

Phenomics for sustainable production in the South African dairy and beef cattle industry

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Implications

- Phenotypic and pedigree recording of livestock remains a challenge in developing countries with informal agricultural sectors.
- Automated technologies would assist commercial farmers to become more efficient and productive, and to make full use of genomics.
- Farmers will benefit from the use of automated technologies in terms of improved animal welfare and economic sustainability in resource-poor areas.

Key words: smallholder, recording, sensors, welfare

Introduction

The impact of the rapidly growing human population on natural resources and in particular on food security has been well documented. As an example of the growth expected in Africa, the current South African human population of approximately 57.7 million people (Statistics South Africa, 2018) are expected to increase to 72.8 million people by 2050 (United Nations, 2017). Nutritional demand, specifically the demand for animal protein, would follow a similar pattern, and the responsibility of meeting this demand will place additional burdens on livestock producers. Climate change will add to this already demanding task, with extreme environmental changes expected for developing countries south of the equator.

Modern genetic improvement in livestock relies on the availability of genomic data (e.g., Single-Nucleotide Polymorphism genotyping and sequencing), as well as accurate recording of relevant phenotypes. The combination of the available phenotypes and genomic data have contributed to identification of

specific genes and quantitative trait loci of economic importance and generation of genome-enhanced estimated breeding values for application in genomic selection. Although the field of molecular genetics has advanced rapidly over the past two decades, accurate phenotyping still remains a serious constraint, and has become the overriding bottleneck in improving livestock production and efficiency.

In South Africa, there are almost 14 million cattle which constitute 1.6 million dairy (604,781 cows in milk) and 12.5 million beef cattle. Of the latter, approximately 53% are kept in commercial systems and the remaining 47% in informal systems (DAFF, 2019). Phenotypic and pedigree recording of livestock in Africa faces constraints in terms of the extensive nature of the farming systems and the large informal livestock sector consisting of communal and small-holder farmers, which is characterized by a general lack of resources such as financial, infrastructural and extension support. Within the commercial sector, participation in collection of data from animal production systems ranges from compulsory participation (100% participation for stud breeders) to extremely poor (mainly within the informal and small-stock industry). Identifying breeding objectives across this wide spectrum of production levels is crucial, followed by the collection of relevant data to address the various issues.

Livestock phenomics is defined as obtaining high-dimensional phenotypic data on an animal-wide scale, which can capture missing heritability, break down composite traits into their components and transform hard-to-measure traits into easily measurable traits (Greenwood et al., 2016). Several state-of-the-art technologies (mostly making use of remote sensing techniques) to enhance phenotyping have been developed and are in various stages of incorporation within the crop production field (Mir et al., 2019). Plant phenomics have the distinct advantage of plants being stationary, and basic crops can be produced rapidly and artificially, with short generation intervals (Greenwood et al., 2016). Object tracking is more complicated in livestock than in either crops or humans, as similar colors and shapes between animals, as well as background clutter often lead to failures (Kim et al., 2017). The use of radio-frequency identification also has limitations, as the range of these sensors is quite restricted. There is a growing interest in low-cost sensor solutions and the use of mobile platforms to address these challenges.

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This review aims to discuss the use of precision phenotyping in the beef and dairy cattle industries of South Africa, highlighting the challenges, limitations and possible contribution of these technologies towards the livestock sector.

Advanced Technologies for Animal Sensing

A key enabling technology for precision phenotyping is sensor networks. A sensor is a device that converts an observed property into an electrical signal. In wireless sensor networks, multiple sensors consolidate their observations wirelessly to provide fine-grained monitoring and automation in challenging environments. An important aspect in designing wireless

sensor networks is in selecting suitable sensors, which is typically application driven. Sensors are classified as attached or nonattached. Attached sensors are composed of sensors inserted inside an animal, and wearable sensors that are fitted to the outside of an animal. Nonattached sensors are off-animal sensors which observe an animal, animal by-products, or the environment. Figure 1 provides an illustration of the general framework of a sensor network which could be applied in the South African dairy and beef industries for precision livestock farming.

