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Article

Biomechanical perspectives on sustainable animal husbandry: Dynamic mechanisms of economic growth and ecological balance

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Abstract: This study explores the intersection of biomechanics and sustainable animal husbandry, with a focus on optimizing animal health and productivity to promote ecological breeding practices. By integrating biomechanical principles with ecological breeding strategies, we aim to enhance both farm efficiency and environmental sustainability. Through an in-depth analysis of the mechanical forces involved in animal movement, posture, and interactions with their environment, we seek to design systems that improve animal welfare and reduce stress, which in turn enhances productivity. We emphasize the role of biomechanics in creating more efficient feeding systems, ergonomic housing, and transportation methods, all of which contribute to reducing injuries and improving overall livestock management. Moreover, we propose that biomechanical models can be applied to farm operations to optimize both animal health and ecological balance. This interdisciplinary approach not only improves animal welfare but also promotes sustainable farming practices that align with environmental conservation goals. By integrating animal biomechanics with ecological breeding techniques, this research highlights the potential for more efficient, sustainable breeding practices that support both economic growth and ecological preservation, thus advancing the long-term goals of sustainable development in animal husbandry.

Keywords: biomechanics; animal husbandry; sustainable agriculture; ecological sustainability; ergonomic design; productivity optimization

1. Introduction

Biomechanics, the study of the mechanical aspects of living organisms, has long been a vital field in understanding the physical forces and motions that influence both human and animal performance. Its application in animal husbandry and sustainable agriculture has become increasingly important in the quest to optimize farm productivity, enhance animal welfare, and promote ecological sustainability [1–3]. As the global population continues to rise, the demand for more efficient, environmentally conscious farming practices has never been greater. In this context, biomechanics offers critical insights that can drive innovations in livestock management, animal care, and the design of farming systems.

The term “biomechanics” encompasses a range of interdisciplinary topics, from the mechanics of muscle movement to the forces exerted on bones and joints under varying conditions. In the agricultural realm, biomechanical principles are applied to understand how animals interact with their environment, whether in terms of locomotion, load-bearing, or ergonomic considerations [4,5]. This understanding is essential for designing farming systems and environments that maximize the health, comfort, and productivity of livestock while minimizing environmental impact.

One of the most significant applications of biomechanics in animal husbandry is the design and improvement of housing systems for livestock. The mechanical forces acting on animals, particularly in confined spaces, can affect their mobility, comfort, and overall well-being. For instance, poorly designed stalls or pens can lead to stress, injuries, or discomfort, which ultimately reduce the productivity and health of the animals [6,7]. Through biomechanical analysis, it is possible to design structures that allow animals to move freely, reducing stress and injury while promoting better overall health. This design consideration also extends to the flooring, which needs to be optimized for traction, comfort, and ease of movement, thereby reducing the risk of slips, falls, and joint stress.

In addition to housing, biomechanics is instrumental in understanding and improving animal movement and behavior. Studies of animal gait, for example, help identify potential issues related to lameness or musculoskeletal disorders, which are common in commercial farming operations. By applying biomechanical principles to the study of these issues, it becomes possible to identify early signs of injury or discomfort, enabling timely intervention and prevention. For example, biomechanical analysis of cows' movements can aid in detecting early-stage lameness, which, if left untreated, can lead to significant reductions in milk production and overall health [8].

Furthermore, biomechanics contributes to the optimization of livestock handling practices. Traditional animal handling techniques, particularly in large-scale farming operations, often involve considerable physical strain on both the animals and the handlers. The application of biomechanical principles to animal handling systems can reduce unnecessary stress and injury to the animals, improving their welfare while also reducing the risk of injury to farm workers [9]. For example, the design of efficient and ergonomic tools for handling livestock—such as gates, chutes, and restraint devices—can minimize the physical effort required by the workers while ensuring the safety and comfort of the animals.

Biomechanics is also central to the design of equipment used in agricultural practices. For example, the study of forces involved in the use of milking machines, feed dispensers, and other farming tools helps optimize these systems for both human and animal health. In the case of milking, for instance, biomechanical analysis can inform the design of milking machines that reduce stress on cows' udders, leading to better milk yields and improved animal welfare [10].

On a broader scale, biomechanical principles can be applied to enhance environmental sustainability in agriculture. By designing farming systems and equipment that reduce energy consumption, labor input, and environmental impact, biomechanics can play a significant role in creating more sustainable farming practices. For instance, optimizing the efficiency of animal transport systems can minimize fuel use and carbon emissions, while improvements in livestock housing can reduce the need for excessive heating or cooling, further reducing energy consumption.

In conclusion, the application of biomechanics to animal husbandry is a powerful tool for improving the welfare of livestock, enhancing productivity, and promoting sustainability. As farming practices continue to evolve in response to global challenges, biomechanics will remain a critical field for driving innovations that balance efficiency with ecological and animal welfare considerations. Whether through improving animal housing, optimizing movement and behavior, or designing more sustainable farming systems, the contributions of biomechanics to modern agriculture are profound and far-reaching.

