agenda, mainly to SDG 2 (Zero Hunger and Sustainable Agriculture) and SDG 12 (Responsible Consumption and Production).

The concept of sustainable animal was recently proposed: "an animal that is well adapted to the environment, productive, feed efficient in converting feed into animal products (milk, meat, wool and honey), clinically healthy, and with low carbon and water footprints, having their animal welfare assured". Silveira et al. (2023) take some of these factors into consideration, such as environmental, productive, animal welfare and adaptive elements, which are essential for sustainable animal production. They were also the first ones to identify and validate the concept of sustainable animal by using beef cattle as animal model in a systematic methodological proposal based on machine learning techniques.

The association between sustainability and animal production is multifaceted, mainly when it comes to the growing concern with climate change (Basiricò et al., 2023). Some questions still need to be answered, such as "what will animal production be like in times of extreme weather events, such as heat waves? How is research developing towards answering the issues we are facing? It is known that climate change already has impact on animal production because animals are unable to regulate their body temperature under thermal stress, and this process changes their physiology, a fact that leads to yield losses and, in many cases, to death (Nzeyimana et al., 2024).

Studies investigating climate change, sustainability and animal production impacts are essential, mainly when they involve mechanistic models to assess causes in complex systems (Silveira et al., 2024a,b). assessed adaptive dynamics by taking into consideration animals from different climate scenarios. The mechanistic model must be able to provide predictive explanation for patterns for a given assessed system by making it useful to help better understanding complex issues that have several variables of different natures (Neethirajan, 2020).

Researchers have also explored meta-analysis and bibliometric analysis in recent years to complete qualitative review outcomes (McManus et al., 2023). Bibliometric analyses can be taken as mechanistic model because they gather a large data volume based on algorithm's application, mainly the machine learning ones. These algorithms are used to interrelate quantitative and qualitative methods to assess scientific production in a given area by focusing on the analysis of large bibliographic-datasets (Nobanee et al., 2023; Wani et al., 2024). This analysis type plays key role in sustainable animal production through the study of its impact on climate change, as herein proposed.

The bibliometric analysis can (i) identify research trends (specific areas of interest whose topics are still emerging and research gaps still need to be filled); (ii) assess sustainable animal production impacts (determining these sustainability studies influence on the scientific community and checking their impact on policies, livestock practices and public perception); (iii) map collaborations and research networks (revealing collaboration patterns between researchers and institutions working in the sustainable animal production and climate change fields, worldwide); (iv) identify research gaps (guide future investigations and direct resources to areas where they are most needed); and (v) support decision-making and policies (informing decision-making related to public policies, to investments in research and development, and to climate change adaptation strategies) (McManus et al., 2023; Mishra et al., 2023; Vieira and McManus, 2023).

Based on this background, the aim of the present study was to answer four questions: (1) What are the topics and research methods related to sustainable animal production in times of climate change? (2) What has been investigated so far about sustainable animal production in times of climate change? (3) What are the research gaps in, and likely orientations for, animal production? (4) How can machine learning using help solving sustainable animal production problems in times of climate change?

2. Materials and methods

2.1. Data collection

The global literature on the use of machine learning models in sustainable animal production in times of global changes has only focused on farm animals (broiler chicken, pigs, cattle, sheep and goats). Data were extracted from Scopus database (Elsevier data). It is worth noticing that publications in this database are widely acknowledged by the academic community for their broader, more accurate and comprehensive content range (Pranckutė, 2021). The research query was formulated in compliance with Scopus Advanced Search tool standards (https://schema.elsevier.com/dtds/document/bkapi/search/SCOPUSSearchTips.htm) and its code is available in Appendix1. Other farm animals were not included in the study because the research focus was the main animal species found in consumer's diets.

The following metadata were chosen for the query on Scopus database: citation information, year of publication, language, journal, title, author, affiliation, author keywords, country of authors and their collaboration to other countries, document type, abstract and citations exported in CSV format. Recovery date was February 20, 2024.

2.2. Data processing

2.2.1. Biblioshiny software (R tool)

Biblioshiny is a free access package developed for R language. It provides a set of modules for research related to bibliometrics and scientometrics. This tool is an open source to data importation from different sources of several bibliometric analysis types (Aria and Cuccurullo, 2017).

2.2.2. VOSviewer

VOSviewer[1] is a bibliometric tool widely used to create bibliometric networks based on associations between different actors (e.g., authors and organizations) that use different network analysis methods, such as co-authoring, co-citation, term competition and bibliographic coupling (van Eck and Waltman, 2010). The term competition analysis was used in the present study to identify the main topics of this research domain. Maps plotted in this software include nodes and edges, and they point out the keywords (nodes) and their associations (edges).

3. Results

Fig. 1 presents an overview of the main metrics in studies selected for the current bibliometric analysis. In total, 1082 documents were selected: they were written by 4670 authors and each document had 22.2 citations, on average. Annual growth rate recorded for the number of publications reached 3.78% per year, with 31.52% international contribution.

The number of publications grew from 2009 onwards; the biggest peak in the number of publications was recorded between 2016 and 2023. The Chinese Academy of Science (China), University of São Paulo (Brazil) and University of Florida (United States) are the main research centers responsible for scientific production related to sustainable animal production supported by machine learning analyses applied as auxiliary method. Interestingly, 97.7% of the selected documents are articles, and only 2.3% of them are literature reviews based on the multidisciplinary approach: agriculture (38.1%), environmental science (14.1%), veterinary (13.9), biochemistry and molecular genetics (12.7%), engineering (2.5%), social sciences (2.5%) and other fields (see Fig. 2).

A world map showing the countries accountable for producing the

[1] Interested readers should access the VOSviewer manual for more details on these different analyses (https://www.vosviewer.com/publications).

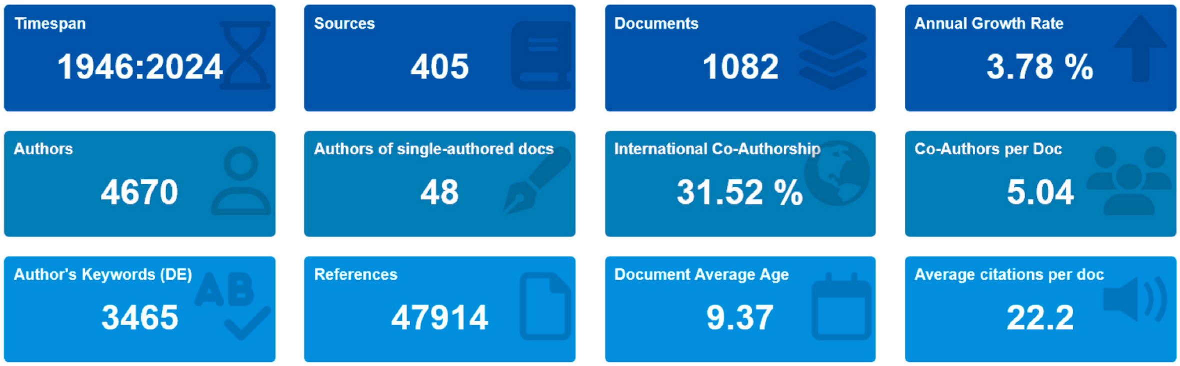

Fig. 1. Overview of the main metrics of publications on machine learning using in sustainable animal production.

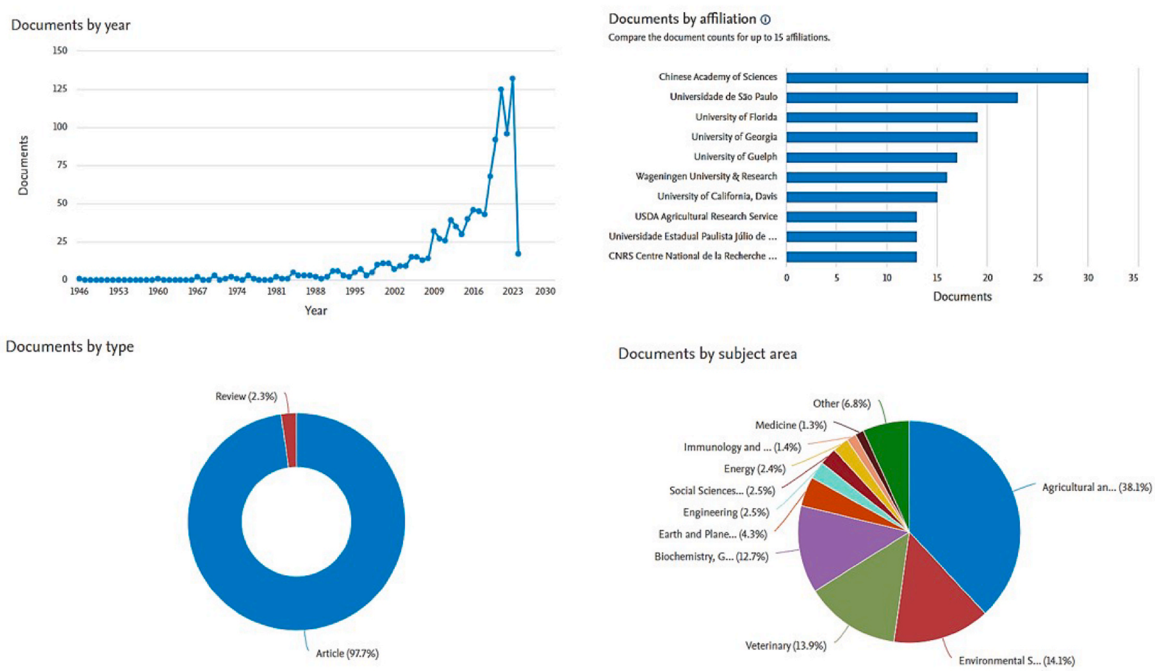

Fig. 2. Documents based on year, type, field and publications on machine learning using in sustainable animal production.

largest number of articles related to the topic addressed in the current study is presented in Fig. 3. Accordingly, China and the United States are the main world leaders in the number of publications in this field. Brazil and Australia are emerging countries in articles published on this topic. Europe and Africa are not highlighted, and Russia does not present publications in this field. The countries producing the largest number of articles also have a network of authorship collaboration between documents (Fig. 4).

