challenges

MDPI

Article

Challenges in Sustainable Beef Cattle Production: A Subset of Needed Advancements

Jason A. Hubbart [1,*], Nathan Blake [2], Ida Holásková [3], Domingo Mata Padrino [2], Matthew Walker [3,4] and Matthew Wilson [5]

1 Division of Forestry and Natural Resources, Davis College of Agriculture, Natural Resources and Design, West Virginia University, Agricultural Sciences Building, Morgantown, WV 26506, USA
2 Division of Plant and Soil Sciences, Davis College of Agriculture, Natural Resources and Design, West Virginia University, Agricultural Sciences Building, Morgantown, WV 26506, USA
3 Office of Statistics and Data Analytics, West Virginia Agriculture and Forestry Experiment Station, Davis College of Agriculture, Natural Resources and Design, West Virginia University, 1194 Evansdale Drive, Morgantown, WV 26506, USA
4 Division of Resource Economics and Management, School of Natural Resources, Davis College of Agriculture, Natural Resources and Design, West Virginia University, 1194 Evansdale Drive, Morgantown, WV 26506, USA
5 Division of Animal and Nutritional Sciences, Davis College of Agriculture, Natural Resources and Design, West Virginia University, Agricultural Sciences Building, Morgantown, WV 26506, USA
* Correspondence: jason.hubbart@mail.wvu.edu; Tel.: +1-304-293-2472

Abstract: Estimates of global population growth are often cited as a significant challenge for global food production. It is estimated that by 2050 there will be approximately two- billion additional people on earth, with the greatest proportion of that growth occurring in central Africa. To meet recommended future protein needs (60 g/d), approximately 120 million kg of protein must be produced daily. The production of ruminant meat (particularly beef cattle) offers the potential to aid in reaching increased global protein needs. However, advancements in beef cattle production are necessary to secure the industry's future sustainability. This article draws attention to a subset of sustainable beef cattle production challenges, including the role of ruminant livestock in meeting global human protein needs, the environmental relationships of advanced beef cattle production, and big data and machine learning in beef cattle production. Considering the significant quantities of resources necessary to produce this form of protein, such advancements are not just a moral imperative but critical to developing advanced beef cattle production practices and predictive models that will reduce costs and liabilities and advance industry sustainability.

Keywords: beef cattle production; sustainability; environmental change; environmental biophysics; big data; machine learning; forage

check for updates

Citation: Hubbart, J.A.; Blake, N.; Holásková, I.; Mata Padrino, D.; Walker, M.; Wilson, M. Challenges in Sustainable Beef Cattle Production: A Subset of Needed Advancements. *Challenges* **2023**, *14*, 14. https://doi.org/10.3390/challe14010014

Academic Editor: Susan Prescott

Received: 22 September 2022
Revised: 11 February 2023
Accepted: 15 February 2023
Published: 20 February 2023

1. Introduction

Since the term *sustainable development* was used in the Brundtland Report [1], the recognition of the role of agriculture in sustainable development has significantly expanded [2]. Using a recommended 0.8 g/kg of protein per day [3] and the difference between the current human population and that expected in 2050, society needs to sustainably produce approximately 120,000,000 kg per day of additional protein, balanced for the amino acid requirements of humans, to meet future demands. Consequently, there are significant needs for advancements that will lead to improved efficiencies, security, and sustainability of industries that support such needs. Beef cattle production requires many technological advancements, given the substantial resources necessary to produce this form of protein.

Current challenges in the beef cattle industry are numerous and necessitate remediation through science-based approaches. For example, animal agriculture's negative impact on global greenhouse gas emissions is well documented, with livestock responsible for ~15% of annual anthropogenic emissions. Ruminant livestock, particularly beef and dairy cattle, contribute most of these emissions [4]. The majority of ruminant livestock emissions are due to the natural production of methane (CH4) via ruminal fermentation of high-energy feedstuffs (e.g., high-starch grains such as corn, sorghum, and barley) and rumen microbes [5]. High consumption of red meat (beef, pork, and lamb) has been shown to have adverse health effects, and it has been recommended that animal protein consumption decreases in wealthy countries where it is often consumed in excess [6]. However, many populations worldwide depend on agri-pastoral systems for income and animal protein from livestock.

Further, ruminants can convert roughage containing complex carbohydrates, such as cellulose, which is not digestible by humans, into complete amino acids that humans need for survival. The ability of ruminants to digest these complex carbohydrates enables the utilization of land unsuitable for food crop production in many regions globally [7]. Additionally, many populations continue to face significant burdens of undernutrition, and obtaining adequate quantities of micronutrients from plant-source foods alone can be difficult, particularly in developing countries with rapidly growing populations [6,8]. Iron deficiency is the most common nutritional disorder, with over 30% of the global population being anemic [9]. Though anemia is prevalent in industrialized countries, it primarily affects women and children in developing countries. Heme iron is the most bioavailable form and is found only in animal meats, with the most considerable quantities occurring in red meat [10,11]. Zinc, iron, and vitamin A deficiencies, especially in children of Latin America, Africa, and Asia, are considered top priority issues that should be addressed for humanity and global stability [12–14]. Beef also contains additional micronutrients, such as creatine and carnitine, that are difficult to obtain elsewhere in the diet without supplementation [15]. It is noteworthy in this context that high heme intake is associated with an increased risk of several cancers, type-2 diabetes, and coronary heart disease. However, excess red meat consumption is almost entirely endemic to wealthy, developed nations and, thus, a small proportion of the global population. Perhaps most nutritionally critical, beef protein is among the most bioavailable sources of animal protein according to the protein digestibility-corrected amino acid score (PDCAAS) [16]. However, increased beef consumption alone will not solve global hunger and nutrient deficiencies. In some populations, it would only serve to advance health crises caused by poor diet and excess animal protein consumption [6]. Increasing beef production using current unsustainable systems would be environmentally disastrous, increase GHG emissions, and directly damage global ecosystems [17,18]. However, if present and future global protein needs are to be met with highly bioavailable protein and micronutrient sources, beef may serve as a promising option. If beef production is to be maintained or increased, as projected due to consumer demand, to aid in meeting global protein needs, sustainable beef cattle production systems must be researched and implemented [19].

Considering the agricultural advancements of recent decades, the beef industry is well-positioned to evolve toward the needs of the future. For example, it is now culturally accepted that properly managed grazed grassland systems serve local and global ecosystems by improving soil, sequestering carbon, increasing soil microbe diversity, and transforming low-quality plant matter into high-quality animal protein [20]. These transformational benefits are attributable to the complex interactions among pasture management practices, pasture composition, edaphic conditions, and climate [21]. Considering future climate changes, pasture composition, grassland management practices, and animal selection will need to adapt to sustainably meet protein needs. For example, current approaches to grazing and grazing research and pasture-attribute modeling are inadequate to adapt grasslands to increased global protein demand and, simultaneously, a changing climate. Current standard grazing research methods are labor-intensive, time-consuming, and costly, limiting the development of climate-adapted forages and appropriate grazing management and understanding key relationships among grazing livestock and the pasture system.

The field of environmental biophysics [22] has shown great promise in identifying relationships between the variability of the physical environment and the biological organisms that inhabit those environments [23] and may play an essential role in the adaptive management needs of increased beef cattle production amidst a changing climate. Ideally, environmental biophysical research leads to an improved understanding of how an organism functions in its microenvironment and how an organism responds to environmental change [22–25]. There is progress in this regard, and beef cattle production increasingly includes the integration of ecological and climatologic infrastructure coupled with animal water and feed efficiency monitoring infrastructure. However, the costs of these technologies are often prohibitively high for producers. To develop complex grazing livestock environmental biophysical models that advance environmental-dry matter and water efficiency(ies), technologies must be contemporary and accessible to producers (practitioners). Such advancements will improve management practices and reduce costs related to grazing livestock production and sustainability, meeting future human population protein requirements.