2. Analysis based on empirical data

Animal goods have a universal and distinct supply and demand under full market competition (**Figure 1**). The quality and consumption of animal products are highly valued by the State since they are a significant by-product of contemporary agriculture and a major source of income for a sizable portion of the populace. Measures like interim storage and placement are necessary for strategic animal products like pork in order to keep supply and demand balanced in the event of a market failure [11,12]. The propagation of early warning signals and the investigation and analysis of patterns in livestock development are also subject to increased demands as a result of these efforts.

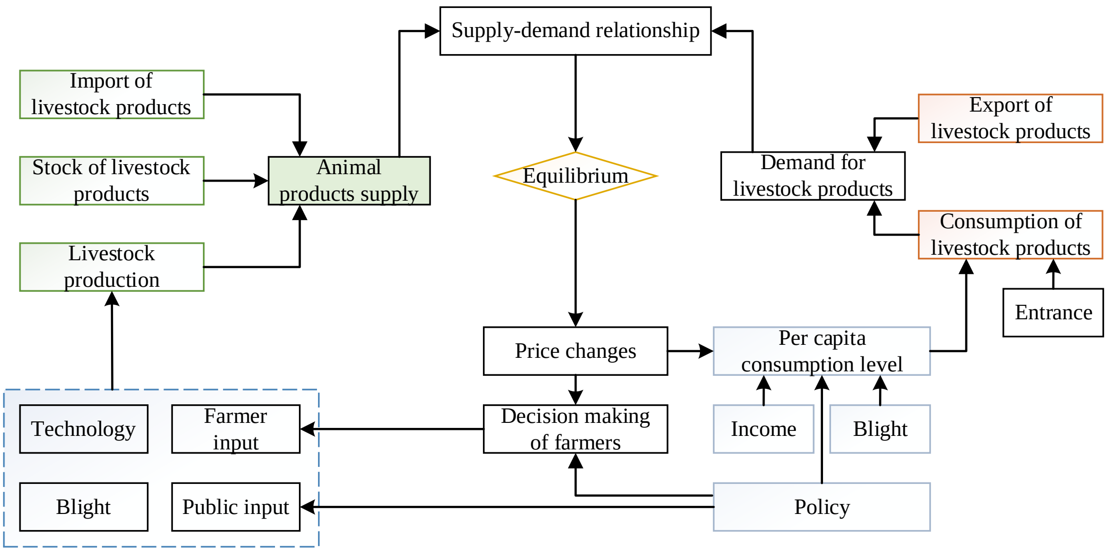

Figure 1. Supply and demand dynamics for livestock products.

The degree of cattle sector concentration is currently measured using a number of techniques, including as the Gini coefficient, location entropy, industry concentration index, Herfindahl index, and others. The Herfindahl index typically depends on enterprise-specific data, the industrial concentration index has trouble accurately reflecting regional and geographical concentration, and the location entropy compensates for the drawbacks of the aforementioned techniques [13]. Furthermore, the impact of firm size is not taken into account by the Gini coefficient or the industrial concentration index. As a result, location entropy is a superior option.

$$QP = \frac{Q_i/G_i}{E_i/J_i} \tag{1}$$

The location entropy index measures the concentration of animal husbandry within different regions, calculated using the following formula:

$$E = -\sum_{i=1}^{n} \quad p_i \times ln(p_i) \tag{2}$$

where: p_i is the proportion of the animal husbandry industry in the $ln(p_i)$ region relative to the total across all regions. n is the total number of regions being studied.

This formula quantifies the concentration of industry in different regions. Higher values of EEE indicate a more concentrated industry, while values closer to 0 suggest a more evenly distributed industry. Location entropy is a key metric to measure regional dominance and industry concentration, particularly useful for understanding imbalances in animal husbandry across provinces.

The Cobb-Douglas production function is used in the analysis of how factors of production contribute to economic output, such as the relationship between cattle concentration and economic growth: This formula describes the relationship between inputs (labor and capital) and output, assuming constant returns to scale [14]. In the context of livestock production, the function can be used to model how different levels of resource allocation (such as labor or capital) influence economic growth, especially in relation to cattle concentration.

$$Y = A \times L^{\alpha} \times K^{\beta} \tag{3}$$

where:

- Y is the total output (economic growth or animal product output);
- A is the total factor productivity (TFP);
- L is the labor input;
- K is the capital input;
- α and β are the output elasticities of labor and capital, respectively.

The basic panel regression model used to estimate the relationship between livestock concentration and economic factors can be expressed as:

$$Y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \epsilon_{it} \tag{4}$$

where:

- Y_{it} is the dependent variable (e.g., economic output, livestock concentration);
- X_{it} represents the independent variables (e.g., concentration of livestock, labor input);
- Z_{it} represents control variables;
- α is the intercept;
- β and γ are the coefficients;
- ϵ is the error term;
- i denotes the individual unit (region, province);
- t denotes the time period.

This formula represents a basic panel data model that accounts for both individual differences (across regions) and temporal effects (over time). It is useful in understanding how various factors affect livestock concentration and economic output over time, especially with data collected from multiple regions or provinces [15].