Fig. 5 presents the compilation of main countries using machine learning in documents related to sustainable animal production. The USA is the world leader in these publications, and it is followed by China, Brazil and Australia. However, China is the main emerging country producing articles related to sustainable animal production supported by machine learning models, in the timeline (see Fig. 6).

The main keywords used in articles related to sustainable animal production are shown in Fig. 7. “Thermal stress”, “climate change”, “machine learning”, “animal welfare” and “dairy cows” are the evidenced keywords. Residual feed intake (RFI) is a sustainable animal efficiency measurement also evidenced in isolated clusters. The main machine learning analyses are principal component analysis and random regression - random regression is mainly related to genetic studies. Only temperature and humidity indices were the evidenced environmental thermal stress indicators.

Fig. 8 reveals the main keywords in the timeline. machine learning, prediction, PCA, immune response, tropical climate and climate change are the only highlighted words. Interestingly, RFI was the only word listed throughout the assessed documents.

Fig. 9 shows the most prominent journals publishing on sustainable animal production supported by machine learning modeling. The Journal of Dairy Science, Animals, Applied Animal Behavior Science, The Journal of Animal Science, The Tropical Animal Health and Production and The Journal of Thermal Biology are the main journals with publications in this field. Journals specifically focused on the sustainability scope, such as The Journal of Clean Production and Sustainability, are highlighted. However, only few of these journals have recently published on machine learning using to assess sustainable animal production. Of the journals cited, ‘Journal of Dairy Science’, ‘Journal of Animal Science’ and ‘Applied Animal Behavior Science’ are the least highlighted in the mentioned journals, lately (see Fig. 10).

Fig. 11 presents the main indexed articles on this topic. The article “Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment?” by Dikmen (2009) is the main study in this field. “Genetic Component of Heat Stress in Dairy Cattle, Development of Heat Index Function”, by Ravagnolo (2000) and

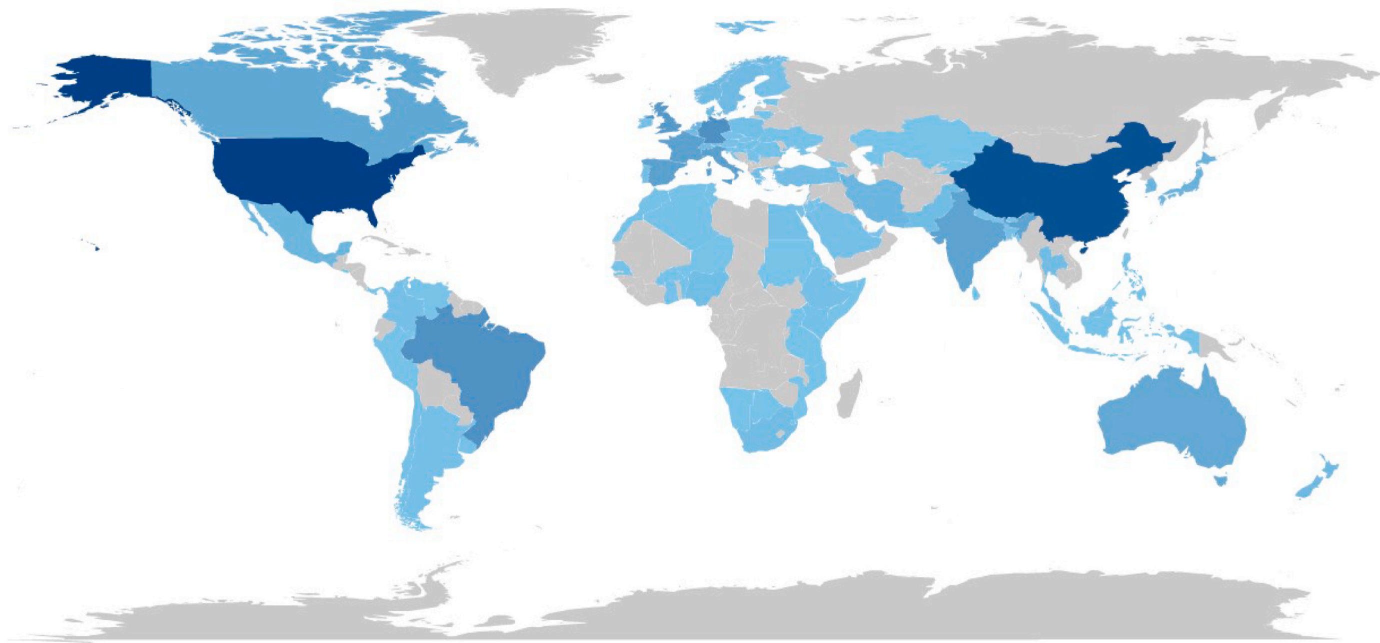

Fig. 3. Map of total number of articles per publication country on machine learning using in sustainable animal production.

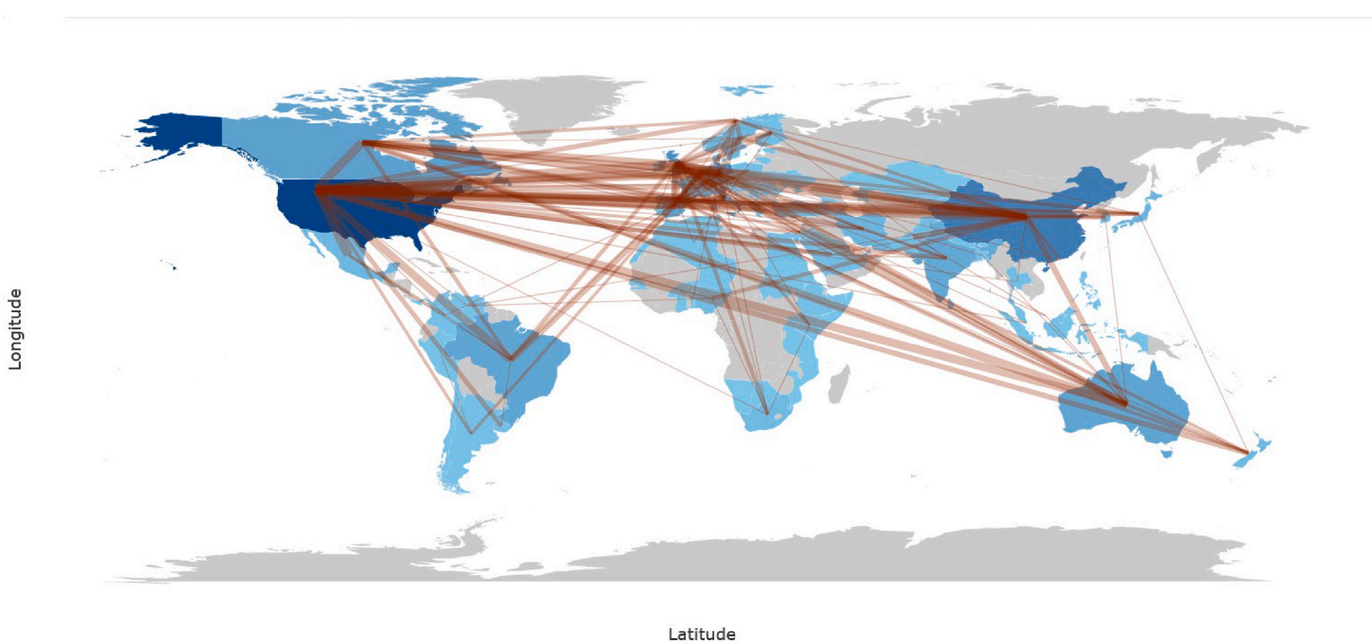

Fig. 4. Collaboration between countries as co-authorship of publications on machine learning using in sustainable animal production. Note: Blue color intensity points out a larger number of collaborations.

"Critical THI thresholds based on the physiological parameters of lactating dairy cows" by Mateus Freitas Silveira et al., 2024 are also highlighted.

Figs. 12 and 13 complete each other and depict the thematic evolution and trend of keywords over the years, respectively. Studies focused on the physiology of thermoregulation, mainly hormonal regulation, such as cortisol, from 1924 to 2023. Furthermore, studies carried out with birds show broiler chicken as the main livestock chain in this timeline. Research focus has changed between 2014 and 2020, and animal welfare and climate change were the highlighted elements. The number of studies conducted with broiler chicken decreased, whereas those conducted with pigs came to the mainstream. Artificial intelligence, and its tools, like neural networks and prediction models, are highlights. Finally, there were some changes deserving attention from 2021 to 2024; sustainable animal production became multidisciplinary and encompassed nutrition, physiology, genetics, mainly omics sciences (such as rna-seq and transcriptomes), greenhouse gases, energy efficiency and sanity studies. Artificial intelligence tools, such as neural network, principal component analysis and other multivariate techniques, are also relevant. It is important pointing out that temperature and humidity index, and heat waves, were in the mainstream during this period. The only word highlighted at all analyzed timelines was "heat stress".