Although a clear abundance of various sensors exists in the literature (corresponding to the physical/communication blocks in Figure 1), there is a lack of intelligence in sensor

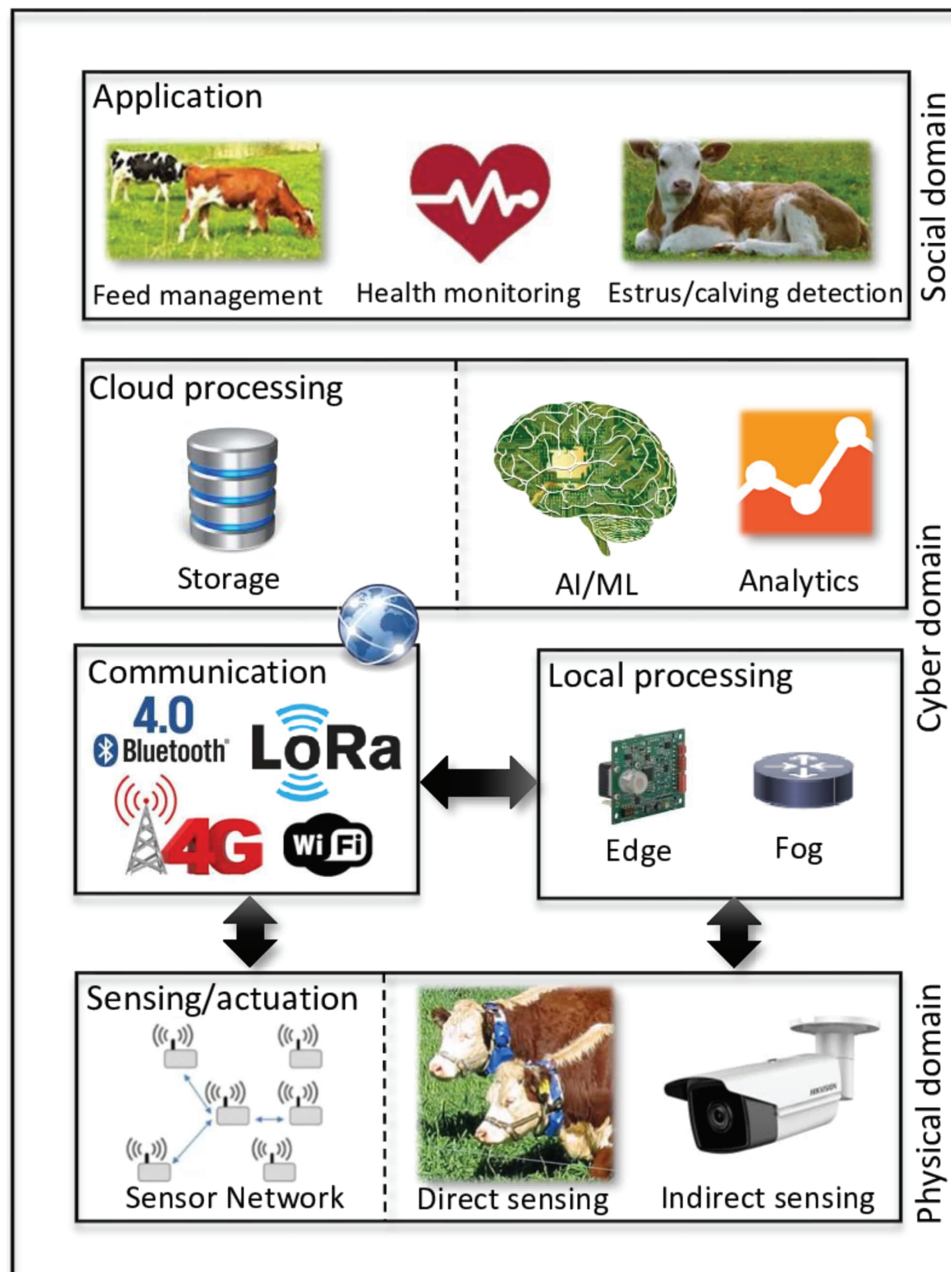


Figure 1. Illustration of the general framework of a sensor network-based precision livestock farming application.