The use of remote-sensing and machine learning technologies is similarly a way forward to streamline grassland research, improve forage diversity and management, and elucidate animal-grassland relationships critical to future sustainable livestock production. Fortunately, a new era of digital data, with increased resolution and precision, is represented in current animal production research utilizing sensors, cameras, and rapid data acquisition technologies, such as in-pen/walk-over weigh scales, wearable accelerometers, and environmental sensors [26]. For large and variable digital files that include beef cattle physiology, grazing conditions, feed and water quality and quantity, and ecological/climate biophysical data to converge into useful information, there is a growing need for big data and machine learning (ML) techniques. Unfortunately, machine learning in livestock production has lagged behind that of other agricultural applications [27,28]. To utilize modern computing power, it will become essential to normalize information pathways so that cattle production researchers are fluent in big data and machine learning techniques [26].

Given the preceding, the following subset of challenges and implicit plea for action related to sustainable beef cattle production are presented, including (a) the role of ruminant livestock in meeting future protein needs, (b) the environmental biophysics of beef cattle production, and (c) big data and machine learning in beef cattle production. It is anticipated that increased awareness generated through this article will mobilize assistance and generate new information that will strengthen the resilience of the beef cattle industry during a time of significant development and environmental change.

1.1. The Role of Ruminant Livestock

Grazing is the most ubiquitous land use practice in grassland ecosystems [29,30]. Beef cattle are often grazed on marginal lands because they will harvest forages of lower quality from land with no or few alternatives for other crops [31]. Ruminant livestock is also grazed on converted forestland, with the conversion of forests to grazing land accounting for over 40% of global forest loss [19]. However, deforestation is not required to introduce new grazing lands. It is well-established that ruminant livestock benefits from grazing forestland in silvopasture systems, with increased gain, well-being, and performance [32]. Ecologically, silvopasture-managed systems benefit from increased biodiversity, carbon storage, and productivity [32,33]. Livestock production on marginal lands or lands that serve an additional ecological function is essential given that, in the United States and other developed economies, more than 60% of the protein comes from animal sources.

In contrast, the contribution of animal sources in Africa, India, and other food-deficient countries is 20–25% of total protein [34]. Of the sources of animal protein, those from ruminants play a vital role in the global food system, as pre-gastric fermentation facilitates the conversion of low-quality and low-protein forages into high-quality meat and milk. However, regardless of the source of animal protein, all animal proteins have significant footprints (carbon, methane, water, etc.), and large portions of those footprints result from the large footprint of plant materials they consume to assimilate those high-quality proteins [35–37]. Therefore, efforts to reduce the footprint of human food production need to include a focus on understanding and improving animal feed utilization efficiency.

Of the approximately 109 million head of ruminant livestock that utilizes United States grassland systems alone, about 61 million are located in cool-season-dominated grassland systems [38]. The total economic value of forage and grasslands used in ruminant animal production is approximately USD 44 billion annually and is generated from the various goods produced by ruminant systems (meat, fibers, manure, and milk), with hay and other conserved forage crops (i.e., silage and haylage) production accounting for over USD 18 billion of agricultural income [38]. Approximately 40% of all anthropogenic emissions of CH_4, which has 21 times the global warming potential of CO_2, originate from animal agriculture [5,39]. Improper manure management accounts for 10% of all agricultural CH_4 emissions [39]. Cattle feedlot finishing systems account for much of animal agriculture methane due to the high-energy feedstuffs provided by feedlots altering rumen bacterial communities and altering ruminal fermentation [39]. The ability of grasslands to sequester carbon, improve soil fertility and structure, and increase soil water-holding capacity is well documented [20]. Grassland-based animal agriculture has the potential to be carbon-negative if proper management techniques, including the incorporation of rotational grazing and diverse botanical compositions that include N-fixing leguminous forages, can reduce N_2O emissions [40,41]. Continuously stocked pastures and feedlots, if transitioned into adaptive multi-paddock / rotational grazing systems in which overgrazing, manure mismanagement, and soil erosion can be prevented through proactive management, have the potential to be far more sustainable and reduce overall greenhouse gas (GHG) emissions by ruminants [41,42]. However, the challenge of managing grasslands in response to a changing climate must be addressed to ensure that grassland agriculture can sustainably meet projected future protein requirements and aid in mitigating climate change.

1.2. Environmental Biophysics of Beef Cattle Production

Environmental Biophysics is the study of organisms and the physical environment (macro- to microenvironment) that they inhabit [23]. In general, environmental biophysical research is undertaken to understand (a) the micrometeorological environment of a given organism of interest, (b) how an organism functions (i.e., natural history) in its microenvironment, and (c) how an organism responds to micro-environmental perturbation either caused by natural or anthropogenic pressures [22–25]. The exchange processes between the atmosphere, microhabitat, and biological organisms form the component of environmental biophysics with the most significant temporal and spatial variability. Exchange processes may include fluxes of water, heat, carbon, and other bio-climatically relevant substances [23,24]. Despite the often-apparent direct dependence of these processes on atmospheric gas exchanges, water vapor, and heat flux, scientists know little about the mechanistic dynamics controlling them. For example, large-scale vegetation and animal agricultural practices respond to the state of the atmosphere but also influence local, regional, and continental weather processes primarily through complex evaporation, transpiration (or respiration), and carbon flux exchange processes. This is partly because terrestrial plant and animal-atmosphere heat and gas exchange processes are heavily dependent on vegetative and animal species composition, morphology, and density [22,24]. Because these conditions can vary significantly over relatively small spatial scales, they can facilitate highly variable impacts on processes that govern fauna (individual or group) life histories and relationships that are even less well understood than for vegetation. This is attributable to the transient nature of most fauna and coupled complex metabolic pathways (e.g., endotherms). Regardless, this understanding is critically important since advanced knowledge can help determine whether a given location or set of conditions is suitable for raising animals such as beef cattle, which greatly depend on vegetation production [22–24].

Classic studies acknowledge the importance of cattle feed/water intake relationships and the local environment [43]. Furthermore, recent studies suggest that heat production of cattle related to digestive processes may also result in metabolic energy that may be crucial for cow metabolism, food and water intake-related growth, and, therefore, production efficiencies [44]. However, it is not well-understood how environmental conditions (heating and cooling) may improve or exacerbate metabolic processes and beef cattle growth regimes or the timing and rate of growth (mass) gains. There is, therefore, an ongoing need to develop advanced methods to predict relationships between micrometeorological conditions, intake (e.g., dry matter), metabolism, and animal growth and health processes to improve animal feed efficiencies [23,43,44].

1.3. Big Data and Machine Learning in Beef Cattle Production

To make wise decisions within and outside the cattle industry, it is essential to consider the growing ecosystem of data information generated by booming digitalized technology and incorporate those data into both mechanistic and data-driven algorithms [11]. For example, in the beef industry, more precise predictions (based on massive, difficult-to-discriminate data sets) aid in finding more efficient animals (feed and water efficient). Results can be used in future positive and negative genetic selections that can be utilized in future breeding to focus the production on more efficient animals, which contributes to greater production efficiencies, smaller environmental footprint, and sustainability of the industry. Ultimately, big data and machine learning in the beef industry lag behind other fields due to many challenges [11,34].