According to Fig. 13, some insights can be observed: 1) In the last

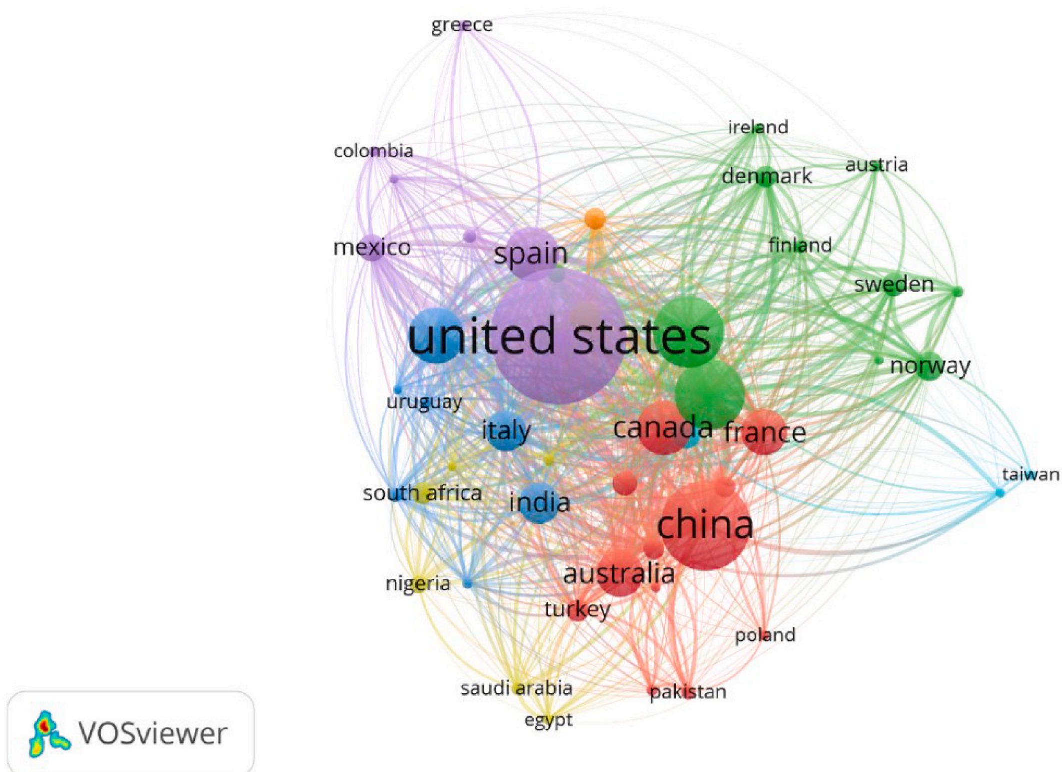

Fig. 5. Compiled bibliography based on publication country of studies on machine learning using in sustainable animal production.

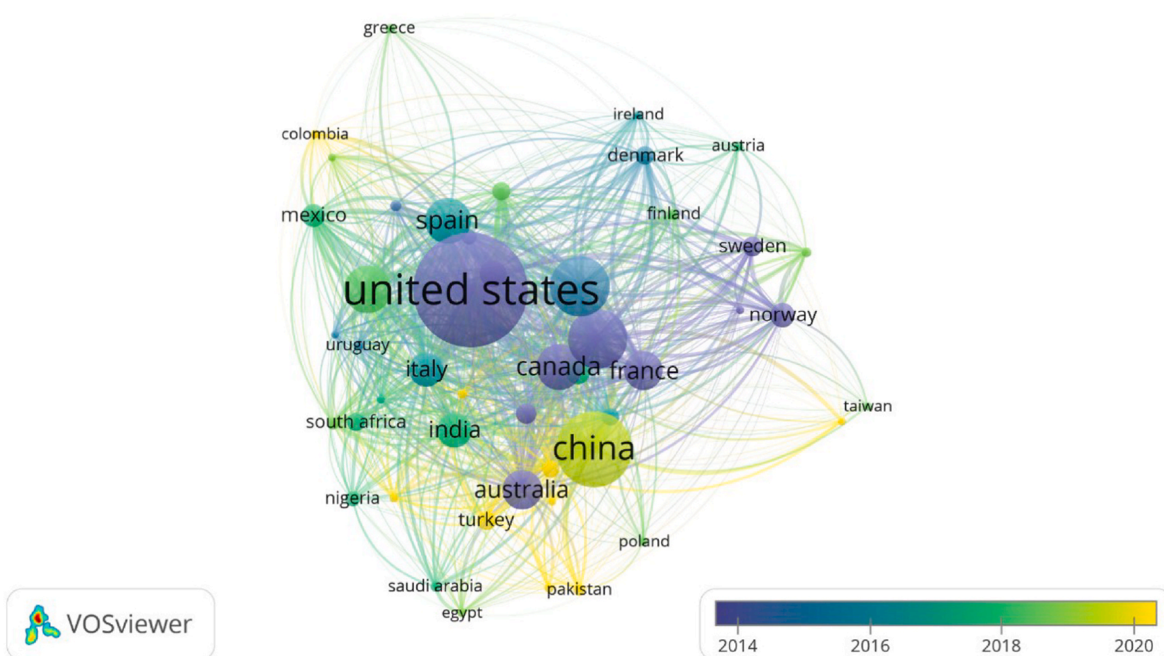

Fig. 6. Timeline of countries' compiled bibliography on machine learning using in sustainable animal production.

century, studies on thermal stress often focused on reproduction, but not anymore; 2) Machine learning models applied to predictions (supervised ones) will be the ones mostly used in research in the future; 3) the number of animal welfare studies is increasing due to the implementation of sustainable animal production; and 4) nutrigenomics has been investigated in recently published studies.

The thematic evolution map showing the relevance and development degree is available in Fig. 14. Thermal stress + dairy cow + animal welfare is the main formed circle, but it is worth highlighting two other circles: 1) prediction + random forest + carbon emission and 2) multivariate analysis, adaptation and dairy cows. Finally, emerging topics were pigs + climate change and machine learning.

4. Discussion

Many insights resulted from the bibliometric analysis, but the

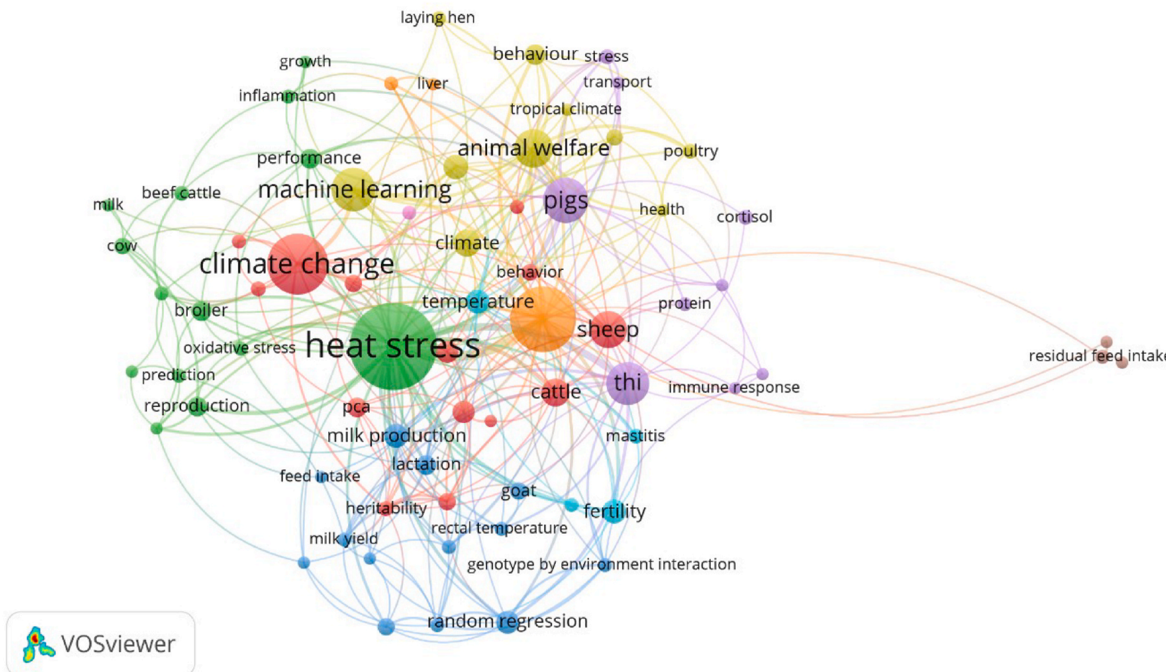

Fig. 7. Keyword neural network of publications on machine learning using in sustainable animal production.

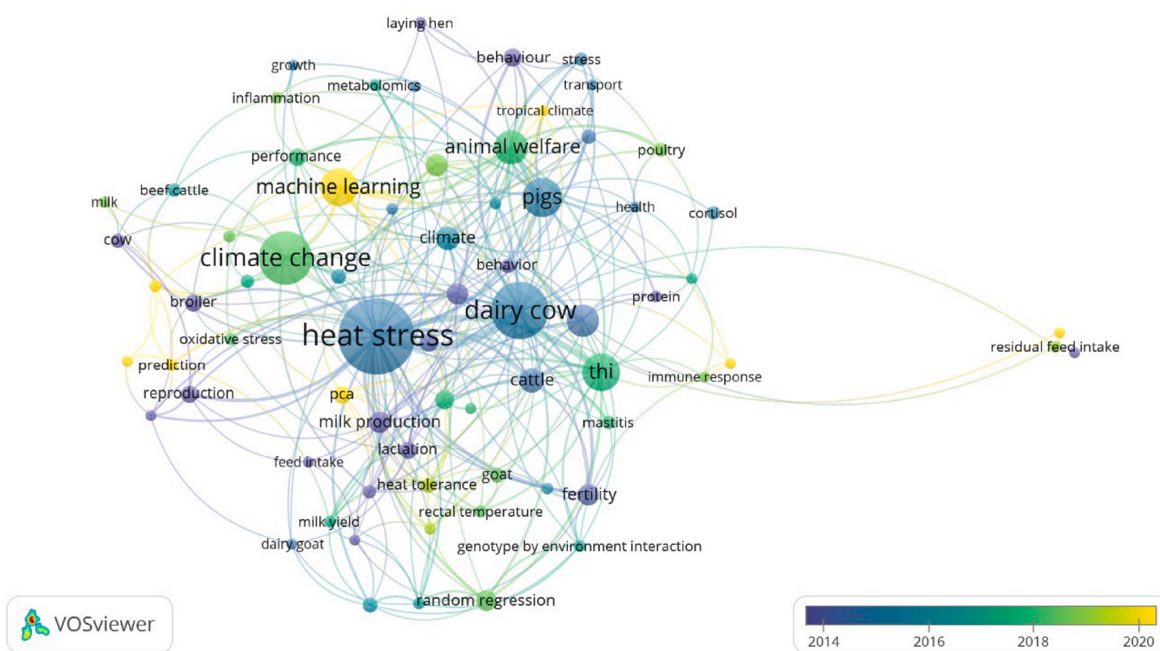

Fig. 8. Keywords neural network timeline on machine learning using in sustainable animal production.