systems (which is provided through the cloud processing/local processing blocks in Figure 1), as sensor measurements are presented to farm personnel directly, or with minor processing, who are then required to draw their own conclusions (Rutten et al., 2013). However, this becomes problematic when there are a large number of animals producing excessive amounts of sensor data that must be interpreted by farm personnel; or when farm personnel do not have the required level of education to interpret sensor readings. This has led to poor adoption rates of intelligent systems by farmers. Poor adoption rates have also been attributed to exorbitant costs of solutions which are difficult to operate, and a lack of solutions that provide meaningful alerts. This is consistent with multiple farmer surveys on drivers of decision making which highlighted economic feasibility, and usability and technical support among others (Eckelkamp, 2019). In the context of Southern Africa, it was also found that technology adoption is linked to farmer's participation with an innovation platform, which is described as a multisectoral and multi-institutional coalition of actors in specific value chain systems (Hanyani-Mlambo et al., 2017). These platforms provide greater access to agricultural advisory services and other support services.

Precision Farming in the South African Dairy Industry

Genetic progress in dairy cattle over the past three decades has been substantial compared to beef cattle or sheep. The extensive use of reproductive technologies in dairy cattle has given this industry an advantage in making genetic progress in production traits and more recently in traits with low heritability with the application of genomics (Miglior et al., 2017). Decades of selection pressure on milk yield has resulted in a number of unfavorable outcomes in fitness traits. DNA marker technology has solved many challenges regarding the identification of recessive genes using diagnostic tests, while genomic selection is contributing to genetic progress in fertility and feed efficiency (Miglior et al., 2017).

The trend worldwide is towards larger dairy farms with economics as the main driver (Rutten et al., 2013). A similar tendency is observed in South Africa where the number of milk producers decreased from 3,551 in 2009 to 1,253 in 2019 (Lacto Data, 2019), while herd sizes have increased. Pasture-based production accounts for up to 70% of dairy production in South Africa, and the remaining 30% are on total mixed ration systems (Meissner, personal communication). The larger dairy units have adopted automated milking systems, which require less labor and have the advantage of automated recording of a large number of phenotypes. The automated milking systems include AfiFarm, DeLaval-Alpro and DeLaval-Delpro management systems as shown in Figure 2. Traditional milk recording schemes are used by less than 10% of South African dairy farmers (SA Stud book, <http://www.sastudbook.co.za/p116/services/logix-milk.html>).

Production, fitness, health, and workability traits have been included in genetic evaluations providing producers

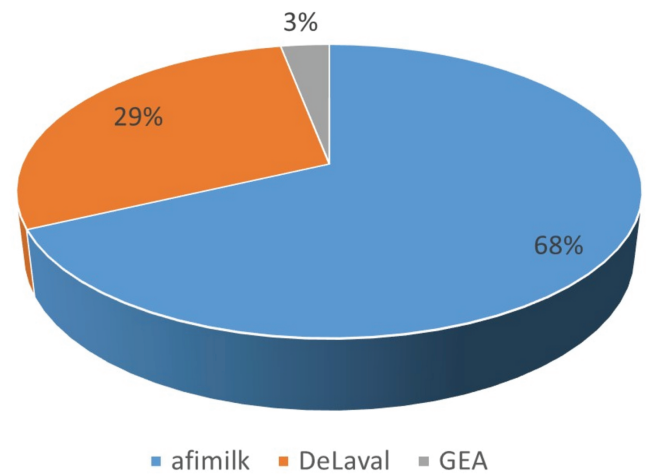


Figure 2. Percentage dairy farmers using the three automated milking systems in South Africa (Gresse, 2018).

with estimated breeding values, genomic enhanced breeding values, and selection indices (Van Marle-Köster & Visser, 2018). Welfare traits in dairy cattle, which include claw health, lameness, mastitis, and other health traits are more difficult to improve due to limitations in effective routine recording, compared to production traits, as well as the low heritability of these traits. Precision or smart farming has presented advanced technologies for automated recording of a large range of welfare phenomes using automated monitoring systems (Hansen et al., 2018; Alsaad et al., 2019), with the primary focus on early detection of a potential problem for timely interventions. Table 1 describes an array of sensors currently used in dairy farms.