The Variance Inflation Factor (VIF) is used to detect multicollinearity in regression models:

$$VIF = \frac{1}{1 - R^2} \quad (5)$$

where:

- R^2 is the coefficient of determination for the regression of each independent variable on all other independent variables in the model.

VIF quantifies how much the variance of a regression coefficient is inflated due to multicollinearity with other predictors. A high VIF indicates a high degree of multicollinearity, meaning that the independent variables are highly correlated, which can distort regression results. It is important to identify and address multicollinearity to ensure reliable estimation of coefficients [16].

Table 1 shows the specific changes in the animal husbandry industry's concentration level in 11 provinces (autonomous areas) of the southern common forest region between 2000 and 2020.

Table 1. The animal husbandry industry's location entropy index.

Particular year	Zhejiang	Fujian	Guangxi	Anhui	Hunan	Hubei	Jiangxi	Guizhou	Sichuan	Yunnan	Jiangsu
2000	1.35	2.54	2.05	1.03	1.58	1.28	1.58	0.47	0.99	1.99	0.36
2005	2.04	2.08	2.78	1.58	1.47	0.56	1.58	0.55	0.87	1.74	0.36
2010	2.26	2.14	2.36	1.09	1.66	0.84	1.82	0.75	0.89	1.89	0.36
2015	2.23	1.88	2.14	0.82	1.28	0.79	1.87	0.68	0.56	1.36	0.36
2020	2.26	1.87	1.91	0.82	1.98	0.84	1.98	0.84	0.74	1.26	0.68

Table 1 demonstrates that there is no discernible pattern in the location entropy indices of the 11 provinces (autonomous areas) in the southern public forest area, and not all of them are clustered in the 0.3–3.33 range. Overall, the nine provinces (autonomous regions) of Zhejiang, Fujian, Guangxi, Anhui, Hunan, Jiangxi, Guizhou, Sichuan, and Yunnan have location entropies that are clearly greater than 1, with Guangxi, Fujian, and Jiangxi having location entropies that are more than 2. This suggests that these three provinces hold a dominant position in the country's animal husbandry industry. Jiangsu has the lowest concentration of animal husbandry; both Jiangsu and Hubei have location entropies below 1, while Jiangsu's location entropy is even below 0.7. The Southern Public Forestry Region's 11 provinces (autonomous areas) have an overall tendency of rising volatility in the animal husbandry sector, but Yunnan Province exhibits a trend of falling volatility. The animal husbandry industry's concentration in Guangxi, Fujian, Anhui, Jiangxi, and Guizhou from 1990 to 2020 indicates a significant potential for growth. Overall, the level of animal husbandry concentration in the southern common forest regions varies clearly by time and location.

2.1. Building a regression model

In addition to examining the influence of other variables, this research investigates the nonlinear link between cattle concentration and economic growth [17]. Panel data were used for analysis and modeling based on the Cobb-Douglas production function, which is the basis for the secondary concentration factor introduced in the paper.

$$T_{it} = \sigma_0 + \sigma_1 LQ_{it} + \sigma_2 LW_{it}^2 + \sigma_3 + \phi_{it} + \gamma_{it} \tag{6}$$

2.2. Analysis of regression and endogenous therapy

Excessive linear correlation may cause the regression findings to be distorted and the regression coefficients' economic significance to diverge from the theory. The correlation coefficient matrix method or the visual observation method can be used to address this. **Table 2** tests the degree of agglomeration because the model include the square term of livestock agglomeration.

Table 2. Test for multicollinearity.

Variables	VIF	1/VIF
LQ	1.25	0.568
LQ^2	1.52	0.656
C	2.25	0.436
S	1.03	0.958
1nL	2.66	0.378
1nF	1.74	0.565
1nK	1.82	0.564
Mean VIF	1.25	-

According to **Table 2**, using raw data directly in panel data regression analysis may result in a high correlation between the independent and dependent variables. However, this could be due to the phenomenon known as "pseudo-regression," which produces unreliable results [18]. To get more representative and reliable results, this study employed three different kinds of root tests: the LLLC test, the IPS test, and the ADF-Fisher test.

According to the test findings, the extreme value of 11,835, which has a negative test slope and a significance level of 5%, lies between the interval's upper and lower bounds. The model must be addressed because it is prone to endogenous issues. Endogenous treatment methods like dynamic panel regression, the instrumental variable method, and the twofold difference method can be applied for this [19]. This research uses the generalized moment estimation (GMM) technique to solve the endogeneity problem using a dynamic panel regression model since economic development has inertia and the present is frequently influenced by the past. The results are displayed in **Table 3**.

The AR (2) model did not exhibit dependency, as indicated in **Table 3**, where the test's *p*-value exceeded 0.05. This finding confirms that the null hypothesis of no second-order serial correlation cannot be rejected. Additionally, the Hansen test result was greater than 0.133, suggesting that the over-identification problem was not caused by the instrumental variables utilized in the model. These outcomes validate the robustness of the chosen instruments and the overall reliability of the model specification.