discussion only addressed the main ones, namely: (i) The United States, China and Brazil are the main countries publishing studies on animal production sustainability, but China is the country aimed at publishing on this topic in recent years, and it can turn this country into a leader of publications on this topic, in the future; (ii) sustainable animal production changed from unidisciplinary science to multidisciplinary study linked to agricultural, social, environmental and engineering sciences, mainly genetics and computing; (iii) the concept of sustainable animal production emerged from animal welfare and climate change concepts disclosed in the UN's 2030 Agenda; (iv) omics sciences, greenhouse gases, energy efficiency and animal welfare are the main keywords assumed to be found in bibliometric analysis carried out in future studies related to sustainable animal production, in the coming centuries; and (v) prediction and classification analyses, i.e., supervised machine learning models are, and will be, the main tools used in animal production.

4.1. Overview

The significant increase in the number of studies related to sustainable animal production from 2016 onwards can be justified by the 2030 Agenda, which was created in September 2015 at the United Nations

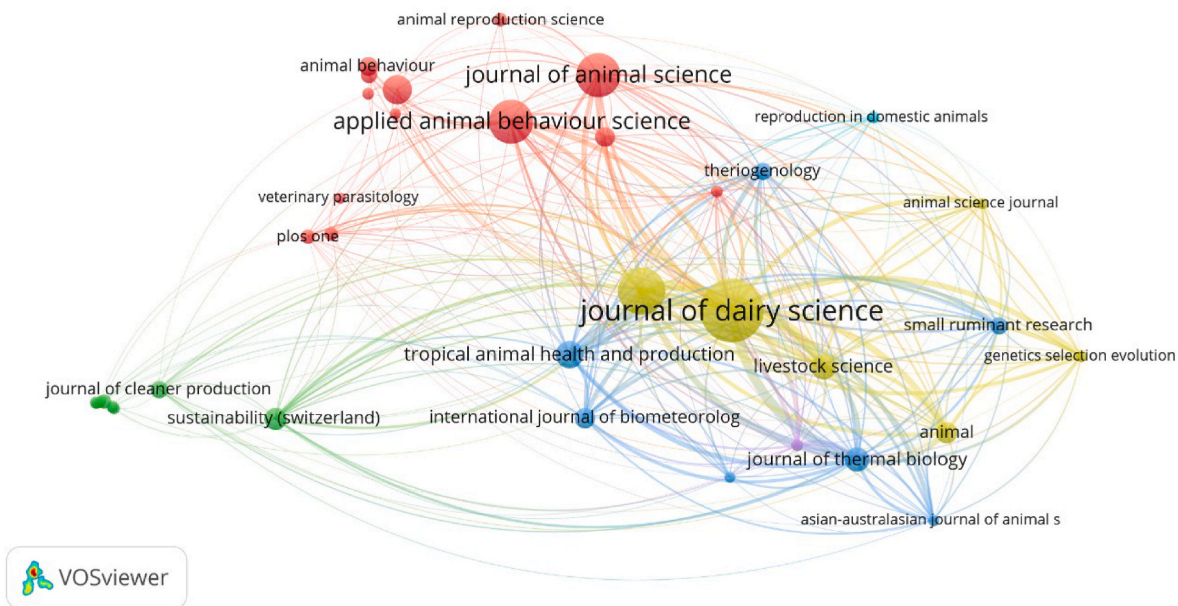

Fig. 9. Timeline of journals' compiled bibliography on machine learning using in sustainable animal production.

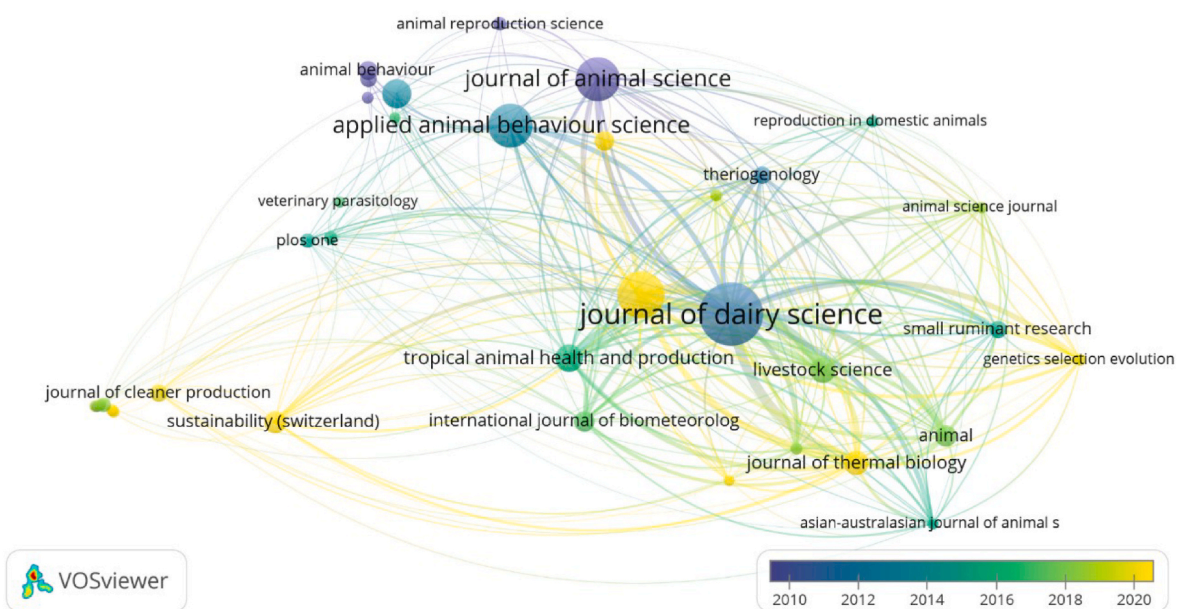

Fig. 10. Timeline of journals' compiled bibliography on machine learning using in sustainable animal production.

Summit on Sustainable Development in order to meet some Sustainable Development Goals (SDG), mainly SDG 2 - Zero Hunger and Sustainable Agriculture, SDG 15 – Terrestrial Life, and SDG 13 - Action Against Global Climate Change. All these goals are mostly related to sustainable food production, greenhouse gas emission reductions, food security, resource optimization and biodiversity loss, since these elements focus on studies selected through bibliometric analysis in the present study. It is also worth highlighting the updates in artificial intelligence using, mainly machine learning models applied to the animal production field, which are relatively recent. We believe that the combination of these two factors is the main explanation for the increased number of publications in this field, in the last decade.

Results in the current research corroborate the systematic bibliometric review conducted to assess the global dynamics of research on the United Nations' 2030 Sustainable Development Goals. The authors of the present article observed annual increase in the number of publications in this field since the UN SDGs were established. They also argue that the UN's 2030 Agenda became an essential global plan to deal with complex social, economic and environmental issues (Yumnam et al., 2024).

The main features explaining China, United States and Brazil leadership in the ranking of the three main research centers using machine learning in sustainable animal production is justified by the fact that they are the main animal-origin products' producers in the world (meat, milk and eggs). However, it is interesting mentioning that Brazil, unlike China and the United States, is an economically emerging country that has invested in research focused on animal production sustainability. University of São Paulo (USP), which is a Brazilian university, ranks the second position as leader in publications related to sustainable animal production supported by machine learning models, and this finding

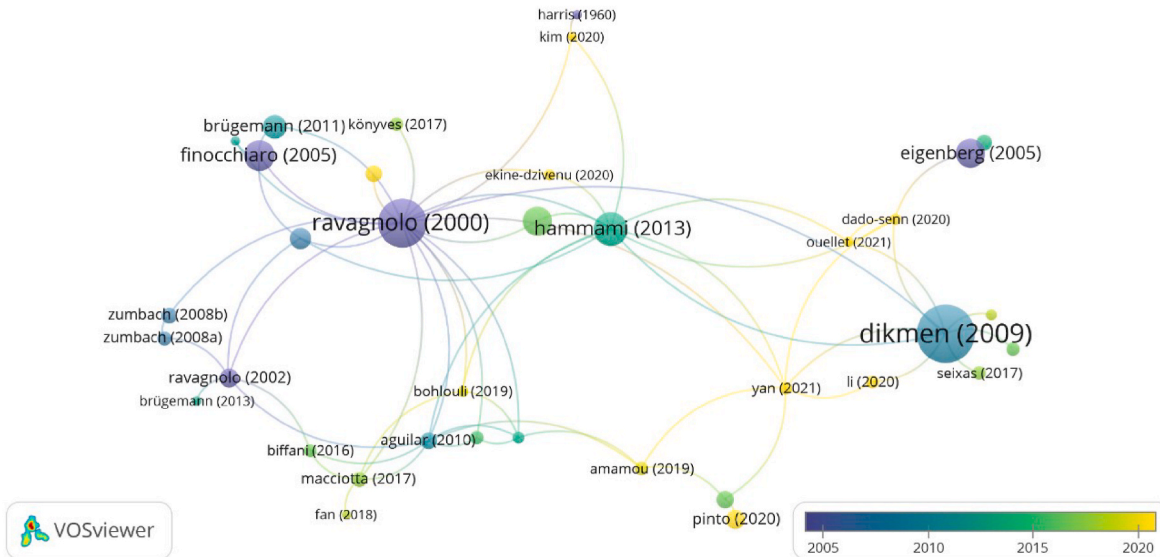

Fig. 11. Most cited articles' compiled bibliography on machine learning using in sustainable animal production.