The average herd size (in terms of cows in milk) in South Africa varies from 918 in the pasture-based provinces to as low as 119 in the drier regions (Lacto data, 2019). The larger operations making use of automated milking systems are primarily found in the coastal regions. Gresse (2018) demonstrated the use of data from automated milking systems for improved cow production, emphasizing the potential of the data for improving a range of dairy production traits. Implementation of precision dairy monitoring technologies in South Africa will be dictated by herd size and feasibility of automated milking systems.

Improvement of fertility relies largely on sound reproductive management and accurate record keeping. Estrus detection is often a primary constraint and various studies have shown that pedometers can improve detection compared to using only observations by herdsman. The reliability of pedometers, however, has been shown to vary and can therefore not yet be implemented as a fool-proof method (Mottram, 2016). Rutten et al. (2017) explored the automatic behavior detection of calving, where each cow was fitted with an ear tag device consisting of sensors which monitored cumulative activity, rumination activity, feeding activity, and temperature on an hourly basis. Based on the sensor data, a predictive model predicted 43.5% of the calving events with 1% false positive alerts. A range of precision dairy monitoring technologies were tested

Table 1. Nonexhaustive list of sensors used for dairy cattle health management (Adapted from Rutten et al., 2013 and Mottram, 2016)

| Animal-health management | Attached sensors | Nonattached sensors |
|--------------------------|---|--|
| Mastitis | <ul style="list-style-type: none"> • Reticular bolus temperature sensors | <ul style="list-style-type: none"> • Electrical conductivity • Milk color sensors • Biosensors able to detect enzymes of interest • Somatic cell count sensors |
| Estrus | <ul style="list-style-type: none"> • Pedometer and 3 dimensional accelerometers (activity sensing) • Pressure pads on cows' back (mounting behavior sensing) • Temperature transducers | <ul style="list-style-type: none"> • Video camera (mounting behavior sensing) • Microphone (cow vocalization sensing) • Biosensors able to measure progesterone |
| Locomotion | <ul style="list-style-type: none"> • Pedometer and 3 dimensional accelerometers (activity sensing) | <ul style="list-style-type: none"> • Video camera (walking behavior sensing) • Balance-weighing floors (weight distribution sensing) |
| Metabolism | <ul style="list-style-type: none"> • Radiotelemetric rumen bolus (pH and temperature of rumen fluid sensing) • Pedometer and three-dimensional accelerometers (activity sensing) | <ul style="list-style-type: none"> • Spectrophotometer (percentage of milk fat sensing) • Spectroscopy (milk ketone bodies level sensing) • Thermal camera (cow body temperature sensing) |

against the reference gold standard (progesterone patterns) and the accuracy of estrus detection was improved by between 15% and 35% compared to human observations (Mayo et al., 2019). The sensors in this study ranged from attachments to the front or rear legs, the ear or neck or a bolus in the reticulorumen, which all monitored activity, eating, rumination and lying times. A primary advantage of precision dairy monitoring technologies is the continuous measurement of these activities which have been linked to health and metabolic disturbances (King et al., 2018). These measurements hold the potential for early detection of estrus and enhanced management as dairy units become larger and the farmer has less time available to inspect the herd.

Development of tri-axial accelerometers and sensors attached to ear tags also holds potential for more effective recognition of other cow activities which include behavioral changes, eating patterns, and locomotion (Mottram, 2016). Rahman et al. (2018) placed accelerometers on a neck collar at the back of the head, on a halter position at the side of the head behind the mouth, and on the ear using a tag. The data were used to train a machine learning-based model to classify three animal behaviors (grazing, standing, or ruminating), and attained accuracies of approximately 90%. In South Africa, collars and pedometers are used for detection of rumination and eating patterns, activity, and estrus, while milk meters and analyzers are popular for milk traits such as milk flow, conductivity and composition. Substantial data are generated in automated milking systems in South Africa, but the data are primarily used for short-term management and economic decisions (Gresse, 2018). Somatic cell counts are used as an indicator trait for incidence of mastitis. An animal with a cell count of less than 50,000 cells/mL is regarded as a noninfected animal (Seegers et al., 2003). Mastitis being a complex trait and influenced by several factors, individual herd data are not available. The Milk Producers' Organization (MPO) of South Africa estimated a loss of 1 billion ZAR for 2019 due to sub-optimal udder health (Chris van Dijk, MPO, personal communication, <https://www.mpo.co.za>).

