A study comparing energy consumption and environmental emissions in ostrich meat and egg production

Behrooz Behboodi,[1] Mohammad Gholami Parashkoohi,[2] Davood Mohammad Zamani,[1] Saeed Firouzi[3]

[1]Department of Biosystem Engineering, Takestan Branch, Islamic Azad University, Takestan; [2]Department of Mechanical Engineering, Shahr-e-Qods Branch, Islamic Azad University, Tehran; [3]Department of Agronomy, College of Agriculture, Rasht Branch, Islamic Azad University, Rasht, Iran

Introduction

An energy audit involves analyzing the energy consumption and usage within a system or process to enhance efficiency, minimize waste, and implement eco-friendly technologies and renewable energy sources (Menghi *et al*., 2019). Enhancing energy management leads to cost reduction, advancement of sustainable technologies, and protection of the environment. The greenhouse gas emissions resulting from energy usage, including carbon dioxide, methane, and nitrogen oxide, have a significant impact on climate change and global warming (Liu *et al*., 2020). In various countries, the breeding of ostriches for economic and industrial purposes has experienced notable growth in recent years. Ostriches, large birds native to dry and desert regions, are primarily raised for their meat. This meat is highly sought after by consumers for its delicious flavor and high protein content, making ostrich breeding a lucrative venture (Manap *et al.,* 2002; Shibak *et al*., 2023). Due to the increase in demand for ostrich products in global and local markets, the number of ostrich breeding units has also increased in recent years. For example, in 2019, the production of ostrich meat in the world has reached more than 100 thousand tons and this figure is growing. Also, the production of ostrich eggs reaches more than 1000 tons per year. These statistics show that breeding ostriches is developing as a growing and profitable industry (Khalid *et al*., 2022; Adams *et al*., 1998). The energy consumption in the production of meat and eggs from ostriches is influenced by several factors, such as the quality of their diet, the conditions in which they are raised, the utilization of advanced equipment and technologies, and the overall volume of ostrich production (Ramedani *et al*., 2019). The development and nourishment phases of animals necessitate significant water intake, putting pressure on water supplies and leading to shortages in regions with high levels of meat production (Kolawole *et al*., 2023). The implementation of animal husbandry practices can have adverse effects on animal health, productivity, and welfare. However, the adoption of sustainable breeding methods has helped mitigate these impacts (Llonch *et al*., 2017) The growth and feeding phases of animals necessitate significant water intake, placing strain on water resources and leading to shortages in regions with high meat production. The use of fertilizers and polluted water in animal breeding can result in water and soil contamination, harming the quality of both and their biodiversity (Chau *et al*., 2015). Gather essential materials for meat and egg production, ensuring they are sourced from sustainable and recyclable sources. Ensure the quality of raw materials by employing efficient processes to minimize emissions. Attention should be paid to using optimal and low-energy processes, reducing greenhouse gas emissions, and reducing the production of biological and non-biological waste for production (Kumar *et al*., 2023).

Sophisticated techniques like artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) can be employed to forecast energy usage, environmental consequences, and exergy in the breeding of ostriches for meat and egg production. These methods can predict energy consumption and environmental impacts and exergy based on available data and observed patterns (Kaab *et al*., 2019. ANN consider the complex production patterns of meat and egg-laying ostriches and make predictions based on them. Also, ANFIS investigates environmental and exergy effects in ostrich production and quantitatively measures and predicts them. To ensure quality, it is important to match the supply of nutrients to the needs of the ostrich during growth. South African trials have assessed feed value and nutrient requirements, but direct applicability to other countries is questionable due to environmental differences and feed resources. Ostriches have better feeding efficiency and can use high fiber feeds. More nutritional research is needed on feed ingredients, nutrient requirements, crop-specific diets, and grazing management strategies (Shibak *et al*., 2023). Brand *et al.* (2003) suggests that a diet with a minimum energy content of 8.5 MJ kg^{-1} and protein content of 105 g kg^{-1} should be used for breeding female ostriches to maintain optimal egg production. The environmental impacts of poultry production indicate that poultry farms are mainly accountable for the assessed environmental consequences. The primary contributors to these impacts are feed production, including chemical use and energy requirements, as well as on-farm emissions from organic waste

Correspondence: Mohammad Gholami Parashkoohi, Department of Mechanical Engineering, Shahr-e-Qods Branch, Islamic Azad University, Tehran, Iran.
E-mail: mohammad.gholamiparashkoohi@gmail.com

Key words: energy use; human health; life cycle assessment; ostrich, sustainability.

Received: 23 May 2024.
Accepted: 4 October 2024.

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Licensee PAGEPress, Italy
Journal of Agricultural Engineering 2025; LVI:1718
doi:10.4081/jae.2025.1718

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decomposition. Ultimately, a multi-objective optimization model was utilized to minimize environmental consequences and maximize economic advantages. The chosen option resulted in a 15.14% decrease in environmental indicators per unit of performance (López-Andrés *et al*., 2018). Proper feed and nutrition management offer an effective strategy for enhancing sustainability by enhancing livestock productivity and minimizing the environmental footprint of livestock operations. In the face of a shifting global climate, prioritizing animal welfare and environmental conservation is crucial for promoting sustainability in animal agriculture and meat processing (Ponnampalam *et al*., 2023). The LCA highlights the importance of addressing climate change, showing that the emissions are 5.58 kg CO_2 eq kg^{-1} per egg produced. Introducing an eco-efficient program that prioritizes energy usage could result in a 49.5% cut in overall energy usage and a 56.3% reduction in environmental footprints (Estrada-González *et al*., 2018). The analysis of environmental impact assessments for livestock products revealed that opting for environmentally friendly choices in one's diet can significantly reduce environmental harm. Among livestock products, the production of 1 kg of beef was found to have the largest land and energy footprint, along with the highest global warming potential (GWP). This was followed by the environmental impact of producing 1 kg of pork, chicken, eggs, and milk. The production of meat (pork, chicken, beef) was notably more impactful compared to producing 1 kg of milk and eggs, primarily due to the higher water content in milk and eggs. Furthermore, the production of 1 kg of beef protein had the most significant effect, followed by pork protein and chicken protein (de Vries *et al*., 2010).

Considering that ostrich breeding is currently known as one of the important industries in many countries, forecasting energy consumption and determining environmental indicators can be used as one of the effective methods to improve performance and optimize ostrich breeding. The use of artificial intelligence as one of the advanced and new technologies can be used as one of the effective methods in predicting energy consumption and determining environmental indicators in ostrich breeding. By using artificial intelligence algorithms such as neural networks, it is possible to collect more accurately and quickly the necessary information to predict energy consumption and determine environmental indicators. The uniqueness of the comparative analysis of energy use and environmental emissions in ostrich meat and egg production lies in its examination of the energy consumption and environmental emissions associated with ostrich meat and egg production. This study provides valuable insights into the environmental impact of ostrich farming, shedding light on the resources and emissions involved in producing ostrich meat and eggs. The implications of this research extend to human health, as understanding the environmental footprint of ostrich farming can inform sustainable practices that benefit both the environment and consumers. By focusing on ostrich production specifically, this analysis offers a novel perspective on sustainable meat and egg production and highlights the potential implications for human health and environmental sustainability.