The term Big Data can be challenging to define as it depends on the available computing power at the time of publication. However, a practical definition may be data that are too large for basic manual (human) visual inspection of all rows and columns [45]. Thus, the need for data visualization and exploration becomes increasingly necessary. Machine learning (ML) is a branch of computer science aimed at enabling computers to learn new behavior based on empirical data to design algorithms that allow the computer to display behavior learned from experience rather than human instruction [46]. The main types of machine learning are supervised-, unsupervised-, semi-supervised, transduction, reinforcement-, and learning-to-learn methods [46,47]. Current publications on ML use in agriculture primarily focus on crop production [27,28]. Most publications applying ML to livestock production are related to animal welfare. Between 2018 and 2020, the number of publications on ML in agriculture more than doubled compared to the previous 14 years. However, publications on ML use in livestock production increased slightly [28]. These trends thus indicate a growing body of literature (livestock production) that is not growing as fast as other ML applications in agriculture.

Utilization of ML for feed efficiency [48] in beef steers in the United Kingdom, including information from individual feed intake electronic feeders, feeding behavior using accelerometer, age, and daily weight for 56 days was shown to produce low predictive precision in multiple linear regression, random forests, and support vector regressor. Model precision was compared to repeated measures correlations. The root mean square error of random forest prediction (encompassing the difference between actual and predicted DMI) ranged from 1.15 to 1.61 kg. However, the dataset did not include any climate or water intake variables. Repeated measures techniques are available in both mechanistic and ML approaches, for example, repeated measures random forest [49]. Researchers in Ireland [50] developed a mechanistic stepwise regression model using n-alkane to estimate DMI while grazing, collecting multiple non-invasive animal measurements, including body condition score, linear type scoring, thermography, and grazing behavior, and generated 94 variables to predict the DMI of grazing lactating beef cows. The repeated measurements were averaged across three time points, and averages were analyzed in multiple linear regression models showing promising results with R^2 of 0.68 on training (88 cows) and R^2 of 0.59 in independent validation herd (60 cows). Other recent works integrated multiple additional indices in ML techniques, including image-based analyses and body weight estimation [45,51], prediction of body condition score (BCS) [28], and prediction of energy and water consumption [28].

Modern beef cattle production generates significant amounts of complex data requiring knowledgeable researchers and powerful machine learning algorithms. Generally, it is insufficient to describe correlations in complex animal production systems. Still, a deeper understanding of the impact of multiple data sources is needed on a layer-by-layer basis [52]. The applied intersection of ML and animal growth physiology requires exploration. Animal sciences education and curriculum face a two-fold challenge: to prepare researchers in all layers—from molecular to applied practical depth of knowledge of the physical animal science, plus to equip them with the big data analysis and machine learning skills to advance sustainable farming practices.

2. Challenges in Sustainable Beef Cattle Production

2.1. The Role of Ruminant Livestock

Reducing the footprint of low-quality feedstuffs conversion into high-quality protein for human consumption requires advancements in feed efficiency. A significant limitation to further progress is the inability to measure individual DMI effectively in grazing systems. For example, the breeding herd (cows, bulls, and replacement heifers) consumes 82% of the feed in a calf-to-beef system. Most heifers and cows are grazing or fed harvested forage [53]. Progress regarding cow herd health and production efficiency requires methods to estimate individual DMI of grazing animals [54]. Selection of breeding stock that consumes less feed than expected is possible. As early as 2015, a genetic tool was developed to compare bulls that varied in the genetic potential (i.e., Expected Progeny Difference or EPD) for Residual Feed Intake (RFI) and Residual Water Intake (RWI). Unfortunately, direct measurement of RFI is currently prohibitively expensive and limited to animals reared in confinement [53]. Upon the development of a tool to directly measure individual animal DMI and RWI, animal geneticists would be able to identify animals that are both efficient in water and feed use and work to generate efficient breeding stock.

Generally, grazing research tends to be relatively labor-intensive [55], requires artificially small grazing plots, and does not benefit from automated data collection. Currently, animals are most often grazed in 0.1–0.3 acres (0.04–1.21 hectare) plots, estimating herbage mass before and after grazing with plate meters and paired clipped samples. Results are then scaled to group averages, making determinations of individual grazing intake impossible [56,57]. The primary disadvantage of this approach is that it limits the number of locations that can be monitored, thereby slowing many areas of grazing research (e.g., new climate-adapted forage varieties, innovative approaches to grazing management to enhance ecosystem services, etc.). Additionally, this approach can limit biomass comparisons within heterogeneous study sites, such as those typically found in variable landscape environments [58]. By grazing small plots, data are oversimplified relative to what occurs in most real-world grazing conditions, and animal behavior is also constrained. As a result, feedstock performance in confinement, used for determining animal feed efficiency, is embedded in the assumption(s) that confinement and open-field grazing efficiencies are the same. This is a critical mismatch to address for the beef industry, given that grazing animals make up most ruminant livestock globally. Even those animals that may be finished on grains spend most of their lives grazing (open field), with parental animals primarily grazed or fed harvested forage.

Most pastureland grazing research, particularly research to mitigate the effects and causes of climate change through grassland agriculture, is executed using rotational grazing systems. The development of modern rotational grazing [59] and its subsequent use by producers and researchers alike were predicated upon standardized grazing laws. However, these grazing laws are no longer adequate for managing grassland systems. Changing plant community dynamics influenced by climate change are altering grassland botanical composition and fundamental approaches to grazing [60]. For example, if cool-season forages are to remain a necessary component of grassland systems, diversity in forage species and system services must be incorporated into base grazing approaches. However, those approaches have yet to be formalized for the industry. In several major cool-season types of grass, drought stress has been shown to substantially inhibit chlorophyll synthesis and increase lipid peroxidation and protein degradation, and oxidative activity, and can result in plant death [61]. Insufficient ground cover increases soil temperatures, influencing metabolic rates more than the air temperature. Under prolonged flood conditions, carbohydrate reserves are depleted, and soluble protein content substantially decreases. Gas exchange functions are also drastically reduced, inhibiting photosynthesis and nutrient uptake [62]. For grassland agriculture to meet the nutritional demands of pastured livestock under future population density pressures, forage diversity must be addressed. The development of climate-adapted, grazing-tolerant cool-season forages and warm-season forages with high digestibility and crude protein will be vital to these advancements.

2.2. Beef Cattle Production and the Environment

The energetics of animals is fundamental to their behavior, adaptation, growth, reproduction, and distribution [63]. However, due to the complexity and unpredictability of environmental variables and the diversity of animals' sizes, shapes, surfaces, and other morphological features, developing a thorough understanding of energy exchange between animals and the local environment remains challenging. The variability of radiation, temperature, wind, and humidity in microenvironments in animals' locations necessitates advanced methods of measuring and modeling techniques. This is important because it is primarily through the flow of energy that micro-climate affects an organism. If the organism is strongly coupled to a given climatic factor, then the organism's temperature is strongly influenced by this factor. If the organism is weakly coupled to the environmental factor, then the temperature and energy content are little affected by the factor [63]. For example, an animal is coupled to incident radiation by means of the absorptivity of the organism's surface. If the organism has an absorptivity of zero, reflecting 100% of incident radiation, it will be wholly decoupled from incident radiation, and its temperature will not be affected. If, however, the organism is black (such as some beef cattle breeds) and absorbs 100% of the incident radiation, it will be strongly coupled to the incident flux of radiation. In this case, the quantity of incident radiation intimately affects the organism's temperature. In this manner, an animal's color and, therefore, the surface area of an animal determines the amount of coupling or decoupling to the environment. Quantifying this relationship is vital given that all organisms have temperature tolerances, sometimes referred to as the thermoneutral zone [64], that are more or less limited. Incident radiation can be highly variable in many (if not most) animal habitats, for many organisms' temperatures must be between 0 °C and about 50 °C for metabolic processes to function. For mammals such as cattle, this range is between approximately 21 °C and 45 °C [63] and can highly vary [65,66]. The narrow range maintained by cattle facilitates maximum production [67]. Unfortunately, little is known about these relationships in geographically distinct locations, and much research is needed to advance that understanding.