Table 3. Estimation of generalized moment.

A variable	GMM
L.1nY	0.1354
LQ	0.4568
LQ^2	−0.2684
C	5.8264
S	−0.0784
1nL	−0.0568
1nF	0.0198
1nK	0.1452
AR (2) Examining	0.368
Inspection by Hansen	0.125

Table 3 further highlights that while most variables were significant at the 5% level, the primary explanatory variables LQ and LQ^2 were highly significant at the 1% and 5% levels, respectively. This underscores the importance of these factors in explaining the variability of the dependent variable and reinforces their theoretical relevance in the context of the study.

Given the high T (time periods) and small N (cross-sectional units) structure of the dataset, the generalized method of moments (GMM) estimation may introduce bias due to the small sample size. To address this limitation, the study adopts the dynamic panel corrected least squares dummy variable method (LSDVC), which is particularly effective in mitigating these biases [20].

Root tests (such as the Augmented Dickey-Fuller test) are used to check for stationarity in panel data. The general formula for testing a unit root is:

$$\Delta Y_{it} = \rho Y_{it-1} + \epsilon_{it} \tag{7}$$

where:

- Y_{it} is the variable of interest;
- ΔY_{it} denotes the first difference operator;
- ρ is the parameter to be tested for unit roots;
- ϵ_{it} is the error term.

Description:

This formula represents the testing of whether a variable has a unit root, indicating it is non-stationary (i.e., its mean and variance change over time). In the context of panel data regression, checking for stationarity is essential before applying models like dynamic panel regression, as non-stationary data could lead to misleading results.

The GMM estimator used in panel data regression with endogeneity problems is given by:

$$\hat{\theta}_{GMM} = argminW\ [\hat{g}(\theta \times W\hat{g}(\theta)] \tag{8}$$

where:

- $\hat{\theta}$ is the vector of estimated coefficients,

- $\hat{g}$ is the vector of moment conditions (e.g., expectations of instruments being uncorrelated with the errors),
- W is the weight matrix (usually the inverse of the covariance matrix of moment conditions).

The GMM method is used to handle endogenous issues in panel data, where the explanatory variables are correlated with the error term. This approach uses instrumental variables to correct for endogeneity, leading to more reliable estimates. It is particularly useful when past economic states influence current outcomes, as in the case of economic inertia in livestock production.

The LSDVC approach leverages a three-step process to enhance estimation accuracy. First, biased estimates are derived using a fixed-effects model. Next, GMM is employed to obtain consistent estimates. Finally, bias is estimated, and parameter standard errors are calculated using a combination of the bootstrap approach and bias correction techniques. Monte Carlo simulation data demonstrate that LSDVC outperforms GMM in scenarios with a high T and small N structure, offering more reliable and precise parameter estimates.

Moreover, the application of LSDVC aligns well with the study's objective of achieving robust and unbiased results, ensuring that the conclusions drawn from the analysis are both statistically and practically valid. These methodological considerations significantly contribute to the credibility of the findings, highlighting the nuanced relationships between the explanatory variables and their impact on the dependent variable.

In summary, the combined use of AR (2), Hansen tests, and LSDVC underscores the rigor of this study's analytical framework, paving the way for accurate inferences and actionable insights into the research domain.

3. Analysis of a case

Ecological animal husbandry is founded on the ideas of animal ecology and ecological economics in order to fully advance the development of animal husbandry, increase productivity, and foster industrial cooperation. These ideas are applied in conjunction with systems engineering, contemporary technology, and ecological regulations.

3.1. Test of correlation

This study examines the spatial relationship between livestock development and sustainable economic growth using two variables and a geospatial weighting matrix. To ascertain the geographical correlation, the majority of the studies employed Moran's I and Geary's C. With the exception of the livestock development index (AGG) in 2018 and the sustainable economic development index (1NPGP) in 2016, the research' findings (refer to **Table 4** and **Figure 2**) demonstrated that the index of sustainable economic development (1NPGP) was still in use in 2020. In order to compare pertinent data and variables, a spatial econometric model must be built.

Table 4. From 2015 to 2021, the Moran and Gilley indices of economic sustainability and the advancement of animal husbandry.

Specific year	1nPGDP		Agg	
	Moran index	**Gilley index**	**Moran index**	**Gilley index**
2015	0.077(15.215)	0.914(−9.615)	0.023(5.466)	0.942(−4.176)
2016	0.061(12.967)	0.917(−8.907)	0.022(5.465)	0.941(−4.664)
2017	0.066(13.888)	0.919(−9.883)	0.034(6.923)	0.935(−5.342)
2018	0.063(12.575)	0.926(−6.493)	0.011(3.714)	0.973(−0.605)
2019	0.042(9.375)	0.947(−2.388)	0.046(9.275)	0.913(−5.856)
2020	0.083(16.286)	0.903(−11.866)	0.056(11.156)	0.914(−7.622)
2021	0.103(20.433)	0.879(−15.321)	0.084(16.675)	0.877(−10.143)