Materials and Methods

Study area

The influence of latitude on the climate of Qazvin province is minor, as altitude exerts a more pronounced impact on temperature fluctuations. As one ascends in altitude, temperatures decline, leading to cooler conditions in the mountainous areas and highlands in contrast to the warmer lowlands and valleys. Additionally, external factors like air masses further shape the climate of Qazvin province. These include the arrival of humid western air masses, cold and arid northern air masses, and hot and dry southern air masses from various directions and seasons, each contributing unique characteristics to the region's climate (Ministry of Agriculture Jihad, 2001) In Figure 1, the positioning of Qazvin province is depicted, indicating the site where data collection from ostriches took place through a questionnaire. The questionnaire encompassed diverse input origins, details from manufacturers, and product functionality. To enhance the precision of data gathering and results, a random sampling approach was employed within the designated research area. The sample size of 55 questionnaires was determined using the Cochran method outlined in Eq. 1 for this study (Cochran, 1997).

$$n = \frac{\frac{z^2 pq}{d^2}}{1 + \frac{1}{N}\left(\frac{z^2 pq}{d^2} - 1\right)} \qquad \text{(Eq. 1)}$$

where n is the required sample size, N is the number of orchards per target population, z is the reliability coefficient (equals to 1.96, denoting 95% confidence level), p is the estimated proportion of an attribute that is present in the population (equals to 0.5), q is 1-p

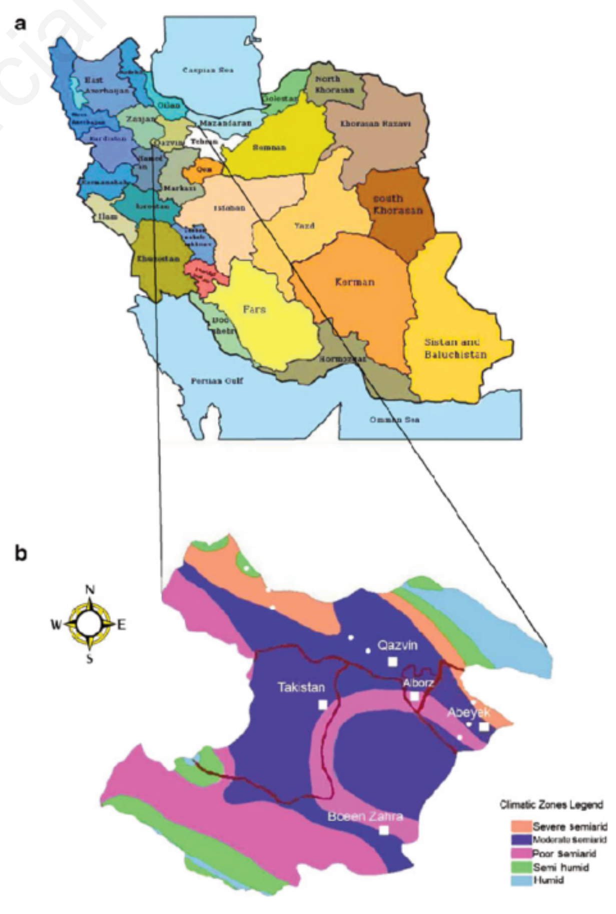

Figure 1. The geographic location of the examined area in Qazvin Province, Iran.

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(equals to 0.5), and *d* is the permitted error ratio deviation from the average population (equals to 0.05).

Energy

Conducting energy analysis can assist manufacturers in enhancing production process efficiency and optimizing energy utilization. By adopting more consistent and energy-efficient practices, businesses can contribute to environmental preservation and mitigate the adverse impacts of energy consumption on the environment (Menghi *et al*., 2019). The assessment of energy consumption factors involved documenting the usage of electricity, gas, fuel, and other energy sources within the ostrich production unit. The study scrutinized energy usage across different activities like lighting, heating, cooling, transportation, processing, and packaging by examining pertinent factors. Additionally, the research entailed measuring and documenting the energy consumption of diverse equipment such as ostrich breeding devices, processing and packaging machinery, and other apparatus associated with feed supply. An essential aspect of this study was the consolidation and detailed analysis of the gathered data to assess energy consumption efficiency and pinpoint areas for enhancement. Energy analysis in ostrich breeding units involves assessing the energy inputs, outputs, and efficiency of the operations. This analysis can help identify areas for improvement in energy use and resource management. Some key components of energy analysis in ostrich breeding units may include:

Energy inputs. This involves quantifying the energy used in various aspects of ostrich breeding, such as feed production, heating and lighting, transportation, and processing. This can include direct energy sources such as electricity and fuel, as well as indirect energy inputs such as embodied energy in materials and equipment.

Energy outputs. This involves evaluating the energy content and value of the products and by-products of ostrich breeding, such as meat, leather, feathers, and eggs. Understanding the energy outputs can help assess the overall energy efficiency and sustainability of the operation. Meat and eggs are our sensitive points.

Energy efficiency. Assessing the efficiency of energy use in ostrich breeding units can help identify opportunities for improvement. This can include evaluating the efficiency of heating and lighting systems, feed conversion ratios, and transportation efficiency.

Renewable energy potential. Assessing the feasibility of incorporating renewable energy sources like solar or wind power into ostrich breeding facilities can aid in decreasing dependence on non-renewable energy sources and cutting down on overall energy expenses.

Through a comprehensive energy assessment, ostrich breeding facilities can pinpoint areas for lowering energy usage, enhancing efficiency, and boosting sustainability. This proactive approach can result in cost reductions, decreased environmental footprint, and enhanced long-term sustainability of the operation. Energy consumption data for ostrich production units was gathered via in-person interviews as outlined in Table 1. The interview provided the possibility of personal communication between the interviewer and the interviewee. The information was received from the face-to-face interviews accurately and completely, and this can lead to a better analysis and interpretation of the information. An opportunity was created to promote communication between the two parties and this communication was useful in various fields, including solving problems, creating cooperation and effective interaction between the two parties (May *et al.,* 2015).

Energy use efficiency is defined as the proportion of useful energy output to total energy input in a given system or process, expressed as output energy (MJ) divided by input energy (MJ). This metric assesses the effectiveness of energy utilization and can be applied across different sectors including industrial operations, transportation, and building infrastructure. A higher energy use efficiency signifies that a system can generate more beneficial output with the same energy input, leading to reduced waste and improved overall performance (Alluvione *et al.,* 2011). Enhancing energy efficiency is a key objective in reducing energy consumption, lessening environmental impact, and optimizing resource use. This can be accomplished through advancements in technology, enhancements in processes, and changes in behavior. Energy pro-

Table 1. Energy inputs-outputs and energy coefficients in ostrich breeding units.