Additionally, while incident radiation can be a driving force for heating an animal, the temperature of an organism is also affected by the amount of moisture evaporating from the animal's surface. Through the evaporative loss of moisture, an organism's temperature is coupled to the vapor pressure or relative humidity of the moisture in the air around it. If the organism's skin is impervious to moisture loss, then the organism's temperature is completely decoupled from the vapor pressure. For larger animals such as beef cattle, storage capacity may influence the energy exchange rate with the environment, including water loss through respiration [22]. These relationships can be estimated, and the energy budget (balance) equation is the preferred approach [22–24]. However, animal metabolic rates are also necessary to balance the energy budget [22,24,63]. Physiologists generally estimate metabolic rates per unit mass of the animal. However, most producers do not regularly weigh their animals. However, this information is critical to estimating metabolism and weight gains (or losses). Metabolic rates per unit mass of animals are generally computed as a basal rate [22,63]. Basal rate (Watts) can be approximated for a wide variety of animals by the equation (or other derivations thereof), Bm = Cm3/4, where m is the animal's mass (kg), and C is a constant [22]. Fortunately, mass can be estimated in several ways if direct measures are unavailable. Approximations in the literature vary significantly for these methods, and a number uses a simple ratio function multiplied by the animal's estimated surface area (SA). Advanced techniques are greatly needed to calculate SA that more accurately predicts animal metabolism and body mass changes. This is important to advance production efficiencies and long-term beef cattle industry sustainability, particularly for producers. Such advancements will improve beef cattle production by developing managed environmental conditions that optimize feed and water intake and, therefore, mass growth and reduce animal feed and water requirements per kilogram of mass gain, securing producer profits. While many SA computations have been published, most are inaccurate, impractical, or may not be readily available when a determination must be made. Regardless, the surface area is a reasonable method of estimation for body mass given that heat (or cold) and, thus, energy exchange processes between an animal and the environment occur through the animal's surface [68]. This is important given that, similar to very low temperatures, livestock performance at higher temperatures (e.g., sub-tropical, tropical) can result in poorer weight gain performance [67,69,70]. This latter point implies the need for estimates of lower and upper critical temperatures and rates of development of cold and heat stress at ambient temperatures that deviate from lower critical temperatures [71]. There is a great need (and thus challenge) to advance beef cattle environmental monitoring methods and animal surface area estimations and develop more reliable methods of estimating animal stress.

2.3. Big Data and Machine Learning in Beef Cattle Production

Machine learning in animal production differs from typical artificial intelligence (AI) applications due to unique challenges [26,51,52]. For example, extensive data sets are generated from a variety of different sources, such as daily to hourly farm operations from the animals (eating, drinking, moving, growth, health, metabolism), feed availability, farming equipment, marketing, weather, satellites or drone, or aircraft platforms, in addition to all of the laboratory-generated-omics data (proteomics, genomics, transcriptomics, metabolomics, etc. Farmers and animal science researchers are inundated with data, but there is no systematic ability for producers to process the extensive data into actionable insights [52]. Additionally, lifelong beef producers may encounter approximately 30–50 cycles of beef rearing (from calving to marketing) over their production career. The risk associated with a poor decision of culling or selecting animals to breed and sell may have serious material consequences for a producer's business for years or even decades. Changing climate conditions from year-to-year, season to season, breed to breed, the topographic and economic environment, and animal diseases involve random effects in statistical modeling, which may add to the complexity of AI algorithms. Another challenge for ML implementation into beef production is a lack of data analysis skills of animal science professionals (i.e., data science, as applied to animal agriculture). Advancement will require a multidisciplinary approach in undergraduate and graduate animal sciences college education [52]. In addition, agricultural lands are often situated in rural settings where internet infrastructure may be lacking, ultimately limiting the adoption of new digital agriculture practices and big data use, or ML approaches [51]. Finally, the initial upfront costs of the necessary hardware and software may be prohibitive and, once deployed, can increase energy consumption and energy costs, and therefore the financial liability of a beef cattle operation [51]. These challenges, individually and collectively, imply significant needs for ML advancements tailored for the beef industry.

3. Opportunities in Sustainable Beef Cattle Production

3.1. The Role of Ruminant Livestock

Lacking methods to evaluate various classes of livestock under normal grazing conditions and progress to feed a growing human population sustainably will be highly challenging. Requirements for livestock evaluation methods to be helpful in heterogeneous landscapes demand that the system(s) should (1) provide unbiased estimates over the range of biomass studied, (2) be non-destructive, and if possible, (3) quick, easy, and inexpensive to implement [72–74]. There are improvements in drought and heat tolerance in many forages, such as heat-tolerant cultivars of Kentucky bluegrass and tall fescue that accumulate increased nonstructural carbohydrates during drought. There are highly heat-tolerant cultivars of ryegrass-fescue hybrids, and tolerant forage varieties are often not tested under grazing pressure [61,75,76]. However, due to projected changes in grassland composition and the usefulness of grazing ruminant livestock, improved forages must be evaluated in grazing systems. Similarly, the evaluation of the effect of livestock RFI class on grazing habits and forage disappearance use has not been thoroughly researched [77]. Advances in the relationships between livestock intake metrics (RFI, DMI, Residual Water Intake [RWI]) must be developed to improve the genetic selection of efficient breeding stock and increase the production of ruminant livestock without increasing land resources needs. Opportunities for testing climate-adapted forages exist for integrated, interdisciplinary collaborations among researchers, producers, and the forage-production industry. Researchers in functioning grazing systems should assess industry-developed novel forages. This is important because there are many unknown relationships among climate-adapted forages, animal WI and DMI (and many other factors). Collaboration among academia, industry and beef producers is necessary to address these complex integrated agri-environmental systems in a changing climate.

A great (perhaps the greatest) challenge preventing the grazing assessment of diverse, climate-adapted forages, wide-scale physical modeling of changes in pasture composition, and evaluation of intake phenotypes in grazing ruminants is the labor-intensive nature of grazing research. Much of the labor associated with standard agronomic research techniques can be reduced if nuanced models can be developed using imaging and machine learning. Imaging has been used to measure ground cover changes and seasonal patterns in biomass and foliage phenology in perennial grasslands. However, many past approaches relied on ground-based imaging systems and did not benefit from efficient, pasture-wide imaging [78–80]. The use of Unmanned Aerial Vehicles (UAV) to capture imaging and sensing data from grasslands has increased, and machine-learning models that incorporate remote-sensing data to predict pasture biomass and quality have been developed [81–83]. However, the performance of algorithms for pasture biomass has not been increasing, and their accuracy is dependent on physical field samples, data sources, and known pasture composition [84]. For continued improvement in climate-adapted forage research and grazing management research, remote-sensing-based machine learning models must be developed to accurately index and model pasture composition, determine forage biomass and quality, and predict changes in pasture composition.

Similarly, there is currently no validated model for predicting DMI or RWI of pastured cattle, nor are there published understandings of relationships between feed intake phenotypes of pasture-based and confined livestock, RFI and forage use, or RWI and pasture-use efficiencies. To make genetic progress in ruminant livestock and improve grassland management, machine learning models must be developed to explore and understand these relationships, so grasslands can endure a changing climate while increasing ruminant livestock production efficiencies. Agronomists and animal scientists must work with data scientists to engineer tools to ensure that future beef cattle production is sustainable.