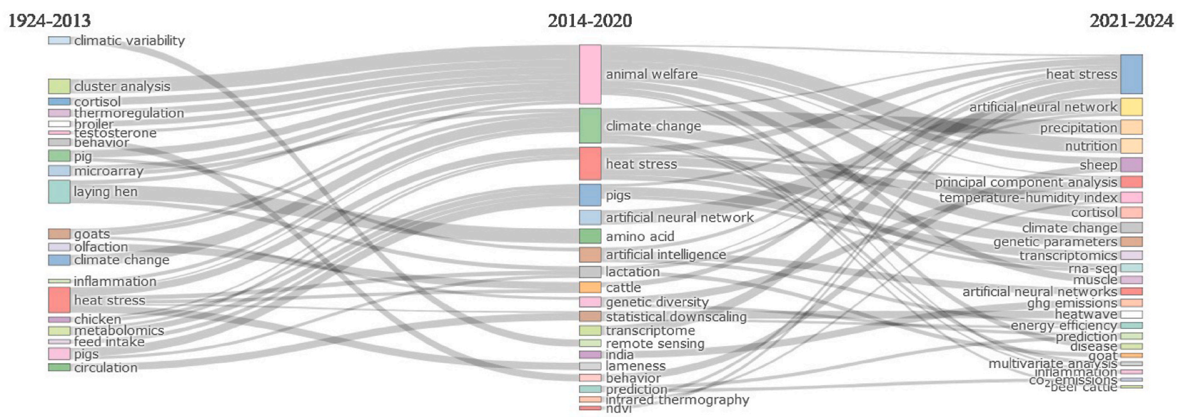

Fig. 12. Thematic evolution map based on co-occurrence of terms found in authors' keywords. Note: Each color indicates a cluster of keywords.

reinforces Brazil's commitment to sustainability, besides corroborating its 8th position in the 2004 UI GreenMetric World University Ranking (https://greenmetric.ui.ac.id/rankings/overall-rankings-2023).

An unprecedented result was found in the present study and it showed that the United States, despite accounting for the largest number of publications, has not published studies in the sustainable animal production field, in recent years, as attempt to keep its leadership, as evidenced by the timeline. Thus, China has expanded the number of studies related to the use of machine learning models in sustainable animal production. This outcome was expected because animal breeding in China has significantly grown in the last three decades (Li et al., 2022). The number of livestock units has tripled in less than 30 years, since their reform and opening, for example, mainly due to industrial livestock production systems grew and increased the production of non-ruminant species (Bai et al., 2018). It is worth mentioning that China is currently one of the largest producers of animal-origin products, along with Brazil and the United States.

The low rate of literature-review publications in the sustainable animal production field reinforces the novelty of the present study, since it is the first bibliometric review investigating this particular topic. Other bibliometric reviews in the animal sciences field have already been carried out, such as that by McManus et al. (2023), who focused on animal thermal stress; by McManus et al. (2024), who investigated researchers aimed at animal genetic resources and genomics' conservation in Brazil; and by Vieira and Mcmanus (2023), who carried out the bibliographic mapping of heat tolerance in times of climate change linked to monogastric animals (broiler chicken and pigs). All these studies were recently published and provided an x-ray of the literature on their main topics. This finding shows the relevance of carrying out bibliometric analysis to help improving research on animal production, mainly planning research impacts, directions and future perspectives in order to answer the main research question, namely: From "what?" to "who, where, why, and when?"

4.2. Background: Where did we come from and where are we going to? Interconnections of subfields in animal science studies

The main conclusion on this topic deriving from the bibliometric analysis, mainly from the keywords and main journals, shows that the animal science has changed from unidisciplinary to multidisciplinary science, over the years, and the machine learning models have helped, and will boost, this process, through the further analysis of large data volumes. It must be done to ensure assertive decisions based on several assessed factors. This conclusion can be observed, overtime; however, it is necessary clarifying studies published in the past, and currently (at smaller scale), focused on only one animal production field, namely: reproduction, health, nutrition or genetics – which are basic knowledge, as shown in the graphic summary. This conclusion is confirmed by the

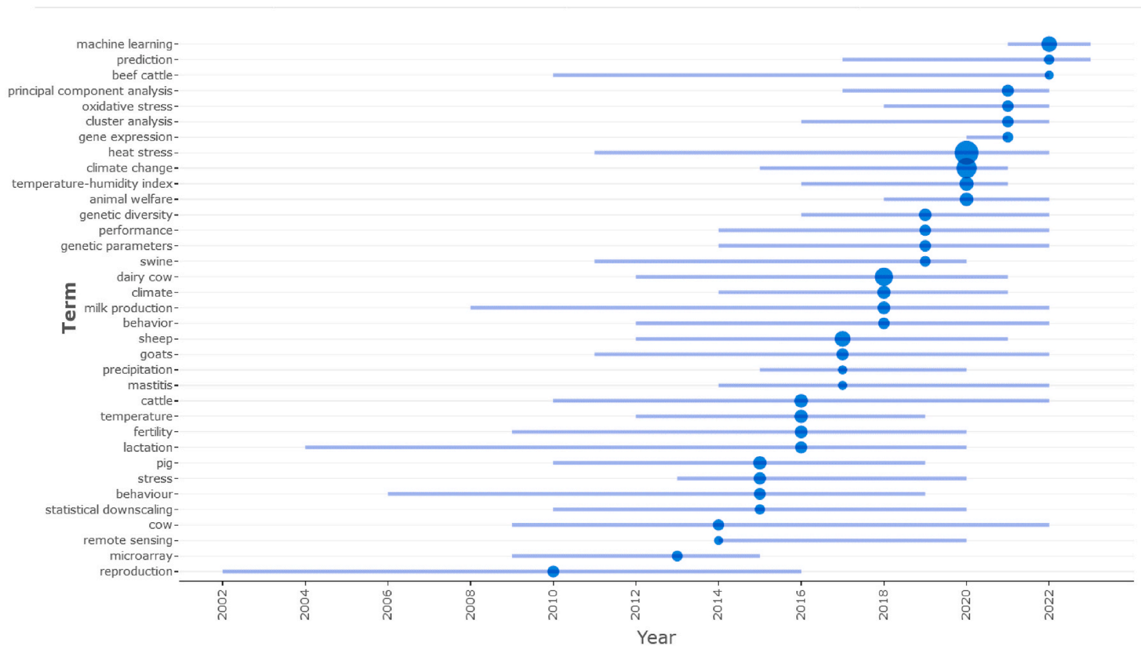

Fig. 13. Trend keyword analysis on machine learning using in sustainable animal production.

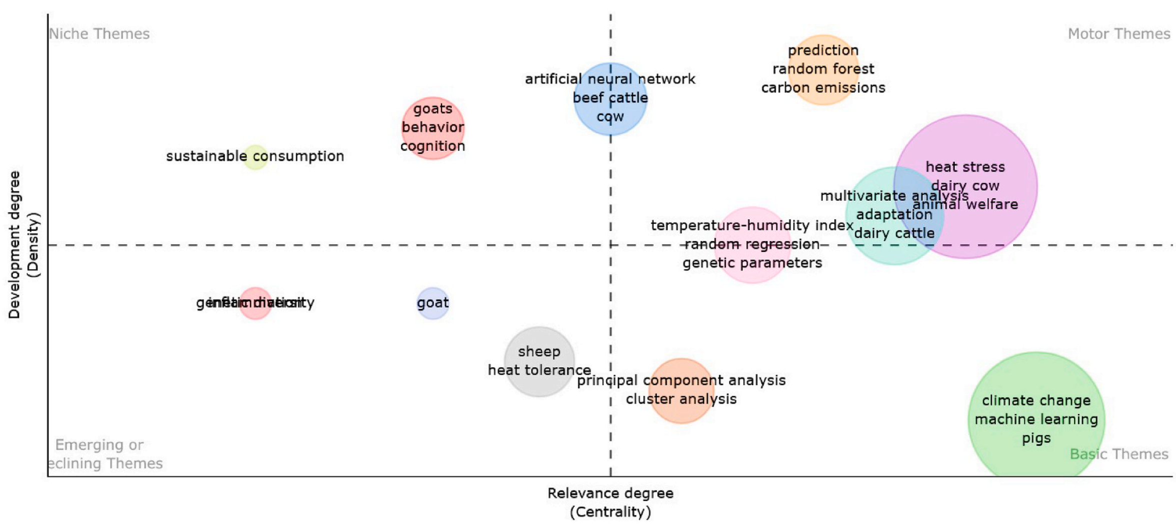

Fig. 14. Time slice graphic plotting the thematic evolution map on machine learning using in sustainable animal production.

main journals that publish articles on sustainable animal production, such as The Journal of Dairy Science, Journal of Animal Science and Applied Animal Behavior Science. These are traditional and specific journals in animal science presenting limited scope in specific fields. On the other hand, when the timeline of journals publishing on sustainable animal production is assessed, the 'Journal of Clean Production, Sustainability (MDPI)' and 'Plos One', which are multidisciplinary scope journals related to sustainability, stand out for publishing articles in this knowledge field, in recent years.