Items	Unit	Energy equivalent (MJ unit^{-1})	References
Inputs			
Human labor	h	1.96	Ghasemi-Mobtaker *et al.,* 2022
Machinery	h	62.7	Kaab *et al.,* 2021
Diesel fuel	L	56.31	Mohammadi Kashka *et al.,* 2023
Natural gas	m3	49.50	Nabavi-Pelesaraei *et al.,* 2014
Electricity	kWh	12.00	Kitani *et al.,* 1999
Feedkg			
Corn		7.90	Kitani *et al.,* 1999
Barley		14.70	Kitani *et al.,* 1999
Alfalfa		15.80	Kitani *et al.,* 1999
Rice bran		14.57	Kitani *et al.,* 1999
Wheat		13.70	Kitani *et al.,* 1999
Soybean meal		12.60	Kitani *et al.,* 1999
Sugar beet pulp		16.80	Kitani *et al.,* 1999
Vitamins and minerals		1.59	Kitani *et al.,* 1999
Salt		1.59	Kitani *et al.,* 1999
Fatty acid		37.00	Kitani *et al.,* 1999
Ostrich chick	kg	10.33	Ramedani *et al.,* 2019
Outputs	kg		
Ostrich meat		10.33	Ramedani *et al.,* 2019
Ostrich egg		7.28	Ramedani *et al.,* 2019

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ductivity is a measure of the economic output generated per unit of energy input, with higher energy productivity indicating more output for the energy used. Specific energy measures the energy content of a material per unit mass or volume, providing insight into the energy required to produce a certain quantity of a substance (Zhang *et al*., 2019).

Life cycle assessment

The series of interconnected stages within a product or service system, spanning from the extraction of natural resources to its ultimate disposal, is referred to as the life cycle assessment (LCA). LCA serves as a valuable tool for assessing the environmental footprint of a product, process, or activity throughout its life cycle, encompassing stages from raw material extraction to processing, transportation, and disposal (van der Werf *et al*., 2020). Initially utilized for product comparisons, such as evaluating the environmental impact of disposable *vs* reusable items, today, LCA finds diverse applications in governmental policies, strategic planning, marketing strategies, consumer education, process enhancements, and product design. It also serves as a foundation for global environmental labeling and consumer education initiatives (Estrada-González *et al*., 2020). LCA is a method for examining potential environmental and related aspects of a product or service (Lai *et al*., 2022), involving the following key steps:

i) Compiling a list of relevant inputs and outputs.
ii) Evaluating the potential environmental impacts associated with these inputs and outputs.
iii) Analyzing the results and their implications in alignment with the study's objectives.

The first step in the study is determining the goal and scope of application, which is crucial as it defines key elements such as purpose, scope, and main hypothesis. This stage typically includes defining the system, its boundaries, data quality, main hypothesis, and limitations. In life cycle assessment, the functional unit serves as a reference unit for comparing products or processes in terms of resource consumption and emissions (Fnais *et al*., 2022). The study focused on one ton of ostrich meat and egg production as the unit of analysis for calculating environmental emissions. The goal was to assess the environmental impact of ostrich production in order to enhance its sustainability. This evaluation involved measuring factors like water usage, energy consumption, greenhouse gas emissions, and environmental degradation. By identifying areas of improvement and implementing strategies to reduce negative environmental effects, the aim was to enhance the overall environmental performance of ostrich production. Inventory analysis is a technical process that involves collecting data to quantify the inputs and outputs of a system within a defined scope. This includes measuring energy and raw material consumption, as well as emissions to air, water, soil, and solid waste produced throughout the entire life cycle of a product or service. To aid in this analysis, the system is broken down into subsystems or processes, with data categorized in the life cycle inventory (LCI) database (Zhu *et al*., 2022). Life cycle impact assessment (LCIA) is then used to identify and characterize the potential environmental effects of the system. This phase builds upon the information gathered in the inventory analysis. The final stage of the LCA process is interpretation, where results are synthesized to highlight key sources of impact and suggest ways to mitigate them. ReCiPe2016 is commonly used in software like SimaPro to evaluate environmental emissions. Interpretation also involves reviewing all steps of the LCA process to ensure the consistency of assumptions and data quality in relation to the study's purpose and scope (Asem-Hiablie *et al*., 2019). The relationship between the different stages of LCA is depicted in Figure 2. The study utilized the ReCiPe 2016 methodology through the SimaPro software. The emphasis was on determining the emissions index for pollutants during paddy production and evaluating the consequent impacts on the ecosystem, human health, and resources as endpoints. Utilizing Figure 3, mid-

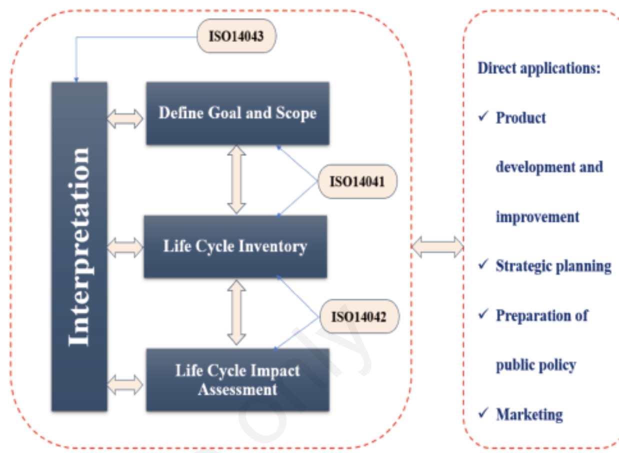

Figure 2. The ISO definition outlines the different phases of a LCA.

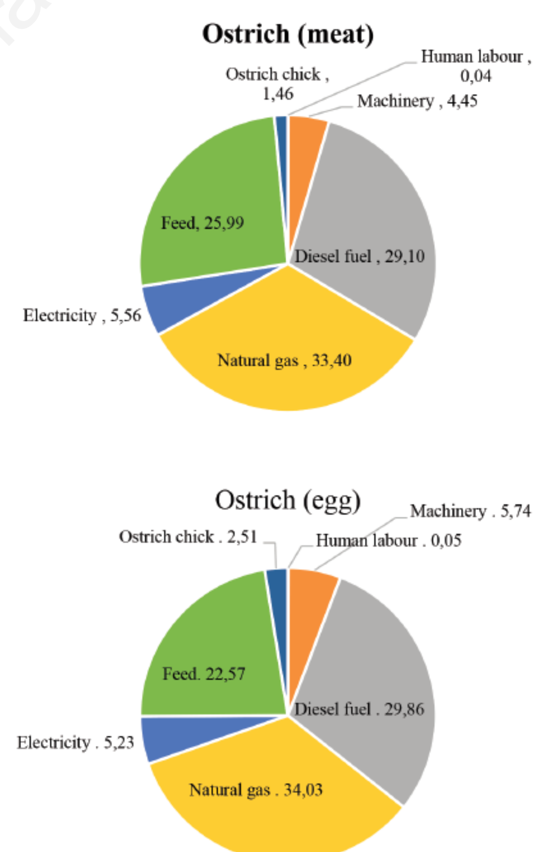

Figure 3. The impact of various energy sources on ostrich breeding units in different production scenarios.

points were identified and the impact of each mid-point was quantified and combined using standard units.