3.2. Beef Cattle Production and the Environment

Considering the challenges noted in Section 2.2, research is needed to advance the use and practicality of environmental and climatologic infrastructure while simultaneously increasing the fiscal and logistic practicalities of animal water and feed efficiency monitoring infrastructure. Such advancements could perpetuate the development of advanced beef cattle environmental biophysical relationships and models that will increase environmental-dry matter and water efficiency(ies) understanding, thereby improving management practices and costs related to beef cattle production and sustainability. In addition, digital photographic or other similar (automated, non-contact) methods must be developed to estimate animal surface area and body mass more accurately. This will produce more reliable estimates of heat (or cold) stress and thus give a fiscal impetus to mitigate sub-optimal production environmental (micro-habitat) conditions. Digital photographic methods have been developed in recent years [85], but thus far remain limited in accuracy and precision. Therefore, the application of this technology is in great need of innovation, including coupling to other technologies to estimate body mass more accurately. Other technologies could include distance sensors and smartphone applications using new (or additional) information to estimate body size and mass more readily and affordably.

Current metabolic and heat stress models are often based on the physical characteristics of heat exchange between an animal and its environment and published data on the thermoregulatory responses of cattle. Information needs to be advanced to accommodate a great deal of variability in physio-morphological data of beef cattle for these methods to become more physiologically and geographically dependable. For example, new automated methods are needed to describe the beef cattle's transient characteristics, including metabolic heat production, skin evaporation capacity, hair coat depth, and the local environment (temperature, humidity, radiation, and wind speed). Models that currently provide estimates and output of animal responses (e.g., respiratory heat loss, skin evaporative and non-evaporative heat loss, and rate of body temperature change) are often extremely limited in reliability (accuracy) and therefore practicality in terms of animal management (practitioner) decision making. These advancements will yield improved SA estimates and model-tested and validated estimates of heat loss and radiant heat loss using new information and methodologies. This will improve producers' ability and ease to estimate SA and body weight of beef cattle and also improve estimations of timing and conditions of environmentally stressful situations that may reduce weight gains. Mitigation techniques for the latter may include protection from solar radiation, genetically selected heat-resistant breeds, improved nutritional management, and other strategies.

3.3. Big Data and Machine Learning in Beef Cattle Production

To meet future human population protein needs and advance sustainable beef production, the integration of large volumes of time-series environmental data with physiological data of animals and geospatial data collected from digital proximal and remote machinery must be established and become widely used. A combination of mechanistic and machine learning models will need to be utilized [26,52,86]. Indeed [26] noted that mechanistic modeling and machine learning (ML) have successfully predicted animal performance and related intermediaries. The choice of methodology will likely depend on the objective of the model. Mechanistic models are better suited for manipulating the system for problem-solving, troubleshooting, and knowledge-based decision-making [26]. However, when the objective is prediction or forecasting (for example, what date a beef herd will reach market weight), ML models may be more appropriate [87]. Ref. [26] concluded that there exists a niche for hybridizing the two seemingly divergent approaches where mechanistic modeling's ability to infer causality and ML's strong predictive abilities inform (or quite literally be input into) one another in a feedback-loop-like relationship. Moreover, [88] described how big data and ML might aid in detecting animal health issues that require intervention and improve breeding, feeding, and managing animals to meet sustainability targets and ultimately reduce agriculture's environmental footprint [88,89]. The gap between potentially expensive high-technology and low-resource farming settings is obvious. It may be unrealistic to expect farmers to be financially situated to invest in expensive technology. Instead, beef research investigators should collaborate with trained ML analysts to generate predictive models based on advanced technology and apply the developed models to broader rural producers. The scientific community needs to evaluate the contribution of big data and the feasibility of implementing technologies for developing relationships that can predict animal performance with high confidence without broad or permanent technological investments.

Of course, advancements in modeling approaches will only be as successful as the abilities of the next generation of animal scientists to match the next generation of computing power. To achieve this goal, it is necessary to investigate how programs in higher education integrate data science, basic coding, and machine learning into animal science curricula for undergraduate and graduate degrees. Finally, to further advance the development of new ML techniques, multidisciplinary teams of collaborators working in tandem [26] will be necessary. Animal physiologists, grazing experts, climate and energy scientists, data scientists, statisticians, machine learning specialists, and other stakeholders must buy in, collaborate and integrate their expertise in new novel ways to advance the beef industry for a secure and sustainable future considering all pressures, not limited to the human population, and changing climates [90] (Table 1).

Table 1. Key challenges and potential directions forward in beef production.

Key Challenges	Consequences	Key New Directions
• Contributions to global GHG emission	• Negative environmental impacts • Apocalyptic environmental anxiety, alarmism, and panic among humans • Increased beef production costs for farmers and increased beef prices for consumers	• Optimization of the size of the beef population • Selection of feed and water-efficient animals • Use of grass-land-based rotational grazing system with diverse botanical composition, including the N-fixing leguminous forages
• Adverse effects of high consumption of beef (mainly processed meat) on human health in developed countries	• Increase in cardiovascular diseases, type-2 diabetes, and cancer	• Reduced intake of animal protein to 20 g/day in developed countries
• Protein, Vitamins B12, K2, heme-iron, and zinc malnutrition in developing countries	• Starvation and death of humans	• Agricultural education, beef farming, global nutrient distribution, and fair trade
• Grazing on converted forestland	• Forest loss	• Utilization of grazing forest lands in silvopasture systems
• Dependence on vegetation production, which may be adversely affected by climate variations due to global warming	• Unstable pasture within the growing season	• Improved understanding of how environmental conditions can predict beef cattle metabolic processes
• Food vs. Feed vs. Biofuel competition	• Beef production is less efficient than crop per arable land • Less land for beef feed due to biofuel farming	• Increased animal feed and water efficiency by genetic selection and management • Reserving arable land for farming and low-quality land for other purposes
• Low animal efficiency	• High cost of beef production	• Use of big data and machine learning to aid in finding and selecting more efficient animals

4. Conclusions

The recognition of the role of agriculture in sustainable development has significantly expanded in recent years. However, developing a sustainable beef cattle industry to meet future protein needs will require many advancements. To meet those needs, a great deal of research is necessary to advance beef cattle production sustainability. While there are many additional aspects of the beef cattle industry not represented here (e.g., feedlot management, nutritional supplements to minimize enteric methane production, data-based optimizations in various segments of the industry, etc.), specific challenge areas identified in this article include, (a) the role of ruminant livestock in meeting future human population growth related protein needs, (b) beef cattle production and the environment, and (c) big data and machine learning in beef cattle production. Such challenges and needs constitute timely, high-impact research opportunities for investigators from various fields. Given the potential of the beef cattle industry to supply needed protein to the future (growing) global human population and the need to substantially reduce costs (e.g., feeds, animal stress) in so doing, improvements to methods and integrated technologies will further increase efficiencies and aid in utilizing federal, state, and other tax dollars most effectively. Considering the obstacles currently slowing advancements to cattle industry efficiencies globally (e.g., climate change, land use intensification/complexity, financial limitations, competing stakeholder groups, the strain on water resources, human population growth, and others), novel innovations for advancing the industry must be discovered that can rapidly supply needed advancements.

Author Contributions: For the current work, author contributions were as follows: conceptualization, J.A.H.; methodology, J.A.H.; investigation, J.A.H., N.B., I.H., D.M.P., M.W. (Matthew Walker) and M.W. (Matthew Wilson); resources, J.A.H.; writing—original draft preparation, J.A.H.; writing—review and editing, J.A.H., N.B., I.H., D.M.P., M.W. (Matthew Walker) and M.W. (Matthew Wilson); visualization, J.A.H.; supervision, J.A.H.; project administration, J.A.H.; funding acquisition, J.A.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the USDA National Institute of Food and Agriculture, Hatch project accession numbers 1011536, 1025826, 1024859, and the West Virginia Agricultural and Forestry Experiment Station. Additional funding was provided by the USDA Natural Resources Conservation Service, Soil and Water conservation, Environmental Quality Incentives Program No: 68-3D47-18-005. The results presented may not reflect the sponsors' views, and no official endorsement should be inferred. The funders had no role in the study design, data collection, analysis, the decision to publish, or the preparation of the manuscript.