The consequences of lameness in dairy cows have been well documented, including adversely affecting genetic improvement, welfare, and farm profitability. Visual inspections and scorings are both time consuming and subjective. Automated methods for lameness detection include kinematic sensors (on the legs and feet) for monitoring body movement with three-dimensional video analyses or accelerometers and pressure-sensitive walkways. There are also kinetic methods using walkways with pressure plates based on ground force reaction (Alsaod et al., 2019). Walkways with pressure sensors can distinguish between lame and non-lame cows and provide an indication of potential claw lesions (Volkman et al., 2019).

Lameness cannot be considered without recognizing the role of claw quality and health, which are both influenced by housing and environmental factors. Literature indicates that claw traits should be considered for improvement of lameness and moderate genetic correlations were reported between claw health and lameness. However, accurate scoring of claw traits and lameness remains the main challenge. In South Africa, claw data are limited to producers who make use of private hoof trimmers, who record the claw lesions on paper and the data is not necessarily captured in an electronic recording system (Mhlongo, 2019). Claw quality and health are not included in goal driven selection and available data have not been explored in research for lameness in South African dairy cattle.

Precision Farming in the South African Beef Industry

Widespread regions of South Africa are experiencing a state of drought, which is the result of the strong El Niño event that occurred in 2015 to 2016 (South African Weather Service, 2016). The shortage of water in the country has raised concerns, among other things, about the amount of water it takes to finish cattle in feedlots (Meissner et al., 2013). Approximately 68.6% of South African land is available for grazing, which is an ideal situation for extensive livestock production systems that rely on natural veld as a feed source. Global warming, however, will be

responsible for fluctuations in the nutritional value of the natural veld (Scholtz et al., 2014).

There is pressure from consumers to produce beef with less greenhouse-gas emissions and limited exploitation of natural resources, while considering the health and well-being of the livestock. Most of the traits relevant to these objectives are difficult and expensive to measure, expressed late in life, and for some new equipment are still being developed. Phenomics aims to make use of advanced technologies and management systems to develop labor saving automated data collection. This would result in the collection of large amounts of phenotypic data, which could be used for genomic prediction and faster genetic improvement.

The level at which phenotypes could be measured varies between traits (i.e., behavioral vs. physiological), and systems (i.e., in-field walk-over vs. animal-attached collars). Traits that are routinely recorded by South African beef breeders commonly reflect easily measured traits that can be measured on farm with no additional financial burden, such as live weights (birth weight to mature weight), growth (average daily gain and Kleiber Ratio) and a smattering of reproduction traits (scrotal circumference, age at first calving and inter calf period), as suggested by Van Marle-Köster & Visser (2018). Traits such as feed conversion ratio, residual feed efficiency and disease resistance are extremely difficult to measure in extensive production systems. Pasture intake is the limiting phenotype for many efficiency parameters, and the measurement of selectivity of pasture would also be important as a variable influencing performance. Chemical markers and *n*-alkanes have been used for this purpose, but have limitations in terms of applying them over long periods of time. In-field walk-over weighing units, as well as on-body sensors to estimate grazing behavior have been developed to overcome this problem, but vary in terms of accuracy. Greenwood et al. (2018) acknowledges that the number of variables that can be measured is limited, and this poses a challenge with regard to developing a single phenotyping approach across systems.