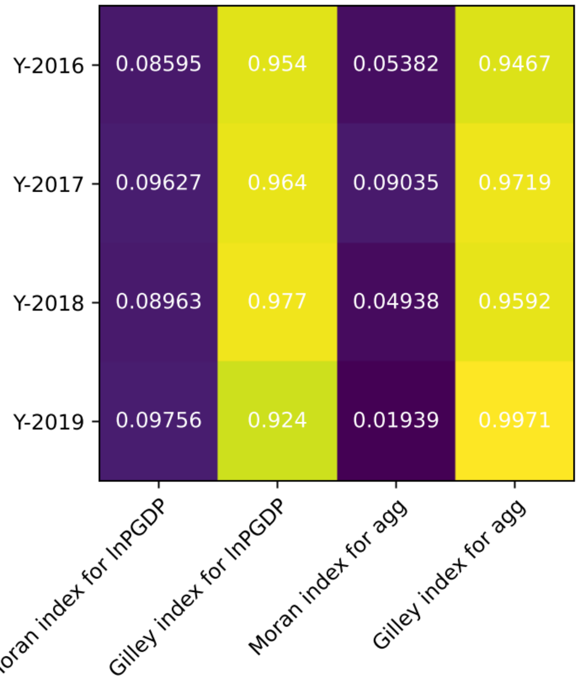

Figure 2. Correlation between the Gilley index and the Moran index.

3.2. Test of robustness

When considering the development of a spatial weight matrix to ensure the stability of regression results, there is no appreciable change. We looked at the relationship between ecological sustainability and the rate of livestock growth, and **Figure 3** illustrates how ecological sustainability significantly affects the growth of different livestock species.

This research proposes several coping mechanisms to promote ecological animal husbandry effectively. A primary recommendation is to prioritize shifting traditional perceptions of animal husbandry toward embracing the principles of ecological animal husbandry. To achieve this, it is crucial for the government to launch widespread awareness campaigns at the grassroots level. Utilizing accessible media such as radio, television, and digital platforms, these campaigns should clearly explain the importance, benefits, and necessity of adopting eco-animal husbandry practices. This approach aims to foster a positive perception and understanding among communities, emphasizing the alignment of ecological practices with long-term economic and environmental sustainability.

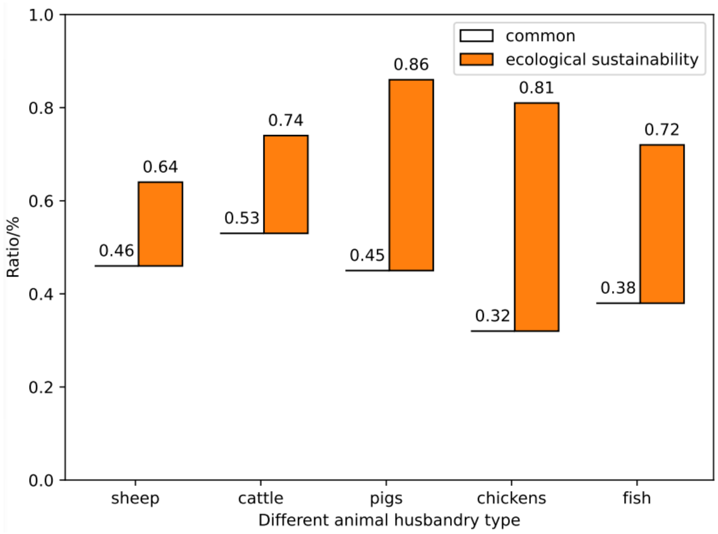

Figure 3. Growth rate change in animal husbandry as a result of ecological sustainability.

Special attention must be directed toward addressing the educational barriers faced by ranchers, who often have lower literacy levels, making it challenging for them to grasp complex concepts. Tailored educational programs, practical demonstrations, and interactive workshops should be implemented to convey these ideas effectively. Local agricultural extension services could also play a key role in providing hands-on training and ongoing support.

Figure 4 illustrates the progressive transformation in public attitudes toward ecological animal husbandry over time, highlighting the increasing acceptance and adoption of these sustainable practices. These shifts in perception reflect the growing recognition of ecological animal husbandry as a viable approach to achieving enhanced productivity while preserving environmental resources.

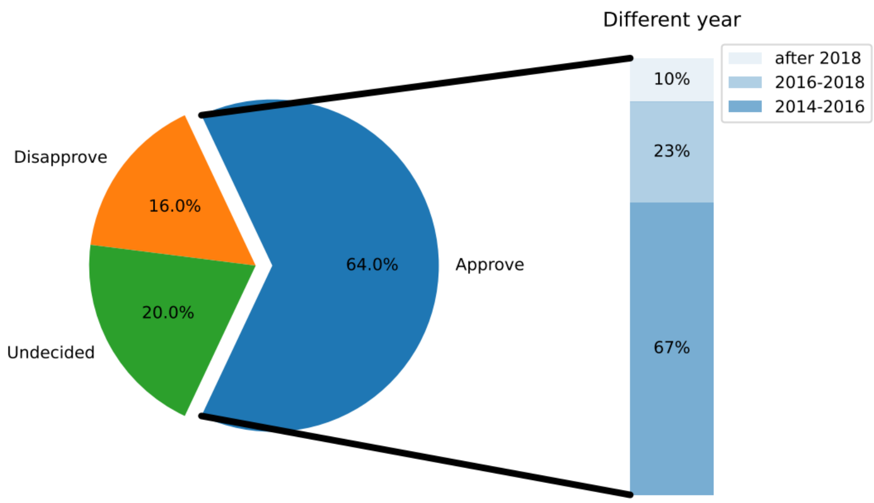

Figure 4. Encouragement of environmentally friendly animal husbandry.