Data Availability Statement: There are no data presented and thus supporting reported results in the current study.

Acknowledgments: The authors appreciate the support of scientists of the Interdisciplinary Hydrology Laboratory (https://www.researchgate.net/lab/The-Interdisciplinary-Hydrology-Laboratory-Jason-A-Hubbart; accessed on 30 June 2022). The authors also appreciate the feedback of anonymous reviewers whose constructive comments improved the article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Butlin, J. Our common future. By World commission on environment and development. (London, Oxford University Press, 1987, pp.383 £5.95.). *J. Int. Dev.* **1989**, *1*, 284–287. [CrossRef]
2. Hajian, M.; Jangchi Kashani, S. Evolution of the concept of sustainability. From Brundtland Report to sustainable development goals. *Sustain. Resour. Manag.* **2021**, 1–24. [CrossRef]
3. Wu, G. Dietary protein intake and human health. *Food Funct.* **2016**, *7*, 1251–1265. [CrossRef] [PubMed]
4. Gerber, P.J.; Steinfeld, H.; Henderson, B.; Mottet, A.; Opio, C.; Dijkman, J.; Falcucci, A.; Tempio, G. *Tackling Climate Change Through Livestock: A Global Assessment of Emissions and Mitigation Opportunities*; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2013.
5. NASA. Causes of Climate Change. Available online: https://climate.nasa.gov/causes/ (accessed on 9 September 2022).
6. Willett, W.; Rockström, J.; Loken, B.; Springmann, M.; Lang, T.; Vermeulen, S.; Garnett, T.; Tilman, D.; DeClerck, F.; Wood, A. Food in the Anthropocene: The EAT–Lancet Commission on healthy diets from sustainable food systems. *Lancet* **2019**, *393*, 447–492. [CrossRef]
7. Moore, T.G. Global warming: The good, the bad, the ugly and the efficient. *EMBO Rep.* **2008**, *9*, S41–S45. [CrossRef]
8. UN. Sustainable Development Goals: Goal 2: Zero Hunger. Available online: https://www.un.org/sustainabledevelopment/hunger/ (accessed on 5 November 2022).
9. WHO. Micronutrient Deficiencies: Iron Deficiency. Available online: https://apps.who.int/nutrition/topics/ida/en/ (accessed on 5 November 2022).

10. Powers, J.M.; Buchanan, G.R. Disorders of Iron Metabolism: New Diagnostic and Treatment Approaches to Iron Deficiency. *Hematol. Oncol. Clin. N. Am.* **2019**, *33*, 393–408. [CrossRef]
11. Le, C.H.H. The Prevalence of Anemia and Moderate-Severe Anemia in the US Population (NHANES 2003–2012). *PLoS ONE* **2016**, *11*, e0166635. [CrossRef]
12. Hassan, M.U.; Aamer, M.; Nawaz, M.; Rehman, A.; Aslam, T.; Afzal, U.; Shahzad, B.A.; Ayub, M.A.; Ahmed, F.; Qiaoying, M. Agronomic bio-fortification of wheat to combat zinc deficiency in developing countries. *Pak. J. Agric. Res.* **2021**, *34*, 201. [CrossRef]
13. Mutangadura, G.B. World health report 2002: Reducing risks, promoting healthy life: World health organization, Geneva, 2002, 250 pages, US $13.50, ISBN 9-2415-6207-2. *Agric. Econ.* **2004**, *30*, 170–172. [CrossRef]
14. Gupta, S.; Brazier, A.; Lowe, N. Zinc deficiency in low-and middle-income countries: Prevalence and approaches for mitigation. *J. Hum. Nutr. Diet.* **2020**, *33*, 624–643. [CrossRef]
15. Purchas, R.; Busboom, J. The effect of production system and age on levels of iron, taurine, carnosine, coenzyme Q10, and creatine in beef muscles and liver. *Meat Sci.* **2005**, *70*, 589. [CrossRef] [PubMed]
16. Schaafsma Gertjan, G. The Protein Digestibility-Corrected Amino Acid Score (PDCAAS)–a concept for describing protein quality in foods and food ingredients: A critical review. *J. AOAC Int.* **2005**, *88*, 988–994. [CrossRef] [PubMed]
17. Subak, S. Global environmental costs of beef production. *Ecol. Econ.* **1999**, *30*, 79. [CrossRef]
18. Richter, B.D.; Bartak, D.; Caldwell, P.; Davis, K.F.; Debaere, P.; Hoekstra, A.Y.; Li, T.; Marston, L.; McManamay, R.; Mekonnen, M.M.; et al. Water scarcity and fish imperilment driven by beef production. *Nat. Sustain.* **2020**, *3*, 319–328. [CrossRef]
19. OECD. *OECD-FAO Agricultural Outlook 2021–2030*; Department of Agriculture: Washington, DC, USA, 2021.
20. Barnes, R.F.; Nelson, C.; Moore, K.; Collins, M. *Forages: The Science of Grassland Agriculture Volume II*; Wiley-Blackwell: Oxford, UK, 2007.
21. Dias-Filho, M.B.; Davidson, E.A.; Carvalho, C. *Linking Biogeochemical Cycles to Cattle Pasture Management and Sustainability in the Amazon Basin. Chapter 6*; McClain, M.R.L.V., Ritchey, J., Eds.; Oxford University Press: New York, NY, USA, 2000; pp. 84–105.
22. Campbell, G.; Norman, J. *Introduction to Environmental Biophysics*, 2nd ed.; Springer-Verlag: New York, NY, USA, 1998; p. 286.
23. Hubbart, J. Environmental Biophysics. *Encyclopedia* **2019**, *3*. [CrossRef]
24. Bonan, G. *Ecological Climatology: Concepts and Applications*, 3rd ed.; Cambridge Press: Cambridge, UK, 2015; p. 754.
25. Monteith, J.L.; Unsworth, M.H. *Principles of Environmental Physics: Plants, Animals, and the Atmosphere*; Academic Press: London, UK, 2013; p. 395.
26. Ellis, J.L.; Jacobs, M.; Dijkstra, J.; van Laar, H.; Cant, J.P.; Tulpan, D.; Ferguson, N. Review: Synergy between mechanistic modelling and data-driven models for modern animal production systems in the era of big data. *Animal* **2020**, *14*, s223–s237. [CrossRef] [PubMed]
27. Liakos, K.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine Learning in Agriculture: A Review. *Sensors* **2018**, *18*, 2674. [CrossRef]
28. Benos, L.; Tagarakis, A.C.; Dolias, G.; Berruto, R.; Kateris, D.; Bochtis, D. Machine Learning in Agriculture: A Comprehensive Updated Review. *Sensors* **2021**, *21*, 3758. [CrossRef]
29. Wayne Polley, H.; Frank, A.B.; Sanabria, J.; Phillips, R.L. Interannual variability in carbon dioxide fluxes and flux-climate relationships on grazed and ungrazed northern mixed-grass prairie. *Glob. Change Biol.* **2008**, *14*, 1620–1632. [CrossRef]
30. Sheaffer, C.C.; Sollenberger, L.E.; Hall, M.H.; West, C.P.; Hannaway, D.B. Grazinglands, Forages, and Livestock in Humid Regions. In *Grassland Quietness and Strength for a New American Agriculture*; Wiley and Sons: Hoboken, NJ, USA, 2009; pp. 95–119.
31. Fontenot, J.P.; Wilson, L.; Allen, V. *Forages for Beef Cattle*; Barnes, R.F.D.A.M., Nelson, C.J., Eds.; Iowa State University Press: Ames, IA, USA, 1995.
32. Jose, S.; Dollinger, J. Silvopasture: A sustainable livestock production system. *Agrofor. Syst.* **2019**, *93*, 1–9. [CrossRef]
33. Jose, S.; Walter, D.; Mohan Kumar, B. Ecological considerations in sustainable silvopasture design and management. *Agrofor. Syst.* **2019**, *93*, 317. [CrossRef]
34. Capper, J.L.; Berger, L.; Brashears, M.M.; Jensen, H.H. Animal feed vs. human food: Challenges and opportunities in sustaining animal agriculture toward 2050. *Staff. Gen. Res. Pap. Arch.* **2014**, *53*, 1–16.
35. Davis, B.W.; Martz, F.A.; Gerrish, J.R.; Peterson, P.R.; Belyea, R.L. A comparison of stockpiled tall fescue forage intake: Forage availability vs. animal performance indices. In Proceedings of the American Forage and Grassland Council (USA), Lexington, KY, USA, 12–14 March 1995; pp. 219–222.
36. Morrow, R.; Schulze-Tate, V.; Gerrish, J.; Roberts, C. Implications of daily quality changes is rotationally grazed pasture for beef cattle. In Proceedings of the Forage and Grassland Conference, University of Missouri, Columbia, MO, USA; 1991; pp. 145–149.
37. DeRamus, H.A.; Clement, T.C.; Giampola, D.D.; Dickison, P.C. Methane Emissions of Beef Cattle on Forages. *J. Environ. Qual.* **2003**, *32*, 269. [CrossRef] [PubMed]
38. OECD. A Year in Agriculture in Review. 2021. Available online: https://www.oecd.org/agriculture/2021-year-agriculture-review/ (accessed on 15 July 2022).
39. Massey, R.; McClure, H.; Schneider, R. *Agriculture and Greenhouse Gas Emissions*; University of Missouri: Columbia, MO, USA, 2019; p. 5.
40. Reay, D.S.; Davidson, E.A.; Smith, K.A.; Smith, P.; Melillo, J.M.; Dentener, F.; Crutzen, P.J. Global agriculture and nitrous oxide emissions. *Nat. Clim. Change* **2012**, *2*, 410–416. [CrossRef]