ANN and ANFIS

The ANN model acts as an information processing system that consists of artificial processing units called “neurons”. These neurons are connected to each other in proximity and transmit information to each other through connections (weights) (Dongare *et al*., 2008). An ANN consists of several different layers, including input layers, hidden layers, and output layers. The input information from the environment enters the input layer and then through various processes in the hidden layers, the information is transferred to the output layers to produce the desired output (Maind and Wankar, 2014). One of the characteristics of artificial neural network is that it can learn from input data and recognize patterns and complex relationships based on them. Also, this model can make predictions and rational decisions based on experience and new data. ANN can be used to improve agricultural products. These networks can be used to predict crop performance, diagnose diseases and pests, optimize water and chemical consumption, diagnose and predict weather conditions, and manage production. By analyzing spatial and temporal data, neural networks can help farmers improve their crops and improve agricultural performance (Niaze *et al*., 2023).

ANFIS, which is a technique used to model complex systems by combining the advantages of fuzzy logic and neural networks (Hakim *et al*., 2013). In the field of energy consumption and environmental indicators related to the production of meat and egg-laying ostriches, ANFIS can be used to analyze and predict the impact of these activities on energy consumption and environmental factors. To develop an ANFIS model for energy consumption, you need historical data on energy consumption in meat and egg production, as well as related environmental indicators such as greenhouse gas emissions, water consumption, and land footprint. The purpose of this model is to create relationships between these variables and identify patterns and trends (Pahlavani *et al*., 2017). The steps of developing an ANFIS model for energy consumption and environmental indicators in meat and egg production are as follows:

i) Data related to energy consumption in meat and egg production as well as environmental indicators such as greenhouse gas emissions, water consumption and land footprint were collected. This data was obtained from research studies, government reports and industry databases.
ii) We cleaned the data by removing outliers, handling missing values, and normalizing variables to ensure they were on the same scale. This step is very important for accurate modeling.
iii) The data was divided into training and testing sets. The training set is used to train the ANFIS model, while the test set is used to evaluate its performance. The ANFIS model learns the relationships between energy consumption and environmental indicators through an iterative process.
iv) The ANFIS model was validated by comparing its predictions with the actual values of the test set. The performance of the model was evaluated using criteria such as the average absolute error, the root mean square of the error and the coefficient of determination (R-squared).
v) To understand the relationship between energy consumption and environmental indicators in meat and egg production, the ANFIS model is analyzed. The most influential variables and their impact on the results are identified.

Using this modeling technique, policy makers, researchers and industry stakeholders can make informed decisions to promote sustainable practices and reduce the environmental impact of these activities (Subah and Nagalakshmi, 2021)

Coefficient of determination, mean square error and root mean square error

The coefficient of determination (R^2) measures the proportion of the variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1, with 1 indicating a perfect fit. The mean square error (MSE) is the average of the squared differences between the actual and predicted values in a regression model. It provides a measure of the average magnitude of the errors in the model. The root mean square error (RMSE) is the square root of the mean square error and provides a measure of the average magnitude of the errors in the model in the same units as the dependent variable. It is often used to compare the accuracy of different models (Kanwisher *et al.,* 2023). Eq2. 2, 3 and 4 show R^2, MSE and RMSE, respectively.

$$R^2 = 1 - \sqrt{\frac{\sum_{i=1}^{n}(P_i - A_i)^2}{\sum_{i=1}^{n} A_i^2}} \quad \text{(Eq. 2)}$$

$$\text{MSE} = \frac{1}{n}\sum_{i}^{n}(P_i - A_i)^2 \quad \text{(Eq. 3)}$$

$$\text{RMSE} = \sqrt{\frac{1}{\text{n}}\sum_{i}^{n}(P_i - A_i)^2} \quad \text{(Eq. 4)}$$

Results and Discussion

Energy results

The comparison of energy analysis results between egg and ostrich meat production provides insights into energy consumption and production. Table 2 outlines the energy inputs per 1000 pieces for the respective product production. Meat production uses 1086825.54 MJ per 1000 pieces, while egg production uses 1197794.25 MJ per 1000 pieces. In contrast, meat production yields 536182.33 MJ per 1000 pieces, while egg production yields 768610.90 MJ per 1000 pieces. Despite egg production requiring more energy than meat production, it also yields more energy for consumers. The energy consumption of each input for every 1000 pieces was calculated by multiplying it by its energy coefficient. When considering protein supply per total energy consumption, egg production is justified compared to meat.

The breakdown of inputs for meat and egg production is shown in Figure 3. Natural gas consumption accounts for over 33.40% in meat production and 34.03% in egg production, making it the most significant contributor. Diesel fuel follows as the second most significant energy consumer. These findings emphasize the importance of fuel and energy supply in ostrich breeding environments, especially for egg production. However, feed (22.57%) and electricity (5.23%) consumption for egg production are lower than that for meat production. As a result, feed supply does not play a crucial role and does not significantly impact producers’ decisions.

The energy contribution of specific feeds, as shown in Table 2, indicates that providing rice bran, sugarbeet pulp, vitamins and minerals, and fatty acids for meat production significantly contributes to total energy consumption. These ingredients are reported to be less in quantity for egg production compared to meat. The

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variation in ingredient amounts between eggs and meat production can be attributed to the differing nutritional and energy requirements of egg-laying ostriches versus meat-producing ostriches. Egg-laying ostriches may require specific fatty acids, vitamins, and minerals for egg production, distinct from the nutritional needs of meat ostriches for overall growth and development. Therefore, the energy contribution of each specific feed may vary depending on the animal's intended purpose and its specific nutritional requirements.

Table 3 displays energy indicators comparing input and output balance for eggs and meat. While eggs have an energy use efficiency of 0.64, higher than meat's 0.49, neither product reaches an efficiency exceeding 1, indicating that energy output falls short of consumption. Both eggs and meat have efficiencies below 1, suggesting output is less than input, meaning production of these foods requires more energy than they ultimately contain. Despite this, eggs are more energy-efficient than meat. Energy productivity of both is low relative to consumption, as shown by energy intensity per kilogram, with meat consuming 21.06 MJ kg^{-1} and eggs 11.40 MJ. This indicates meat production is less energy-productive than egg production. Such insights can guide resource allocation and production processes to boost overall energy efficiency, given the negative net energy output.