Articles published, in the last two years, in the Journal of Clean Production, encompass that by Silveira et al. (2023), who defined the concept of sustainable animal by using more than 40 thermoregulatory, hormonal, hematological, biochemical variables; carcass data, productive performance and food efficiency based on machine learning models and the main conclusion was that the sustainable animal is adapted, food efficient and productive; and by Fiorilla et al. (2024) who assessed sustainability in free-range broilers breeding based on using alternative dietary proteins, and concluded that broiler chicken slaughtered at the age of 147 days were more appropriate for consumption and caused lower environmental impact. Her study also showed that the environmental impact of experimental diets without soybean meal is significantly lower than that of conventional diets, for all considered parameters (CO_2 impact on human health, ecosystems and resources). Studies like these represent the global trend towards multidisciplinary studies in animal science aimed at relating numerous factors in animal production to sustainability.

Studies focusing on only one knowledge field are too limited when it comes to sustainable animal production, and this mistake was made by animal science for many years. An example of it is observed in production chains, such as those of broiler chicken and dairy cattle. Geneticists have historically focused on selecting animals for productive traits, such as growth rate, feed efficiency and milk production, without taking into consideration other traits of interest for production system sustainability. Therefore, this exclusive approach to select productive traits has been criticized for several reasons: (1) reduced genetic diversity - intensive selection for specific productive traits can lead to reduced genetic diversity in animal populations (Wanjala et al., 2023); (2) animal health and welfare issues - selection only focusing on productive traits can lead to animal health and welfare issues (Sundrum, 2023). Fast-growing broiler chicken species are more susceptible to lameness and they can account for significant mortality rates in comparison to slow-growing broilers. Genetic selection has been successful in improving broilers' meat yield. However, some of their support systems, such as the cardiovascular and skeletal systems, did not follow the body-mass increase, and it has made broilers increasingly susceptible to these systems' impairment or failure (Dibner et al., 2007). Another example of it was observed in high-yield dairy cows who are more prone to metabolic disorders and heat stress (Nzeyimana et al., 2024); (3) neglect of adaptive traits - exclusive emphasis on productive traits can neglect important adaptive traits, such as disease resistance, maternal abilities and natural behaviors (Façanha et al., 2020). This process can compromise animals' ability to adapt to different environments and handling conditions (an exclusive topic on this field will be approached in the present discussion) -; and (4) Environmental impact – the selection of productive traits can have negative environmental impacts, such as greater demand for natural resources, increased waste production and greenhouse gas emissions.

These concerns led to growing awareness of the relevance of adopting more holistic approaches to animal selection that take into consideration aspects related to health, welfare and adaptability, that can result in production system sustainability, rather than just to yield features. This selection may include incorporating resilience, genetic diversity and adaptive trait measurements in animal selection programs in order to promote more robust and sustainable production systems (Silveira et al., 2023, 2024).

Another trend observed in the thematic evolution and trend analyses applied to the keywords (Figs. 12 and 13) lied on the application of omics science, mainly rna-seq, transcriptome, gene expression and genetic parameters, along with machine learning models. It will help animal science in identifying and incorporating genes related to sustainability features in animal production in times of climate change. This information is corroborated by McManus et al. (2023) who pointed out the growing interest in genetic aspects, especially in SNPs, sequencing and selection signatures, in a biometric review based on the co-occurrence of keywords. Authors in this field show a shift from research focusing on quantitative genetics to molecular genetics, crossings and heterosis.

4.3. Phenotypic plasticity or thermal stress: What to study in times of climate change?

Does a goat with respiratory rate of 150 breats per minute, at 12 noon, in the Brazilian equatorial semi-arid region, present phenotypic plasticity or is it under heat stress? It is essential stating that phenotypic plasticity is the ability of a given genotype to produce different phenotypes adapted to different environments. They may present morphological, physiological and behavioral changes to the phenotype of an organism throughout natural selection. Although important, phenotypic plasticity has long been an underappreciated and largely neglected evolution mechanism and concept (Sommer, 2020), mainly in farm animal studies. However, this perspective is changing due to new studies that point towards the relevance of phenotypic plasticity in times of climate change and to the understanding of animals' morphological, physiological, behavioral and yield features (Rovelli et al., 2020).

Finding "thermal stress" as main keyword in the bibliometric review is an interesting outcome because this condition does not present phenotypic plasticity; therefore, this observation points out that studies mainly focus on mitigating thermal stress effects on animal production – this stress might have been caused by productive-index selection. Yet, it is important mentioning that dairy cattle, which is highly susceptible to thermal stress due to high metabolic heat production, was the most prominent domestic animal in keywords among all bred animals. This finding corroborates the importance of publications of "thermal stress" studies.

It is worth stating that the concept of thermal stress applied to farm animals (homeotherms) means the imbalance condition of animals' thermodynamic system, because when the heat balance is positive (the thermoregulation mechanisms do not efficiently dissipate all the heat from the animal), one finds thermal stress due to the heat. The opposite is valid for thermal stress due to cold. The importance of thermal stress in animal production will also due to compromised homeostasis, since it reduces production rates and increases greenhouse gas production (Ferreira et al., 2019; Wankar et al., 2024); therefore, animals under heat stress are not sustainable.

It is possible returning to the initial question of this topic after these basic concepts were established. Although animals presented increase by five times the normal respiratory frequency range for the species (Reece, 2004), the assessed animals were efficient in dissipating heat over the day (Façanha et al., 2020). In addition, animals' yield response was significantly similar throughout the experimental time, i.e., these animals showed phenotypic plasticity. Only their physiological response was changed to dissipate heat during high temperature events in the semi-arid regions. Ferreira et al. (2020) assessed the efficiency of the adaptive dynamics of heat dissipated from these animals' bodies during the day. They concluded that, although the animals received heat through radiation, they dissipated heat throughout the day, and it allowed considering them phenotypic-plasticity holders.

Geneticists are trying to overcome errors in genetic selection for productive traits after being aware of the importance of phenotypic plasticity, as already mentioned. The strategy is to select animals with heat tolerance, since these traits' heritability is moderate, even when animal yield is reduced (Cartwright et al., 2023). A study on dairy cow production in Australia is an example of adopting this strategy. According to this research, genomic genetic values related to production traits were established as heat-tolerance indicators (Nguyen et al., 2016). Another potential genetic enhancement strategy used worldwide, mainly in tropical regions, lies on selection combined to taurine cattle crossbreeding with zebu cattle to increase taurine animals' thermal capacity to control body temperature. This process justifies the lower metabolic rate recorded for zebu animals (Lima et al., 2022). Yet, the greater volume of sweat glands account for sweat production [lower energy expenditure in comparison to respiratory frequency – (Silveira et al., 2021)]. However, even with adherence to these features, these crossbred animals present lower milk yield than taurine bred under temperate conditions. Finally, studies seem to be going backwards, as they no longer focus on selection based on yield indices under thermal stress, mainly in times of climate change, as well as to embody features of animals with phenotypic plasticity (adaptive traits) into genetic improvement programs, even if they result in lower yield rates, this process results in seeking balance between welfare (animal under thermal comfort conditions) and animal yield.

4.4. What is the environmental index to assess animals' thermal comfort?

This sub-section was added to the text due to two results presented by the bibliometric analysis: 1) Temperature and Humidity Index (THI) was the only environmental comfort index among the keywords and 2) the main articles cited in the bibliometric analysis are those presenting dairy cows' THI thresholds (Fig. 11). It is worth clarifying that THI was not an index developed to assess thermal stress in animal production, but rather for humans (Thom, 1959). However, it is still the index mostly used to assess thermal stress in animal science.

As researcher trained in bioclimatology, I have come across manuscript submission reports from the main journals in this field, and they used to provide the following comment: "Calculate the THI to assess thermal stress in the evaluated animals" even if other thermal comfort indices were calculated. This same situation was faced by other researchers in this field. Unfortunately, these comments are common due to broad use of THI in several articles. It seems to have become "fashionable" in bioclimatology and thermal biology studies. Some examples of THI using can be observed in cell and physiological response (Sharma et al., 2023), thermoregulation (Ferreira et al., 2023), milk production and reproduction (Rodríguez-Godina et al., 2024) and ambience in broiler chicken studies (Jongbo et al., 2024), as well as in many other published articles focused on heat stress effect on animals' yield, health, genetics, ambience and reproduction.

Some studies point out THI "fad" to studies focused on advantage THI calculation, because data necessary for its calculation can be easily gathered in farms or at nearby weather stations, whereas data on other thermal comfort indices, such thermal radiation received from the animal, black globe temperature and wind speed, are more difficult to register, because they depend on specific equipment and on necessary data that are often not disclosed (Nascimento et al., 2019; Pinto et al., 2020). However, we disagree with this justification, as there are other environmental indices available to assess animal thermal stress, and they only use three psychometric variables that are easy to measure in farm environment.

THI results are underestimated for two reasons: 1) There are numerous THI formulas (Bianca, 1962; Mader et al., 2006; NRC, 1972; Thom, 1959); each one of them with different value, environmental variable and coefficient combinations. However, each of the variables can have a dominant effect, in certain situations, but they are not necessarily additive or linear (Rodrigues et al., 2011). The other error, which is even more serious, lies on incorrectly using reference values, as general rule: THI $\leq$74 is considered "normal", "alert" 75–78, "danger" 79–83 and "emergency" $\geq$ 84 (Hahn et al., 2009). However, these values are not absolute, and this finding corroborates observations by Martello et al. (2004), who presented some observations on thermal comfort indices using. However, if they are seen as generic tools, they cannot express the physiological needs of animals.