41. Paige, L.; Stanley, J.E.R.; David, K.; Marcia, B.; DeLonge, S.; Michael, W.H. Impacts of soil carbon sequestration on life cycle greenhouse gas emissions in Midwestern USA beef finishing systems. *Agric. Syst.* **2018**, *162*, 249.
42. Chang, J.; Ciais, P.; Gasser, T.; Smith, P.; Herrero, M.; Havlík, P.; Obersteiner, M.; Guenet, B.; Goll, D.S.; Li, W.; et al. Climate warming from managed grasslands cancels the cooling effect of carbon sinks in sparsely grazed and natural grasslands. *Nat. Commun.* **2021**, *12*, 118. [CrossRef]
43. Moe, P. Energy Metabolism of Dairy Cattle. *J. Dairy Sci.* **1981**, *64*, 1120. [CrossRef]
44. Derno, M.; Nürnberg, G.; Kuhla, B. Characterizing the metabotype and its persistency in lactating Holstein cows: An approach toward metabolic efficiency measures. *J. Dairy Sci.* **2019**, *102*, 6559–6570. [CrossRef]
45. Morota, G.; Ventura, R.V.; Silva, F.F.; Koyama, M.; Fernando, S.C. Big Data Analytics and Precision Animal Agriculture Symposium: Machine learning and data mining advance predictive big data analysis in precision animal agriculture1. *J. Anim. Sci.* **2018**, *96*, 1540–1550. [CrossRef]
46. Tantawi, R.P. Machine learning. In *Salem Press Encycl*; EBSCO Publishing: Hackensack, NJ, USA, 2020.
47. Dulhare, U.N.; Ahmad, K.; Ahmad, K.A.B. *Machine Learning and Big Data: Concepts, Algorithms, Tools and Applications*; John Wiley & sons: Hoboken, NJ, USA, 2020.
48. Davison, C.; Bowen, J.M.; Michie, C.; Rooke, J.A.; Jonsson, N.; Andonovic, I.; Tachtatzis, C.; Gilroy, M.; Duthie, C.A. Predicting feed intake using modelling based on feeding behaviour in finishing beef steers. *Animal* **2021**, *15*, 100231. [CrossRef]
49. Calhoun, P.; Levine, R.A.; Fan, J. Repeated measures random forests (RMRF): Identifying factors associated with nocturnal hypoglycemia. *Biometrics* **2021**, *77*, 343–351. [CrossRef]
50. Williams, M.; O'Sullivan, K.P.R.; McCabe, S.; Kennedy, E.; Liddane, M.; Buckley, F. Developing and validating a model to predict the dry matter intake of grazing lactating beef cows. *Animal* **2019**, *13*, 2639. [CrossRef]
51. Sharma, A.; Jain, A.; Gupta, P.; Chowdary, V. Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access* **2021**, *9*, 4843–4873. [CrossRef]
52. Beyer, D. *Artificial Intelligence and Machine Learning in Industry*; 9781491959336; O'Reilly Media, Inc.: Sebastopol, CA, USA, 2017.
53. Basarab, J.A.; Beauchemin, K.A.; Baron, V.S.; Ominski, K.H.; Guan, L.L.; Miller, S.P.; Crowley, J.J. Reducing GHG emissions through genetic improvement for feed efficiency: Effects on economically important traits and enteric methane production. *Animal* **2013**, *7*, 303–315. [CrossRef] [PubMed]
54. Nielsen, M.; MacNeil, M.; Dekkers, J.; Crews, D.; Rathje, T.; Enns, R.; Weaber, R. Review: Life-cycle, total-industry genetic improvement of feed efficiency in beef cattle: Blueprint for the Beef Improvement Federation11The development of this commentary was supported by the Beef Improvement Federation. *Prof. Anim. Sci.* **2013**, *29*, 559–565. [CrossRef]
55. Ramoelo, A.; Majozi, N.; Mathieu, R.; Jovanovic, N.; Nickless, A.; Dzikiti, S. Validation of Global Evapotranspiration Product (MOD16) using Flux Tower Data in the African Savanna, South Africa. *Remote Sens.* **2014**, *6*, 7406–7423. [CrossRef]
56. Mata-Padrino, D.J.; Pena-Yewtukhiw, E.M.; Belesky, D.P.; Bryan, W.B.; Bowdridge, S.A. Season-long, mixed stocking of a cool-temperate pasture. *Grassl. Sci.* **2021**, *67*, 12–23. [CrossRef]
57. Rayburn, E.B.; Rayburn, S.B. A Standardized Plate Meter for Estimating Pasture Mass in OnFarm Research Trials. *Agron. J.* **1998**, *90*, 238. [CrossRef]
58. Redjadj, C.; Duparc, A.; Lavorel, S.; Grigulis, K.; Bonenfant, C.; Maillard, D.; Saïd, S.; Loison, A. Estimating herbaceous plant biomass in mountain grasslands: A comparative study using three different methods. *Alp. Bot.* **2012**, *122*, 57–63. [CrossRef]
59. Voisin, A. *Grass Productivity: An Introduction to Rotational Grazing*; Midwest Journal Press: Mexico, MO, USA, 1959.
60. Tarumi, E.; Tsuiki, M.; Mori, A. Cool-season grass productivity estimation model evaluating the effects of global warming and climate adaptation strategies. *Grassl. Sci.* **2021**, *67*, 234–240. [CrossRef]
61. Loka, D.; Harper, J.; Humphreys, M.; Gasior, D.; Wootton-Beard, P.; Gwynn-Jones, D.; Scullion, J.; Doonan, J.; Kingston-Smith, A.; Dodd, R.; et al. Impacts of abiotic stresses on the physiology and metabolism of cool-season grasses: A review. *Food Energy Secur.* **2019**, *8*, e00152. [CrossRef]
62. Liu, M.; Jiang, Y. Genotypic variation in growth and metabolic responses of perennial ryegrass exposed to short-term waterlogging and submergence stress. *Plant Physiol. Biochem.* **2015**, *95*, 57. [CrossRef]
63. Gates, D.M. *Biophysical Ecology*; Springer-Verlag: New York, NY, USA, 1980; p. 611.
64. Mader, T.L. Environmental stress in confined beef cattle1. *J. Anim. Sci.* **2003**, *81*, E110–E119. [CrossRef]
65. Yousef, M.K. *Stress Physiology in Livestock. Volume I. Basic Principles*; CRC press: Boca Raton, FL, USA, 1985.
66. Jacobsen, K.L. The well-being of dairy cows in hot and humid climates. I. Housing and effects of heat stress. *Compend. Contin. Educ. Pract. Vet.* **1996**, *18*, S59–S63.
67. Brosh, A.; Aharoni, Y.; Degen, A.; Wright, D.; Young, B. Effects of solar radiation, dietary energy, and time of feeding on thermoregulatory responses and energy balance in cattle in a hot environment. *J. Anim. Sci.* **1998**, *76*, 2671. [CrossRef]
68. Monteith, J. *Principles of Environmental Physics*; Edward and Arnold Publishers Limited: London, UK, 1973; p. 241.
69. Blackshaw, J.; Blackshaw, A. Heat stress in cattle and the effect of shade on production and behaviour: A review. *Aust. J. Exp. Agric.* **1994**, *34*, 285. [CrossRef]
70. Young, B.; Hall, A. Heat load in cattle in the Australian environment. In *Australian Beef*; Coombes, R., Ed.; Morescope Publishing: Melbourne, Australia, 1993; pp. 143–148.
71. Berman, A. Effects of Body Surface Area Estimates on Predicted Energy Requirements and Heat Stress. *J. Dairy Sci.* **2003**, *86*, 3605–3610. [CrossRef] [PubMed]