LCA results

Table 4 displays energy indicators comparing input and output balance for eggs and meat. While eggs have an energy use efficiency of 0.64, higher than meat's 0.49, neither product reaches an efficiency exceeding 1, indicating that energy output falls short of consumption. Both eggs and meat have efficiencies below 1, suggesting output is less than input, meaning production of these foods requires more energy than they ultimately contain. Despite this, eggs are more energy-efficient than meat. Energy productivity of both is low relative to consumption, as shown by energy intensity per kilogram, with meat consuming 21.06 MJ kg^{-1} and eggs 11.40 MJ. This indicates meat production is less energy-productive than egg production. Such insights can guide resource allocation and production processes to boost overall energy efficiency, given the negative net energy output. Likewise, the amount of emissions produced from energy utilization at ostrich breeding facilities can differ based on the types of energy sources utilized, such as electricity, natural gas, or diesel, along with how effectively energy is used and incorporated renewable energy sources. The emissions associated with moving materials to and from ostrich breeding sites may be affected by variables like distance traveled, mode of transport, and the fuel efficiency of vehicles. Several aspects, including feed manufacturing, waste management, energy consumption, transportation, and water usage, have the potential to influence emissions from ostrich breeding facilities operating under different production schemes. Therefore, ostrich farmers should consider these factors and implement strategies that lower emissions and promote environmental sustainability, as highlighted by Bhavani *et al.* (2023) and Guinée *et al.* (2010).

The results from the endpoints of the ReCiPe2016 approach

Table 2. Amounts of inputs-outputs energy in ostrich breeding units under different production.

	Ostrich (meet)		Ostrich (egg)	
	Unit per ha	Energy use (MJ 1000 pieces $^{-1}$)	Unit per ha	Energy use (MJ 1000 pieces $^{-1}$)
Items				
Human labor	213.42	418.31	302.76	593.41
Machinery	772.21	48417.83	1096.94	68778.60
Diesel fuel	5616.21	316249.02	6352.34	357700.38
Natural gas	7332.66	362967.00	8233.55	407560.85
Electricity	5034.19	60410.28	5222.18	62666.21
Feed				
Corn	3496.00	27618.46	3590.76	28367.02
Barley	2331.98	34280.13	2458.42	36138.78
Alfalfa	1603.17	25330.15	2070.18	32708.91
Rice bran	7644.41	111379.09	6335.26	92304.78
Wheat	1640.92	22480.71	1651.94	22631.67
Soybean meal	1372.00	17287.23	1425.47	17960.96
Sugar beet pulp	1254.64	21077.98	1250.05	21000.88
Vitamins and minerals	1453.60	2311.22	1160.84	1845.73
Salt	356.12	566.24	402.60	640.14
Fatty acid	544.78	20157.07	453.73	16788.26
Ostrich chick	1536.76	15874.75	2914.57	30107.60
Total energy use (MJ)	-	1086825.54	-	1197794.25
Output (kg)				
Ostrich meat	51905.35	536182.33		
Ostrich egg			105578.42	768610.90

Table 3. Energy indices in ostrich farming facilities vary depending on the type of production.

Items	Ostrich (meet)	Ostrich (egg)
Energy use efficiency (ratio)	0.49	0.64
Energy productivity (kg MJ^{-1})	0.04	0.08
Specific energy (MJ kg^{-1})	21.06	11.40
Net energy gain (MJ 1000 $pieces^{-1}$)	-550643.20	-429183.35

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are available in Table 5. Positive figures indicate a detrimental effect on the environment, while negative figures suggest a positive impact. Specifically, the positive values linked to all critical 4aspects associated with meat and egg production underscore the harmful ecological repercussions of these goods. When comparing the effect on human health from egg and meat production, with a slight 0.23 DALY variance, it implies that egg production may have a slightly more adverse effect on human health than meat production. The ecological impacts of meat production on the ecosystem (0.003 species.yr) and resources (9215.47 USD2013) are deemed more favorable, indicating that meat production has a relatively lower impact on both ecosystem and resource use compared to egg production, according to the ReCiPe2016 method (Figure 4). It's crucial to note that these conclusions are based on

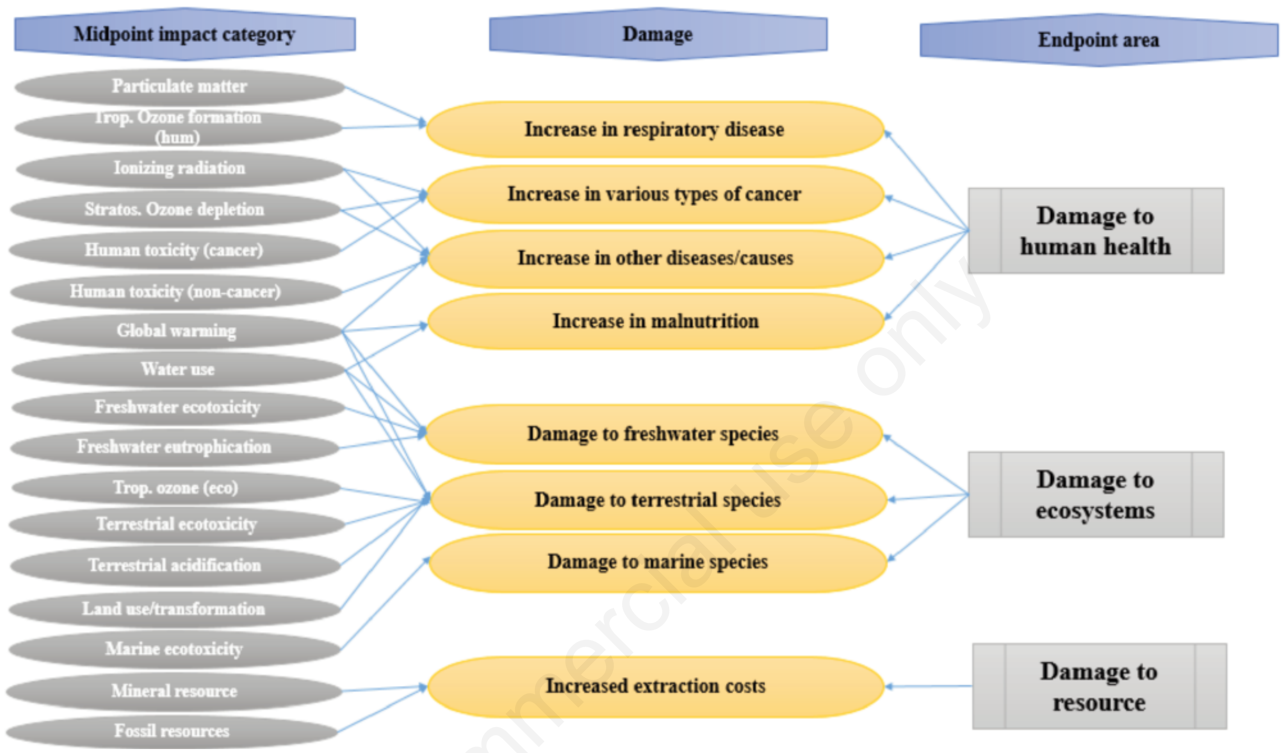

Figure 4. ReCiPe2016 method addresses various mid-points.