A small number of individual breeders representing only seven beef cattle breeds perform real-time ultrasound scanning



Figure 3. Scoring of carcass quality using the MIJ-30 (photo courtesy of the SA Wagyu breed society).

for carcass traits. This methodology is not readily available to all farmers (and comes at an additional cost), and farmers should have an economic incentive to pursue such additional phenotyping. South Africa has a meat classification system, which includes the age of the animal, fat content, conformation of the carcass and any damage to the carcass (Soji & Muchenje, 2017). It includes a visual assessment of the subcutaneous carcass fat content and fat distribution and does not make provision for grading of carcasses based on marbling. However, the Wagyu breed has recently entered the South African beef industry, and in this breed marbling score is highly correlated with the price paid for the carcass. A reliable measure of marbling is the use of a carcass camera. The MIJ-30 Digital Carcass camera used by Wagyu SA (<http://wagyu.org.za/>) allows objective measurement of marbling score, marbling fineness, marbling percentage, and eye muscle area (as shown in Figure 3), and will also be used to score fat and meat color.

Very few automated interventions have been introduced to the South African beef industry. One of the easiest to implement would be in-field walk-over weighing systems, such as those used in the Australian BreedPlan system (Greenwood et al., 2016). Wireless sensor data could also be used for deeper phenotyping and estimation of feed intake on pasture, as well as normal and aberrant behavior data.

Measuring physiological parameters such as temperature, rumen function, heart rate and metabolites would be the ultimate application of phenomics. These presently require invasive sampling such as tissue or blood collection, but could become more accessible if the sample used for genotyping could be applied for phenotyping as well. This would assist extensive commercial farmers in becoming more competitive and profitable, as precision phenotyping would be done without any additional costs to the farmer. A graphical illustration of some deep phenotyping interventions is given in Figure 4.

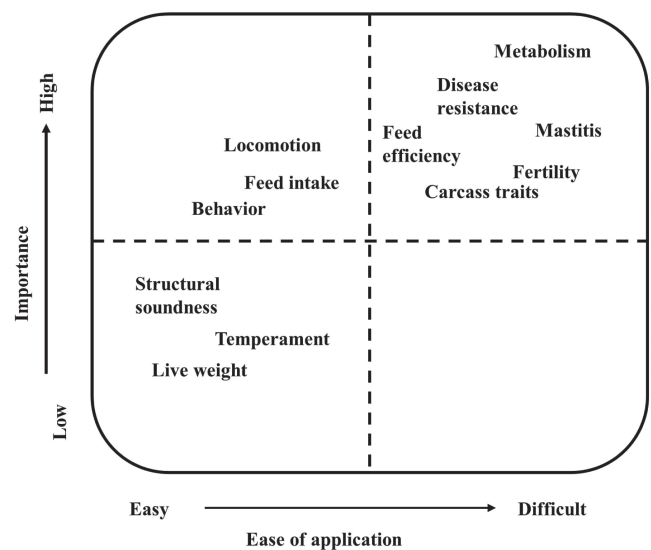


Figure 4. A summary of some traits that would benefit from precision phenotyping in both beef and dairy cattle in South Africa.

Automated, precision phenotyping would also improve animal health and welfare in resource-poor areas by early diagnosing subclinically ill animals, and even preventing antimicrobial resistance (Ramirez et al., 2019). Additionally, it could have a downstream impact on rural economies by creating jobs and sustaining businesses. Unfortunately, even if the technologies were commonly available, several challenges in terms of internet connectivity and signal quality would have to be overcome before this could become a reality.

Opportunities Within the South African Framework

The fourth industrial revolution (4IR) inaugurates a new chapter in human development, where technological advances of the past few decades are harnessed to change and improve the way we live and work (World Economic Forum, 2019). It involves the merging of the physical, digital and biological, and it is set to disrupt the largest global industries. The advent of high speed communication networks, Artificial Intelligence and Machine Learning, combined with a myriad of available sensors, will pave the way for improving the efficiency and productivity of the agricultural sector. These technologies will enable critical information to be available to the farmer in real-time and automation of key farming processes, which will lead to increased efficiency and productivity, while reducing the cost of production. The 4IR will be key in affecting social upliftment and empowerment of small and emerging farmers, enabling sustainable businesses and social change.