Additionally, policy interventions such as financial incentives, subsidies for eco-friendly farming technologies, and recognition programs for exemplary practitioners can further encourage the adoption of sustainable practices. By integrating these mechanisms, a comprehensive framework can be established to transition from traditional to ecological animal husbandry, ensuring a harmonious balance between economic growth, animal welfare, and environmental stewardship.

As shown in **Figure 5**. In this study, we analyzed the behaviours of meerkats using a dataset that contained 105,604 video-labelled 2-second bouts, focusing on four key behaviours: vigilance, resting, foraging, and running. These behaviours were observed in different environmental contexts, and the signals generated by the meerkats during these activities were recorded for further analysis.

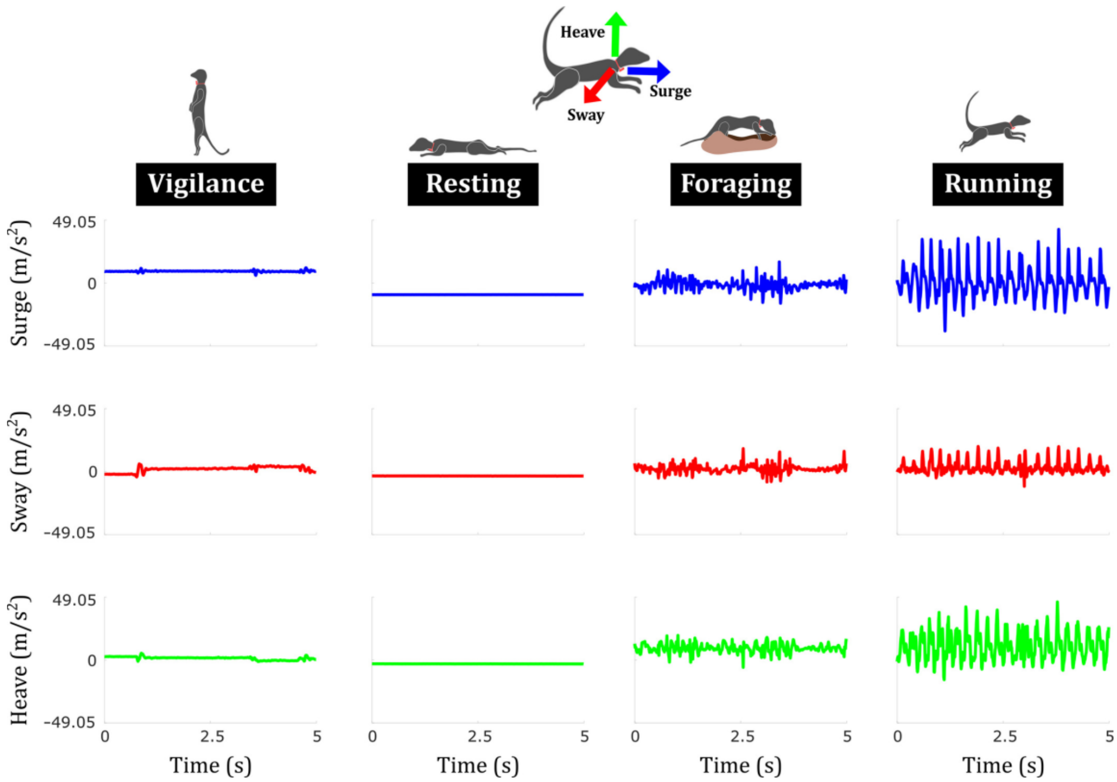

Figure 5. Animal performance data.

Vigilance is a behaviour during which the meerkat remains still, maintaining a focused attention on its surroundings. The signal during vigilance shows occasional short perturbations, corresponding to slight head movements as the animal scans its environment. This indicates that although the meerkat is not moving significantly, it is still actively monitoring its surroundings. The stability of the signal is a key feature of this behaviour, with small interruptions caused by the animal's head turns for visual scanning. The signal pattern during vigilance is more stable compared to other behaviours like foraging or running, as it is primarily driven by the meerkat's alert posture rather than active locomotion or digging.

Resting is another behaviour where the meerkat remains motionless. However, the signal during resting has a different intercept compared to the vigilance state, reflecting a different physiological state of the animal. Unlike vigilance, where the meerkat's alertness is maintained, resting signals suggest that the meerkat is in a relaxed state, without the need to constantly monitor its surroundings. The signal during resting is typically more stable and continuous, lacking the short, sharp perturbations seen in vigilance. This provides a clear distinction between the two states, where vigilance is marked by occasional activity, while resting is characterized by stillness and reduced physiological activity.