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Table 4. Direct emissions in ostrich breeding units under different production based on 1 ton.

Ostrich (meet)	Ostrich (egg)	
Emissions by diesel fuel to air (kg)		
CO_2	23560.55	26648.67
SO_2	7.62	8.62
CH_4	0.97	1.10
Benzene	0.05	0.06
Cd	7.55E-05	8.54E-05
Cr	0.0003	0.0004
Cu	0.01	0.01
N_2O	0.90	1.02
Ni	0.0005	0.0005
Zn	0.007	0.008
Benzo (a) pyrene	0.0002	0.0002
NH_3	0.15	0.17
Se	7.55E-05	8.54E-05
PAH (polycyclic hydrocarbons)	0.02	0.02
Hydrocarbons (HC, as NMVOC)	21.50	24.32
NOx	335.22	379.16
CO	47.43	53.65
Particulates (b2.5 µm)	33.83	38.27
Emission by human labor to air (kg)		
CO_2	149.39	211.93

specific criteria and the ReCiPe2016 methodology, which may not encompass the complete range of environmental impacts. Factors like animal welfare, land use, and greenhouse gas emissions should also be taken into account when assessing the overall sustainability of meat and egg production (Guinée *et al.,* 2010). Furthermore, the interpretation of these results should consider a broader sustainability context, including social and economic aspects. Additional research and analysis may be required to comprehensively grasp the environmental impacts of meat and egg production (Alves *et al*., 2023).

The evaluation of environmental emissions from different sources at three key stages, as illustrated in Figure 5, has revealed significant effects arising from the use of machinery and diesel fuel in ostrich breeding environments. The study specifically indicates that the use of machinery is responsible for a 60% impact on both ecosystem health and human well-being, highlighting the necessity of implementing measures to control and diminish the environmental effects of machinery in ostrich breeding operations. Additionally, the research underscores that the consumption of diesel fuel leads to a 30% impact on resource utilization, emphasizing the notable consequences of using diesel fuel on resource consumption and sustainability within this context. These findings emphasize the importance of evaluating and dealing with the environmental consequences of inputs such as machinery and fuel in ostrich breeding, suggesting that targeted efforts to reduce these impacts could be vital for improving the overall environmental sustainability of ostrich farming practices.

Results of modeling techniques

Using ANN to predict energy output and environmental emis-

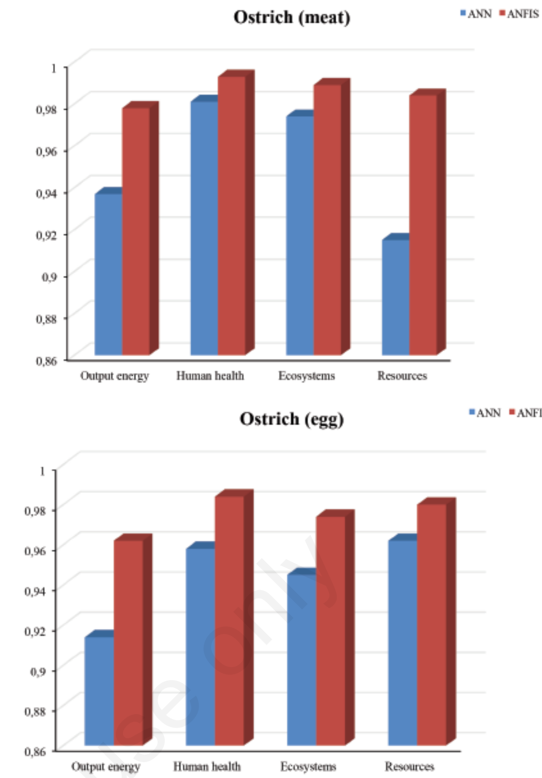

Figure 5. The impact of various input factors on the damages incurred in ostrich breeding units across different production methods.

Table 5. Assessment values for damage per ton in ostrich breeding units vary across different production methods.

Items	Unit	Ostrich (meet)	Ostrich (egg)
Human health	DALY	2.15	2.38
Ecosystems	species.yr	0.003	0.004
Resources	USD2013	9215.47	10227.76

DALY, disability adjusted life years - a damage of 1 is equal to: loss of 1 life year of 1 individual, or 1 person suffers 4 years from a disability with a weight of 0.25; species.yr: the unit for ecosystems is the local species loss integrated over time.

Table 6. The results of different arrangement of models in ostrich breeding units under different production.

Type of crops (best topology)	Items of ANN model	Statistics indices	Independent variables			
			Output energy	Human health	Ecosystems	Resources
Ostrich (meet) (7-4-6-4)	Overall	R2	0.937	0.981	0.974	0.915
		RMSE	0.214	0.102	0.109	0.147
		MAPE (%)	0.049	0.062	0.008	0.319
	Train	R2	0.935	0.984	0.912	0.956
		RMSE	0.419	0.325	0.348	0.259
		MAPE (%)	0.082	0.098	0.116	0.113
	Test	R2	0.884	0.946	0.889	0.916
		RMSE	0.364	0.084	0.036	0.168
		MAPE (%)	0.009	0.364	0.321	0.458
Ostrich (egg) (7-6-5-4)	Overall	R2	0.914	0.958	0.945	0.962
		RMSE	0.236	0.315	0.381	0.256
		MAPE (%)	0.056	0.136	0.096	0.039
	Train	R2	0.945	0.916	0.889	0.906
		RMSE	0.212	0.430	0.162	0.542
		MAPE (%)	0.036	0.056	0.047	0.126
	Test	R2	0.887	0.923	0.965	0.886
		RMSE	0.236	0.136	0.148	0.198
		MAPE (%)	0.036	0.087	0.149	0.176

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sions in meat and egg production offers valuable insights for enhancing sustainability in agriculture. By identifying the most effective networks and understanding their strengths and weaknesses, targeted strategies can be developed to minimize environmental impact and enhance energy efficiency in meat and egg production. The findings from the artificial neural network analysis (Table 6) indicate that the well-trained network for meat production under experimental conditions exhibits a high determination coefficient, highlighting its accuracy in estimating energy output and environmental emissions. This implies that implementing measures to reduce machinery, diesel fuel, and energy consumption can enhance performance in meat production. Specific neurons dedicated to eggs and meat are discernible. The best-trained network in the experimental mode for four aspects of meat production shows a determination coefficient exceeding 0.915. The determination coefficient for estimating energy output in meat production in the test mode is 0.884. The determination coefficients for energy output (0.914), human health (0.958), ecosystem (0.945), and resources (0.962) for eggs collectively indicate that only the resource factor presents more favorable results than meat. Furthermore, the analysis demonstrates that the determination coefficient for the factors influencing eggs in the overall context is particularly favorable for the resource factor, indicating the potential for greater resource efficiency in egg production compared to meat production. Therefore, prioritizing resource efficiency measures in egg production could result in positive environmental and energy outcomes.