The standardization of THI equal to 68 as starting point for heat stress in dairy cows is another example of the aforementioned values (Pinto et al., 2019), but other studies use THI equal to 72 (Carrara et al., 2023; Salvian et al., 2023). However, assumingly, do Holstein cows with the same genetics in Brazil or the United States show the first signs of heat stress at THI 68 or 72? Of course not, it is necessary taking into account the environmental conditions and thermal exchanges between animals and the environment. Therefore, it is not possible summarizing an ideal value for all species, animal categories, physiological conditions, ages, breeds and thermal environments.

Another flaw in THI using, mainly in studies carried out in tropical climate regions, lies on the fact that this index does not take into account animals' thermal sensation, which can be measured through the black globe temperature, since it changes depending on wind speed and has direct impact on thermal exchanges, mainly on thermal convection. Both the black globe temperature and the humidity index were developed based on this limitation (Buffington et al., 1981).

It is necessary taking into consideration the air psychometric properties to develop thermal comfort indices and avoid such limitations. Psychometrics is defined as "the science that studies changes in moist air properties by using physical criteria, conventions and hypotheses" [American Society of Heating, Refrigerating and Air-Conditioning Engineers – ASHRAE (ASHRAE, 2009)] based on thermodynamics principles. It is also worth taking into consideration that air is featured as a complex and dynamic system made up of interdependent physical properties (de Castro Júnior and Silva, 2021).

Given these basic concepts, it was possible defining that the specific air enthalpy "is physically defined as the total amount of energy existing in a unit of dry air mass (kJ/Kg of dry air)" (Britto, 2010). The heat (thermal energy) flowing between bodies when there is temperature difference between them is the characteristic energy in psychometric processes. It is also worth noticing that specific enthalpy, which is the only psychometric variable, encompasses the concept of thermal energy in the environment and comprises the sum of latent and sensible heat (de Castro Júnior and Silva, 2021). The latent heat promotes temperature variation in the body without changing the aggregation state, whereas the sensible heat does not promote temperature changes, but it can change the body's physical state (Dal Piva et al., 2008). Because of such properties, the justification for using specific air enthalpy as thermal comfort index lies on applying these physical concepts of heat exchange to both animals and their environment (de Castro Júnior and Silva, 2021).

Initially, the enthalpy calculation was proposed by Albright (1990); it presents other psychometric variables of interest, as shown in Equation (1).

$$h = 1.006\ T + w\ (2501 + 1.805T) \qquad \text{Equation 1}$$

However, Furlan, 2001 adapted Equation (1) to Equation (2) by replacing w by RH, which are both psychometric properties, but w is easy to measure and producers can use it to assess heat stress in production animals.

$$h = \left(6.7 + 0.243\ T + 2.216\left(\left(\frac{RH}{100}\right) 10^{\frac{7.5T}{237.3+T}} - 1\right)\right)^{*}4.18 \qquad \text{Equation 2}$$

Finally, the last adjustment to the equation was carried out by Rodrigues et al. (2011) (Equation (3)), who included atmospheric pressure in it since, in principle, psychometric variables change depending on local atmospheric pressure (Beltrán-Prieto et al., 2016).

$$h = 1.006T + 10^{\frac{7.5T}{237.3+T}} * (71.28 + 0.052T) \qquad \text{Equation 3}$$

Wherein.

T – air temperature (°C);
RH – relative humidity (%);
Pb - barometric pressure (mmHg).
W – mix ratio (*ms*, g of water steam/Kg of dry air)

More details about the equation adjusted by Rodrigues et al. (2011) can be found in the article "A correct enthalpy relationship as thermal comfort index for livestock" and it has currently been used in 73 articles (Web of Science – accessed on March 26, 2024). It is also used in different studies conducted with different animal species. This previous bibliographic survey allows stating that THI is not the most suitable thermal comfort index to assess thermal stress in farm animals. The lack of information on psychometrics, mainly on thermodynamics, for animal science professionals has led to the use of THI "fad" in studies conducted in this field. Future studies focused on defining critical and comfort ranges of specific enthalpy for different species and physiological stages in production animals should be encouraged.

4.5. *Intelligence methodologies*

To the best of our knowledge, the term "intelligence methodology" in animal science was proposed in the article "Intelligence methodologies: An integrated multi-modeling approach to predict adaptive mechanisms in farm animals" (Silveira et al., 2024a). This methodology is recommended, as it uses tools capable of defining predictive modeling, identifying complex patterns, revealing phenotypic biomarkers, as well as reducing and associating variables by taking into consideration the global biological dataset (Silveira et al., 2024a,b).

The bibliometric analysis has shown some interesting results about the future perspectives linked to the main machine learning models in sustainable animal science, mainly in the keyword's timeline (Fig. 8), thematic trend maps (Fig. 12), keyword trends (Fig. 13) and thematic evolution (Fig. 14), where words, such as prediction (predictive models), random forest, neural network and cluster analysis (less important) were the main machine learning models. It is possible inferring that supervised machine learning models will be the ones mostly used in sustainable animal science studies to be conducted in the coming decades. This scenario is justified by the fact that the goal of using these machine learning tools is to "predict" events. This understanding corroborates the conclusion by Zhang et al. (2024), who discovered that prediction models are the ones mostly used in early prediction, rigorous monitoring and accurate diagnosis of animal diseases when they reviewed the literature on artificial intelligence using, since it ensures healthier and more sustainable livestock management.

As a critique to current works published in the animal science field, it is necessary reflecting a little on the use of univariate models, mainly of analysis of variance (ANOVA), as single statistical tool to assess other studies. This technique is only effective to compare means between groups/treatments, but it may not be able to capture more complex or non-linear association between variables and this process prevents more assertive inferences to be made by taking into consideration the set of variables in these studies. It is important encouraging the adoption of intelligence methodologies for global data understanding, since science is multifactorial and the adoption of mechanistic models is a global trend when it comes to sustainable animal production.

4.6. One Welfare and ESG

The thematic evolution graphs pointed towards animal welfare as the main keyword in the 2014–2020 timeframe, which is certainly related to the 2030 Agenda. It is so, because at least five contributions from animal welfare actions take place in both fields: Zero Hunger and Sustainable Agriculture (SDG 2); Health and Welfare (SDG 3); Decent Work and Economic Growth (SDG 8); Industry Innovation and Infrastructure (SDG 9); and Responsible Consumption and Production (SDG 12).

The term 'animal welfare' is not something relatively new, such as the increased number of studies in this field. The first research group on animal welfare, in the world, was launched in 1986, at Cambridge University, by Professor Donald Broom. He defined animal welfare based on many initial notions of attitudes linked to animals' basic needs (Balthazar et al., 2024a; Balthazar et al., 2024b). This concept has evolved, over the years, and it is currently focused on understanding the cognitive abilities and subjective experiences of animals and on working to introduce positive experiences that respect the five animal-welfare domains (Mellor et al., 2020).

"One Welfare" and "ESG", in their turn, are two more holistic concepts intersecting the sustainability and social responsibility domain. Sustainability emphasizes the interconnection among the welfare of humans, animals and the environment. It suggests that efforts to promote well-being should not be limited to humans, but should also be extended to both animals and the environment. It is worth noticing that this approach understands that the welfare of one aspect (human, animal or environmental) can have impact on the welfare of others. On the other hand, ESG is a consolidated term referring to the impact of a given business on both society and the environment (Oliveira and Gebreyes, 2022).

Assumingly, sustainable animal production will take place through the symbiosis between these two terms. The industry will value producers who present their production system certified for animal welfare (sustainable animal production). Therefore, these industries' products go to supermarkets with this certification stamp and these establishments will prefer to work with these producers, as shown by Arno et al. (2023), who featured the profile of producers based on their holistic perception about egg production in Brazil. They found an emerging typology of producers who choose eggs with care, based on animal welfare procedures, even if they pay more for the final product.

4.7. Green AI for Sustainability

The growing demand for sustainable practices in production systems highlights the role of Green Artificial Intelligence (Green AI) as a central tool in the search for innovative solutions. With the advancement of machine learning, it becomes possible to develop predictive and optimized models that directly contribute to the implementation of a circular economy (Ali, 2023). This approach promotes the efficient use of resources, reducing waste and minimizing environmental impacts throughout the entire production chain. The sustainable animal proposal is a classic example of how intelligent modeling is capable of identifying animals that consume less food and produce more, possibly with a low carbon and water footprint. In addition, these animals are clinically healthy and adapted to the environment (Silveira et al., 2023).

In this context, studies should also extrapolate the use of machine learning to the complex analysis of large volumes of data collected in production systems, such as environmental, productive and economic indicators - pillars of sustainability - in a synergistic way. For example, supervised learning algorithms and multivariate techniques are used to predict water and food consumption patterns, assess animal welfare, and optimize nutritional and climate management of animals (Silva et al., 2024). This continuous monitoring ensures more assertive decisions, reducing the unnecessary use of natural resources and increasing production efficiency. The application of Green AI also enables and promotes significant gains in animal welfare and the efficiency of production systems. Through sensors, cameras, and other IoT devices integrated with deep learning algorithms, it is possible to monitor, in real time, the behavior (Baltazar et al., 2024a), health (Mitsunaga et al., 2024), thermal comfort (Baltazar et al., 2024b), and identify stress situations through vocalization (Silva et al., 2024). This not only improves breeding conditions, but also ensures that animals are adapted, productive and efficient in feed conversion, with a lower environmental impact and promoting the rational use of natural resources (Silveira et al., 2023).

The synergy between machine learning and sustainability emerges as an essential strategy to drive a circular economy in the production sector, which is the main objective of Green AI. It offers accurate, intelligent and integrated solutions. By aligning science, technology and sustainability, machine learning plays a fundamental role in building more efficient and responsible production systems that are aligned with global demands for conservation of natural resources and food security.

5. Limitations

The present study has some methodological limitations regarding data processing. Firstly, the keyword-search methodology may not have captured all articles available in the dataset for the analysis. Although the combination of synonymous words was used to avoid such a limitation, it is important taking into account that it could have led to likely terminology errors. The query was shared with international researchers to further reduce this limitation. These researchers were essential to expand the keywords and to capture as many articles related to the assessed topic as possible.