Foraging involves more dynamic movements, such as digging and manoeuvring, which cause erratic variations in the signal. The site-dependent nature of foraging means that the meerkat's actions can vary greatly depending on the environment, leading to more variable signals. This can include rapid, short bursts of activity when the meerkat digs, as well as slower, more deliberate movements as it searches for food. These fluctuations in the signal are reflective of the meerkat's interaction with its environment as it locates and retrieves food, making foraging one of the most variable behaviours in terms of signal patterns.

Running is a high-intensity, rhythmic behaviour that produces a highly periodic signal. The running signal is marked by regular intervals, which correspond to the meerkat's rhythmic movements as it accelerates and decelerates. This behaviour is the least common in the dataset, accounting for only 1% of the bouts. However, its periodic nature allows for easy identification and classification, standing in contrast to the more erratic signals produced during foraging.

As shown in **Figure 6**, the dataset used in this study was meticulously processed to exclude bouts where transitions between behaviours occurred, where the animal was not visible in the camera frame, or where social interactions such as grooming were observed. These exclusions left a total of 82,550 bouts, with the majority of them classified as either foraging (56.2%) or vigilance (38.2%). Running, being the rarest behaviour, only accounted for 1% of the retained bouts, making it more challenging to classify but still detectable due to its highly rhythmic signal pattern.

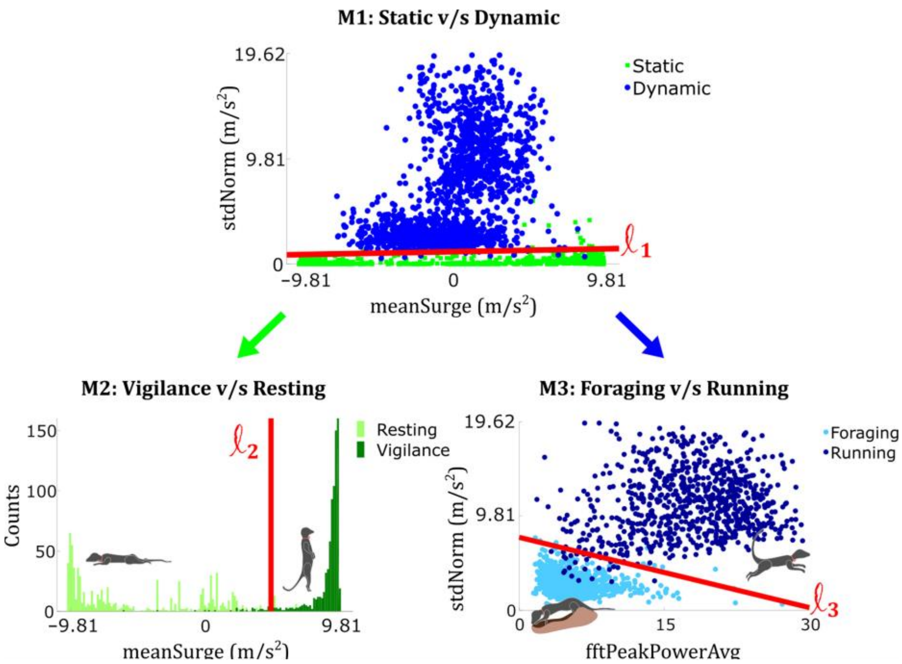

Figure 6. Comparison of animals in various states.

In terms of data analysis, the performance of different machine learning models was evaluated using the M1-M2-M3 hybrid model. Out of the 64 possible combinations, the SVM-SVM-SVM hybrid model emerged as the best performer across all three cross-validation methods. The linear-kernel support vector machine (SVM) was particularly effective because it automated the search for robust feature-value thresholds, which enabled the model to classify the behaviours with high accuracy. The decision boundaries derived from the linear-kernel SVM were simple and intuitive, making the classification scheme transparent and physically interpretable. The classification rules, based on these linear decision boundaries, allowed for a clear understanding of how each behaviour was distinguished from the others.

To benchmark the SVM-SVM-SVM model's performance, results were compared against classical machine learning methods using the same number of features. While classical methods yielded satisfactory results, the SVM-SVM-SVM hybrid model performed better in terms of both accuracy and interpretability. The transparency of the classification rules makes the model particularly valuable in ecological studies, where understanding the behavioural patterns of animals is crucial for understanding their interactions with the environment.

In summary, this study demonstrates the effectiveness of using machine learning, particularly the SVM-SVM-SVM hybrid model, to classify and understand the behaviour of meerkats in their natural environment. The different signal patterns associated with vigilance, resting, foraging, and running were successfully identified and classified, with clear distinctions drawn between each behaviour. This approach opens up new avenues for studying animal behaviour in a more automated and objective manner, with implications for broader ecological research.