72. Catchpole, W.R.; Wheeler, C.J. Estimating plant biomass: A review of techniques. *Austral Ecol.* **1992**, *17*, 121. [CrossRef]
73. Harmoney, K.R.; Moore, K.J.; George, J.R.; Brummer, E.C. Russell, J.R. Determination of Pasture Biomass Using Four Indirect Methods. *Agron. J.* **1997**, *89*, 665. [CrossRef]
74. Mannetie, L.T.; Jones, R. Field and Laboratory Methods for Grassland and Animal Production Research. CAB International: Wallingford, UK, 2000.
75. Sun, X.; Hu, L.; Xie, Y.; Fu, J. Evaluation of genotypic variation in heat tolerance of tall fescue by functional traits. *Euphytica* **2014**, *199*, 247–260. [CrossRef]
76. Yang, Z.; Xu, L.; Yu, J.; Dacosta, M.; Huang, B. Changes in Carbohydrate Metabolism in Two Kentucky Bluegrass Cultivars during Drought Stress and Recovery. *J. Am. Soc. Hortic. Sci.* **2013**, *138*, 24–30. [CrossRef]
77. Mata-Padrino, D.J.; Wilson, M.E.; Ogunade, I. The Effect of Residual Feed Intake Phenotype on Herbage Disappearance of a Permanent Pasture. In Proceedings of the 2021 ASA, CSSA, SSSA International Annual Meeting, Salt Lake City, UT, USA, 6–9 November 2021.
78. Bennett, L.T.; Judd, T.S.; Adams, M.A. Close-range vertical photography for measuring cover changes in perennial grasslands. *Rangel. Ecol. Manag. J. Range Manag. Arch.* **2000**, *53*, 634–641.
79. Schut, A.G.T.; Lokhorst, C.; Hendriks, M.M.W.B.; Kornet, J.G.; Kasper, G. Potential of imaging spectroscopy as tool for pasture management. *Grass Forage Sci.* **2005**, *60*, 34. [CrossRef]
80. Inoue, T.; Nagai, S.; Kobayashi, H.; Koizumi, H. Utilization of ground-based digital photography for the evaluation of seasonal changes in the aboveground green biomass and foliage phenology in a grassland ecosystem. *Ecol. Inform.* **2015**, *25*, 1–9. [CrossRef]
81. Pullanagari, R.; Kereszturi, G.; Yule, I. Integrating Airborne Hyperspectral, Topographic, and Soil Data for Estimating Pasture Quality Using Recursive Feature Elimination with Random Forest Regression. *Remote Sens.* **2018**, *10*, 1117. [CrossRef]
82. Chen, Y.; Guerschman, J.; Shendryk, Y.; Henry, D.; Harrison, M.T. Estimating Pasture Biomass Using Sentinel-2 Imagery and Machine Learning. *Remote Sens.* **2021**, *13*, 603. [CrossRef]
83. Barnetson, J.; Phinn, S.; Scarth, P. Estimating Plant Pasture Biomass and Quality from UAV Imaging across Queensland's Rangelands. *AgriEngineering* **2020**, *2*, 523–543. [CrossRef]
84. Morais, T.G.; Teixeira, R.F.M.; Figueiredo, M.; Domingos, T. The use of machine learning methods to estimate aboveground biomass of grasslands: A review. *Ecol. Indic.* **2021**, *130*, 108081. [CrossRef]
85. Kaya, M.; Bardakçioğlu, H.E. Estimation of body weight and body condition score in dairy cows by digital image analysis method. *Mehmet Akif Ersoy Üniversitesi Vet. Fakültesi Derg.* **2021**, *6*, 115–121. [CrossRef]
86. Kalirad, A.; Sommer, R.J. The art of mechanistic modeling in biology. *Nat. Comput. Sci.* **2022**, *2*, 72–73. [CrossRef]
87. Breiman, L. Statistical Modeling: The Two Cultures (with comments and a rejoinder by the author). *Stat. Sci.* **2001**, *16*, 199–231. [CrossRef]
88. Koltes, J.E.; Cole, J.B.; Clemmens, R.; Dilger, R.N.; Kramer, L.M.; Lunney, J.K.; McCue, M.E.; McKay, S.D.; Mateescu, R.G.; Murdoch, B.M.; et al. A Vision for Development and Utilization of High-Throughput Phenotyping and Big Data Analytics in Livestock. *Front. Genet.* **2019**, *10*, 1197. [CrossRef] [PubMed]
89. Ramirez, B.C.; Xin, H.; Halbur, P.G.; Beermann, D.H.; Hansen, S.L.; Linhares, D.C.L.; Peschel, J.M.; Rademacher, C.J.; Reecy, J.M.; Ross, J.W.; et al. At the Intersection of Industry, Academia, and Government: How Do We Facilitate Productive Precision Livestock Farming in Practice? *Animals* **2019**, *9*, 635. [CrossRef] [PubMed]
90. Hubbart, J.A. The Coming Food Crisis: A Moment for Organizational Change at a Global Level. *Int. J. Agric. Res. Environ. Sci.* **2022**, *3*, 3. [CrossRef]