Another limitation of the present study lies on the fact that it was exclusively based on Scopus database. Although the advantages of using multiple databases are acknowledged, Scopus is one of the main libraries of scientific articles in the world. The choice for using only one platform derived from data consistency and analysis to minimize potential discrepancies likely arising from the incorporation of different databases. It is worth mentioning that studies presenting bibliometric review mainly use Scopus as the only database in their work (McManus et al., 2023, 2024; Vieira and McManus, 2023). This limitation may reduce the reliability of the present results; however, they do not discourage future researchers from exploring multi-databases to gather complementary knowledge. Another important point also seen as limitation, but that may be interpreted by some authors as such, is the fact that not all documents available on this topic were taken into consideration, such as documents like conference articles, theses, dissertations, reviews, book chapters, books, reviews of conferences and correction. The current review only comprised peer-reviewed articles, such as literature reviews and papers, since the goal was to maintain the high-quality profile of the academic literature.

Yet, this study may present data collection and processing limitations, since the bibliometric methodology depends on literature digitalization and on establishing online data and information-sharing platforms, mainly on articles published in the initial years of the review. Consequently, data in these databases may provide incomplete information (downloaded articles may lack intrinsic information necessary for process visualization and potentially lead to discrepancies in visualization results.

6. Implications

The current study generated unprecedented insights, never discussed before. They will help defining public policies to collaborate with future sustainable production systems linked to challenges in the 2030 Agenda for Sustainable Development, such as social inclusion; food security; increased equity, education and health care; biodiversity conservation; water security; climate change adaptation and mitigation; and animal welfare.

The present review provided an in-depth view of machine learning using in sustainable animal production in times of climate change by mapping the current literature; providing an overview of publication trends and collaboration patterns, number of citations and reference overlap, in order to determine research critical points and to identify sustainable solutions for animal production. Furthermore, it provides propositions for future research to encourage researchers to expand their work. In addition, the discussion section raised many questions that were initially explained by basic concepts and that now demand deeper understanding. In other words, a mini literature review was carried out to understand physiology or even psychometrics to determine new paths for future studies, since the works' procedures were incorrect. Finally, the present review provided a longitudinal perspective on the current state of academic research when it comes to the emerging field of machine learning using in sustainable animal production in times of climate change. It provided scholars and professionals with a holistic view of studies' current state, of opportunities and associated risks, as well as pathways for future research in this emerging and promising field.

7. Potential future directions

Future prospects for the application of machine learning in sustainable animal production point to the need for a more holistic and multidisciplinary approach, aiming to overcome the challenges posed by climate change and the increase in global demand for food. First, it is essential to explore more robust and integrated models that combine supervised learning algorithms and deep learning. These methodologies will allow a more accurate and transparent understanding of the complex processes involving animal physiology, production efficiency and environmental impacts. It is worth noting, as discussed, that articles published in the main animal science journals still mostly use univariate approaches.

Another promising path lies in the advancement and application of omics sciences (genomics, transcriptomics and metabolomics) in synergy with machine learning. The integration of these areas will enable the identification of genetic and phenotypic markers related to sustainability, such as feed efficiency, heat adaptation and reduction of greenhouse gas emissions. Future work should focus on incorporating adaptive traits into breeding programs, considering the potential for phenotypic plasticity in contexts of thermal stress and extreme conditions such as heat waves, which is already a reality worldwide.

In addition, the creation of digital platforms based on big data and the Internet of Things (IoT) will be essential to optimize real-time monitoring of the breeding environment, behavior, and health of animals. These tools, combined with predictive models, will enable rapid responses to climate change, better management of natural resources, and improved animal welfare. The integration of automated data collection systems, such as environmental sensors and smart cameras, will enable more complete and accurate analyses of production systems.

Finally, it is imperative that future research prioritize the development of public policies and guidelines based on scientific evidence, in order to encourage the adoption of sustainable technologies on a global scale. Collaboration between academia, the production sector, and governments will be crucial to implement solutions based on machine learning, ensuring more resilient, efficient production systems that are aligned with the Sustainable Development Goals (SDGs).

8. Conclusion

Results allowed concluding that the growing number of publication in the sustainable animal production field is driven by the UN's 2030 Agenda, mainly the Sustainable Development Goals (SDGs). These goals have led to research and studies on how to improve animal production efficiency, reduce environmental impacts of livestock, promote animal welfare and ensure that food production will remain socially and economically viable, in the long term. These elements feature current animal production as multidisciplinary science involving other sciences, such as environmental, veterinary, social, engineering and exact sciences. It was also noticed that artificial intelligence application - intelligence methodologies, mainly prediction models - helped making more assertive decisions, mainly at the time to process large data volumes to identify complex patterns. Machine algorithms learning provided valuable insights to help scientists improving efficiency, reducing costs and minimizing the environmental impacts of animal farming. Finally, the application of these intelligence methodologies will be used in synergy with omics sciences, greenhouse gases, phenotypic plasticity and energy efficiency in order to maximize sustainable animal production and to ensure that food production is environmentally responsible, economically feasible and socially acceptable for the coming decades.

CRediT authorship contribution statement

Robson Mateus Freitas Silveira: Writing – review & editing, Data curation, Conceptualization. **Concepta Mcmanus:** Writing – original draft, Visualization. **Iran José Oliveira da Siva:** Writing – original draft, Software, Resources, Project administration.

Consent to participate

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Appendix

(TITLE-ABS-KEY (sustainable AND animal) OR TITLE-ABS-KEY (sustainable AND animal AND production) OR TITLE-ABS-KEY (climate AND change) OR TITLE-ABS-KEY (adaptive AND profile) OR TITLE-ABS-KEY (physiological AND response) OR TITLE-ABS-KEY (heat AND tolerance) OR TITLE-ABS-KEY (morphophysiological AND response*) OR TITLE-ABS-KEY (behaviour AND response*) OR TITLE-ABS-KEY (heat AND stress) OR TITLE-ABS-KEY (thermoregulatory AND response) AND TITLE-ABS-KEY (cda) OR TITLE-ABS-KEY (cluster*) OR TITLE-ABS-KEY (discrim*) OR TITLE-ABS-KEY (canonical) OR TITLE-ABS-KEY (regression) OR TITLE-ABS-KEY (proc AND factor) OR TITLE-ABS-KEY (artificial AND intelligence) OR TITLE-ABS-KEY (princomp) OR TITLE-ABS-KEY (random AND forest*) OR TITLE-ABS-KEY (pca) OR TITLE-ABS-KEY (machine AND learning) OR TITLE-ABS-KEY (principal AND component AND analysis) OR TITLE-ABS-KEY (neural AND network) AND TITLE-ABS-KEY (animal AND farm) OR TITLE-ABS-KEY (dairy AND cow) OR TITLE-ABS-KEY (beef AND cow) OR TITLE-ABS-KEY (goat*) OR TITLE-ABS-KEY (ovinis) OR TITLE-ABS-KEY (lamb*) OR TITLE-ABS-KEY (ewe*) OR TITLE-ABS-KEY (caprine) OR TITLE-ABS-KEY (chicken*) OR TITLE-ABS-KEY (hen*) OR TITLE-ABS-KEY (pig) AND NOT TITLE-ABS-KEY (plant*) AND NOT TITLE-ABS-KEY (human*) AND NOT TITLE-ABS-KEY (land) AND NOT TITLE-ABS-KEY (agriculture) AND NOT TITLE-ABS-KEY (felino) AND NOT TITLE-ABS-KEY (dog*) AND NOT TITLE-ABS-KEY (fish*) AND NOT TITLE-ABS-KEY (horse*) AND NOT TITLE-ABS-KEY (neuroscience) AND NOT TITLE-ABS-KEY (memory) AND NOT TITLE-ABS-KEY (rabbit*) AND NOT TITLE-ABS-KEY (soil*) AND NOT TITLE-ABS-KEY (covid 19) AND NOT TITLE-ABS-KEY (sus AND scrofa) AND NOT TITLE-ABS-KEY (prrsv) AND NOT TITLE-ABS-KEY (stream AND temperature) AND NOT TITLE-ABS-KEY (pesticide) AND NOT TITLE-ABS-KEY (microalga) AND NOT TITLE-ABS-KEY (insecticides) AND NOT TITLE-ABS-KEY (biogeographic) AND NOT TITLE-ABS-KEY (glycocalyx) AND NOT TITLE-ABS-KEY (pinus) AND NOT TITLE-ABS-KEY (bird*) AND NOT TITLE-ABS-KEY (flood) AND NOT TITLE-ABS-KEY (pivotal) AND NOT TITLE-ABS-KEY (endangered) AND NOT TITLE-ABS-KEY (phytoplankton) AND NOT TITLE-ABS-KEY (tourism) AND NOT TITLE-ABS-KEY (brics) AND NOT TITLE-ABS-KEY (potato) AND NOT TITLE-ABS-KEY (cricket) AND NOT TITLE-ABS-KEY (sexual AND selection) AND NOT TITLE-ABS-KEY (dengue) AND NOT TITLE-ABS-KEY (virus) AND NOT TITLE-ABS-KEY (fungus) AND NOT TITLE-ABS-KEY (bacterium) AND NOT TITLE-ABS-KEY (crop) AND NOT TITLE-ABS-KEY (amphibia) AND NOT TITLE-ABS-KEY (urban AND growth) AND NOT TITLE-ABS-KEY (river)) AND (LIMIT-TO (SUBJAREA, "AGRI") OR LIMIT-TO (SUBJAREA, "VETE") OR LIMIT-TO (SUBJAREA, "ENVI")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j")).

Data availability

Data will be made available on request.

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