Based on the information presented in Tables 7 and 8, it is clear that utilizing a combination of Gbell functions and linear membership for input and output values in ANFIS 4 yielded superior outcomes when compared to other combinations. The coefficient of determination for all four factors in ANFIS 4 demonstrated a more

Table 7. The characteristics of the best structure of first ANFIS architecture for prediction of output energy and damage assessment of ostrich (meat) production by applying three-level ANFIS.

Types of crops	ANFIS model	Type of MF		Number of MF		Learning method	R^2	RMSE	MAPE (%)
		Input	Output	Input	Epoch				
Output energy	ANFIS (1)	Gbell	Linear	5,6	32	Hybrid	0.380	0.689	0.118
	ANFIS (2)	Gbell	Linear	5,6	32	Hybrid	0.587	0.348	0.147
	ANFIS (3)	Gbell	Linear	5,6	32	Hybrid	0.880	0.365	0.103
	ANFIS (4)	Gbell	Linear	5,6	32	Hybrid	0.978	0.256	0.087
Human health	ANFIS (1)	Gbell	Linear	5,6	32	Hybrid	0.458	0.546	0.098
	ANFIS (2)	Gbell	Linear	5,6	32	Hybrid	0.884	0.245	0.036
	ANFIS (3)	Gbell	Linear	5,6	32	Hybrid	0.948	0.265	0.084
	ANFIS (4)	Gbell	Linear	5,6	32	Hybrid	0.993	0.231	0.039
Ecosystems	ANFIS (1)	Gbell	Linear	5,6	32	Hybrid	0.452	0.641	0.039
	ANFIS (2)	Gbell	Linear	5,6	32	Hybrid	0.548	0.425	0.115
	ANFIS (3)	Gbell	Linear	5,6	32	Hybrid	0.890	0.325	0.096
	ANFIS (4)	Gbell	Linear	5,6	32	Hybrid	0.989	0.115	0.034
Resources	ANFIS (1)	Gbell	Linear	5,6	32	Hybrid	0.569	0.253	0.114
	ANFIS (2)	Gbell	Linear	5,6	32	Hybrid	0.745	0.326	0.089
	ANFIS (3)	Gbell	Linear	5,6	32	Hybrid	0.912	0.116	0.035
	ANFIS (4)	Gbell	Linear	5,6	32	Hybrid	0.984	0.110	0.108

Table 8. The characteristics of the best structure of first ANFIS architecture for prediction of output energy and damage assessment of ostrich (egg) production by applying three-level ANFIS.

Types of crops	ANFIS model	Type of MF		Number of MF		Learning method	R^2	RMSE	MAPE (%)
		Input	Output	Input	Epoch				
Output energy	ANFIS (1)	Gbell	Linear	5.6	32	Hybrid	0.412	0.426	0.118
	ANFIS (2)	Gbell	Linear	5.6	32	Hybrid	0.563	0.498	0.147
	ANFIS (3)	Gbell	Linear	5.6	32	Hybrid	0.840	0.426	0.103
	ANFIS (4)	Gbell	Linear	5.6	32	Hybrid	0.962	0.236	0.087
Human health	ANFIS (1)	Gbell	Linear	5.6	32	Hybrid	0.458	0.412	0.098
	ANFIS (2)	Gbell	Linear	5.6	32	Hybrid	0.562	0.362	0.036
	ANFIS (3)	Gbell	Linear	5.6	32	Hybrid	0.694	0.212	0.084
	ANFIS (4)	Gbell	Linear	5.6	32	Hybrid	0.984	0.131	0.039
Ecosystems	ANFIS (1)	Gbell	Linear	5.6	32	Hybrid	0.440	0.356	0.039
	ANFIS (2)	Gbell	Linear	5.6	32	Hybrid	0.660	0.216	0.115
	ANFIS (3)	Gbell	Linear	5.6	32	Hybrid	0.846	0.112	0.096
	ANFIS (4)	Gbell	Linear	5.6	32	Hybrid	0.974	0.078	0.034
Resources	ANFIS (1)	Gbell	Linear	5.6	32	Hybrid	0.550	0.256	0.114
	ANFIS (2)	Gbell	Linear	5.6	32	Hybrid	0.631	0.116	0.089
	ANFIS (3)	Gbell	Linear	5.6	32	Hybrid	0.900	0.102	0.035
	ANFIS (4)	Gbell	Linear	5.6	32	Hybrid	0.980	0.990	0.108

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optimal value, particularly showing values closer to one for meat factors than for eggs. Furthermore, the mean squared error value was below 1, signifying a high level of accuracy in the output results. A coefficient of determination approaching 1 indicates that the ANFIS model effectively captures the data and makes precise predictions. Through optimizing the coefficient of determination, the ANFIS model can offer the best possible fit to the data, resulting in improved performance. The average root percentage of the mean squared error further supported the accuracy of the results. Considering the importance of predicting environmental greenhouse gas emissions to address temperature rise, global warming, and potential health consequences, this ANFIS model holds value for managers and planners in their decision-making and strategic processes. Figure 6 illustrates a comparison of two prominent models within meat and egg production, indicating that ANFIS outperforms due to its utilization of evolutionary algorithms and natural selections in both production processes. These algorithms, inspired by biological principles, operate simultaneously and in parallel fashion. In addition, ANFIS uses historical information and past experiences to achieve better results. In contrast, the artificial neural network usually learns from limited input data and may sometimes get trapped and lead to unstable results (Abdollahizad *et al*., 2021). In presenting the results, the discussion could deepen the implications of these results for industry practices and policy recommendations about energy results.

The comparison of energy analysis results between egg and ostrich meat production provides insights into energy consumption and production. The energy inputs per 1000 pieces for the respective product production. Meat production uses 1086825.54 MJ per 1000 pieces, while egg production uses 1197794.25 MJ per 1000 pieces. In contrast, meat production yields 536182.33 MJ per 1000 pieces, while egg production yields 768610.90 MJ per 1000 pieces. Despite egg production requiring more energy than meat production, it also yields more energy for consumers. The energy consumption of each input for every 1000 pieces was calculated by multiplying it by its energy coefficient.