4. Discussion

In this study, we investigated the behaviour of meerkats by analyzing a large dataset of 2-second bouts of video-labelled behavioural data, focusing on four key behaviours: vigilance, resting, foraging, and running. The primary aim of the research was to explore the potential of machine learning, particularly support vector machines (SVMs), for classifying these behaviours based on the signals generated during each activity. The results indicate that machine learning models, particularly the SVM-SVM-SVM hybrid model, can successfully differentiate between these behaviours, with strong potential for automating the analysis of animal behaviour in natural settings.

Our findings highlight distinct signal characteristics for each behaviour. Vigilance and resting, while both involving periods of stillness, are clearly distinguishable based on their signal patterns. Vigilance is characterized by brief perturbations as the meerkat scans its surroundings, reflecting the animal's active state of alertness. On the other hand, resting signals are generally more stable, corresponding to a relaxed state with minimal movement. This distinction between vigilance and resting underscores the importance of physiological and behavioural context in interpreting animal signals. The clear separation of these two states, despite their apparent similarity in terms of physical stillness, emphasizes the need for accurate, context-specific analysis in animal behaviour studies.

Foraging, as expected, produced the most erratic signal patterns, reflecting the dynamic and site-dependent nature of the behaviour. The variation in foraging signals is likely due to the meerkat's interactions with the environment, such as digging, searching for food, and maneuvering around obstacles. This variability in the signal makes foraging one of the most challenging behaviours to classify but also one of the most informative in understanding the meerkat's interaction with its habitat. The model successfully captured these variations, highlighting the power of machine learning to process complex, real-world data with a high degree of accuracy.

Running, though the least common behaviour in the dataset, exhibited a highly rhythmic and periodic signal, making it easily distinguishable from the other behaviours. The simplicity of this signal pattern makes running an ideal candidate for machine learning classification, but its relative rarity in the dataset posed challenges in terms of balancing the data and ensuring robust performance. Despite accounting for only 1% of the total bouts, the periodic nature of the running signal was effectively identified by the SVM-SVM-SVM model, demonstrating the model's capability in handling both common and rare behaviours.

One of the key strengths of this study lies in the application of the SVM-SVM-SVM hybrid model, which outperformed classical machine learning methods. The use of linear-kernel SVMs to define simple decision boundaries not only improved classification accuracy but also enhanced interpretability. The transparency of the model's decision-making process allows researchers to gain a deeper understanding of the behavioural patterns of meerkats, providing insights into the underlying mechanisms that drive these behaviours. The ability to automate the identification of behaviours based on their signal patterns opens up new possibilities for large-scale, real-time monitoring of animal populations, which could have significant applications in ecological research, wildlife conservation, and behavioural ecology.

Moreover, the study underscores the importance of data quality and preprocessing in behavioural analysis. Excluding bouts with transitions between behaviours, missing animal data, or social behaviours such as grooming was crucial to ensuring that the dataset remained focused on the four key behaviours of interest. By carefully selecting the data for analysis, we were able to improve the accuracy and robustness of the machine learning models, allowing for clearer distinctions between behaviours.

While the results are promising, there are several limitations and avenues for future research. The dataset, while large, still only accounted for a limited range of environmental conditions, which could influence the behavioural signals. Future studies should explore how these behaviours manifest under different ecological pressures, such as predation risk, food scarcity, or social dynamics. Additionally, expanding the range of behaviours analysed, including social interactions and other context-dependent behaviours, could further enrich our understanding of meerkat behaviour and the potential applications of machine learning in animal behaviour research.

In conclusion, this study demonstrates the efficacy of machine learning, specifically SVM-based models, in the classification of meerkat behaviours. The distinct signal characteristics for vigilance, resting, foraging, and running provide valuable insights into the behavioural ecology of meerkats, while the transparency and interpretability of the SVM-SVM-SVM hybrid model offer a new approach for behavioural analysis in natural settings. As technology advances and more complex datasets become available, the integration of machine learning techniques will likely become an indispensable tool in the field of animal behaviour research, enabling more efficient, scalable, and accurate analyses of animal activity.

5. Conclusion

Biomechanics plays a pivotal role in advancing animal husbandry by optimizing health, welfare, and productivity in livestock management. By applying principles of motion and mechanics, it enables the design of animal-friendly environments that minimize stress and injuries, thereby enhancing overall well-being and performance. Biomechanics also improves the efficiency of equipment and processes, such as feeding systems, housing structures, and transportation methods, ensuring that they are ergonomically suited to the animals' physical needs.

Beyond animal care, biomechanics contributes significantly to sustainable farming by developing eco-friendly systems that lower resource consumption, reduce waste, and mitigate environmental impacts. For instance, biomechanical insights can guide the creation of energy-efficient housing designs or waste management systems that align with environmental conservation goals. Moreover, understanding animal movement and behavior helps optimize space utilization, improving farm productivity while maintaining ethical standards.

As the global demand for food continues to grow, biomechanics will become increasingly essential in shaping the future of agriculture. It offers a pathway to achieving a harmonious balance between high productivity, enhanced animal welfare, and environmental sustainability, fostering resilient and ethical agricultural systems capable of meeting the challenges of the 21st century.

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