Development of real-time intelligent cattle monitoring and behavior modeling systems will enable identification and tracking of individual cattle in the kraal, as well as measuring vital parameters and predicting various future occurrences. For instance, one can measure the activity level, temperature, and weight of an individual animal over time, in order to detect sickness before it exacerbates to the point of death. Weight measurement is especially useful in the developing sector where infrastructure is not available. It could provide insight into the nutritional needs of the livestock, timing of the mating period, the possibility of disease, or internal and external parasites. Temperature measurement would be helpful to detect the onset of estrus, which could help improve the success of artificial insemination and therefore higher production rates and the rate of genetic improvement. Such monitoring systems would typically make use of high definition cameras installed above the kraal to provide a real-time video stream of the cattle. Radio-frequency identification scanners at the gate of the kraal could identify individual animals entering/exiting through the gate. The data extracted and information gathered from this system could be sent to a centralized system, using various wireless communication technologies, from where total farm surveillance would be possible.

Active livestock monitoring and behavior modeling offers a number of opportunities for commercial and especially emerging farmers to monitor the health of their animals, giving them real-time information which can be used to make critical decisions to

About the Authors



Dr Carina Visser obtained her BScAgric (Animal Science) and Masters and PhD degrees in Animal Breeding in the Department of Animal and Wildlife Sciences, University of Pretoria, South Africa. After working for the Department of Agriculture she returned to the University and is currently a senior lecturer. Her research focus is primarily on the molecular-based investigation of small stock, including population genetic studies on local and indigenous breeds and populations. As food security is a burning

issue globally, she also focuses on the genetic improvement of indigenous livestock species, which can contribute to the mitigation of this problem.

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Prof Herman C. Myburgh obtained his Bachelor's in Computer Engineering, Master's in Electronic Engineering and PhD (wireless communication specialization) from the University of Pretoria, South Africa. He has been working at this institution in the Department of Electrical, Electronic, and Computer Engineering since 2009, where he is the head of the Advanced Sensor Networks research group. His current research interests are in wireless communication systems, sensor fusion, machine learning, and mobile health. He is the co-inventor of the hearScreen, hearZA, and hearScope smartphone-based hearing assessment solutions and is a co-founder of the hearX Group (Pty) Ltd company.



Prof Este van Marle-Köster joined the Department of Animal & Wildlife Sciences, University of Pretoria in 1995 as a lecturer after working in the agricultural industry for 7 years. For her PhD research, she applied microsatellite markers for the first South African study on genetic characterization of native fowl. Locally developed

and indigenous breeds used in Southern Africa have been included in her genetic diversity studies and in other projects. Her current research interest is on the application of genomic technology for genetic improvement of livestock with a preference for beef and dairy cattle in South Africa. She has interest in genomics to improve our understanding of the underlying genetic mechanisms governing traits of economic importance and gives priority to traits associated with animal welfare and sustainable production in a South African context.

Allan De Freitas obtained the B.Eng., B.Eng. (Hons), and M.Eng. degrees in Electronic Engineering from the University of Pretoria, South Africa. He received a PhD from the Automatic Control and Systems Engineering Department at the University of Sheffield, UK. He is a senior lecturer in the Department of Electrical, Electronic, and Computer Engineering at the University of Pretoria. His principal scientific interests are in the areas of signal processing and machine learning in object tracking, sensor networks, and complex systems.



help ensure sustainability and improve productivity. This would empower emerging farmers to optimize productivity by providing critical information to the farmer at any given time. Such systems could be extended to any number of farms for large scale surveillance and farming operation optimization.

Evidently, there are a number of problems in need of solving in the cattle farming industry with the potential to greatly increase productivity and empower emerging farmers. The social impact that such a system could have is enormous, especially if it is provided at scale. New and emerging farmers will be able to participate in the agriculture economy, which will have a lasting effect of upliftment and empowerment on their generation and also contribute to the country's agriculture output and its gross domestic product.

Conclusion

The use of automated, objective measurement technologies would assist South African commercial producers to become more efficient and meet market specifications, thus increasing profitability. Choosing objective, relevant phenotypes will enable the construction of comprehensive databases, which will assist in making full use of genomic tools. On the other side of the spectrum, it could assist in improving animal welfare and productivity of small holder farmers, as well as contributing to economic sustainability in rural areas.

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