When considering protein supply per total energy consumption, egg production is justified compared to meat. The breakdown of inputs for meat and egg production shows that natural gas consumption accounts for over 33.40% in meat production and 34.03% in egg production, making it the most significant contributor. Diesel fuel follows as the second most significant energy consumer. These findings emphasize the importance of fuel and energy supply in ostrich breeding environments, especially for egg production. However, feed (22.57%) and electricity (5.23%) consumption for egg production are lower than that for meat production. As a result, feed supply does not play a crucial role and does not significantly impact producers' decisions.

The energy contribution of specific feeds indicates that providing certain ingredients like rice bran, sugar beet pulp, vitamins and minerals, and fatty acids for meat production significantly contributes to total energy consumption. These ingredients are reported to be less in quantity for egg production compared to meat. The variation in ingredient amounts between eggs and meat production can be attributed to the differing nutritional and energy requirements of egg-laying ostriches versus meat-producing ostriches.

The information provided discusses the use of ANN and ANFIS to predict energy output and environmental emissions in meat and egg production. The results indicate that ANFIS models, particularly ANFIS 4, show superior outcomes compared to other models in predicting factors related to meat production. ANFIS 4 demonstrated higher coefficient of determination values and lower mean squared error values, suggesting greater accuracy in output results, especially for meat factors. The ANFIS model is highlighted for its use of evolutionary algorithms and natural selection, which lead to more accurate predictions and better performance compared to traditional ANN models that may have limitations in handling complex data.The discussion emphasizes the significance of these modeling techniques for enhancing sustainability in agriculture by minimizing environmental impact and improving energy efficiency in meat and egg production. By identifying effective networks and optimizing coefficient of determination values, targeted strategies can be developed to enhance resource efficiency and reduce environmental footprint in agricultural practices. The findings suggest that prioritizing resource efficiency measures in egg production could lead to positive environmental and energy outcomes. Additionally, the ANFIS model holds value for managers and planners in decision-making processes regarding environmental greenhouse gas emissions and addressing broader issues like global warming and health consequences.

There are several strategies that can be implemented to improve energy efficiency and reduce environmental impact. Some potential detailed strategies include:

Energy audits. Conducting regular energy audits to identify areas where energy is being wasted and implementing measures to reduce energy consumption. This may include upgrading to energy-efficient appliances and equipment, optimizing heating and cooling systems, and improving insulation.

Renewable energy sources. Investing in renewable energy sources such as solar, wind, or geothermal power to reduce reliance on fossil fuels and decrease carbon emissions. Installing solar panels, wind turbines, or geothermal heating and cooling systems can help lower energy costs and lessen environmental impact.

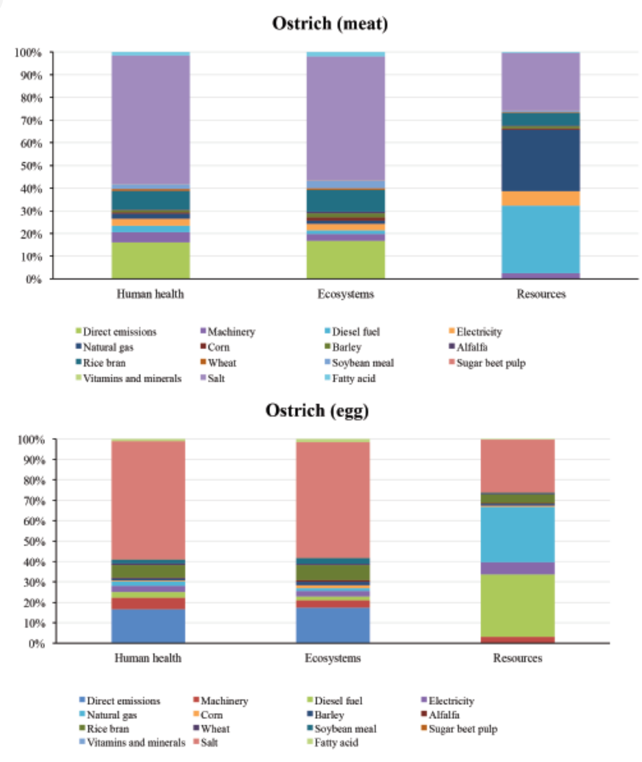

Figure 6. Comparison of two prominent models within meat and egg production.

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Energy-efficient lighting. Switching to energy-efficient lighting options such as LED bulbs can significantly reduce electricity usage. LED bulbs consume less energy and have a longer lifespan compared to traditional incandescent or fluorescent bulbs.

Smart technology. Implementing smart technology solutions like programmable thermostats, smart lighting systems, and energy monitoring devices can help optimize energy use and identify opportunities for energy savings. These technologies allow for better control and management of energy consumption in homes and buildings.

Energy-efficient building design. Incorporating energy-efficient design principles in new construction or renovations can improve energy performance and reduce environmental impact. This may include using sustainable building materials, optimizing natural lighting and ventilation, and incorporating energy-efficient appliances and systems.

Behavior change initiatives. Educating and incentivizing individuals to adopt energy-saving behaviors such as turning off lights when not in use, unplugging electronics, and using energy-efficient appliances can make a significant impact on reducing energy consumption and lowering environmental impact.

Transportation alternatives. Encouraging the use of public transportation, carpooling, cycling, or electric vehicles can help reduce greenhouse gas emissions associated with transportation. Providing infrastructure and incentives for sustainable transportation options can contribute to lowering overall energy consumption and environmental impact.

Waste reduction and recycling. Implementing waste reduction strategies, recycling programs, and composting initiatives can help minimize energy used in the manufacturing and disposal of products. By reducing waste and recycling materials, less energy is required for producing new products, leading to a lower environmental footprint.

By combining these detailed strategies and customized solutions tailored to specific contexts and needs, significant improvements in energy efficiency and reductions in environmental impact can be achieved.

Conclusions

Meat and eggs are the main contributors to natural gas consumption, accounting for approximately 33.40% and 34.03%, respectively. In ostrich breeding environments, diesel fuel consumption follows closely behind in terms of energy usage. Efficient fuel and energy management are crucial in these settings, particularly for optimizing egg production. Decision-makers in the ostrich industry can leverage these findings to streamline energy usage, reducing production costs for meat and eggs. While egg production may have a slightly higher negative impact on human health compared to meat production, the latter demonstrates more favorable outcomes in terms of its effects on ecosystems and resource consumption. According to the ReCiPe2016 method, meat production has an eco-friendlier footprint than egg production. These findings serve as a guide for policymakers and environmental planners to promote both human health and environmental sustainability. The utilization of ANN to predict energy output and environmental emissions in meat and egg production opens avenues for enhancing agricultural sustainability. Identifying effective neural networks and understanding their capabilities can facilitate the development of targeted strategies to minimize environmental impact and boost energy efficiency in meat and egg production. The high coefficient of determination associated with the ANFIS model underscores its accuracy in predicting data, offering valuable insights for managing greenhouse gas emissions and addressing climate change challenges. This model stands as a practical tool for decision-makers and planners striving to reduce environmental impact and protect human health.

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