Available at www.sciencedirect.com

INFORMATION PROCESSING IN AGRICULTURE 4 (2017) 179–187

journal homepage: www.elsevier.com/locate/inpa

Modelling the smart farm

Michael J. O'Grady [a,*], Gregory M.P. O'Hare [b,a]

[a] School of Computer Science, University College Dublin, Belfield, Dublin 4, Ireland
[b] Earth Institute, University College Dublin, Belfield, Dublin 4, Ireland

ARTICLE INFO

Article history:
Received 30 November 2016
Received in revised form
7 April 2017
Accepted 8 May 2017
Available online 17 May 2017

Keywords:
Smart agriculture
Modelling
Sensing
Internet of things

ABSTRACT

Smart farming envisages the harnessing of Information and Communication Technologies as an enabler of more efficient, productive, and profitable farming enterprises. Such technologies do not suffice on their own; rather they must be judiciously combined to deliver meaningful information in near real-time. Decision-support tools incorporating models of disparate farming activities, either on their own or in combination with other models, offer one popular approach; exemplars include GPFARM, APSIM, GRAZPLAN amongst many others. Such models tend to be generic in nature and their adoption by individual farmers is minimal. Smart technologies offer an opportunity to remedy this situation; *farm-specific* models that can reflect near real-time events become tractable using such technologies. Research on the development, and application of farm-specific models is at a very early stage. This paper thus presents an overview of models within the farming enterprise; it then reviews the state-of the art in smart technologies that promise to enable a new generation of enterprise-specific models that will underpin future smart farming enterprises.

Contents

* Corresponding author.
E-mail addresses: michael.j.ogrady@ucd.ie (M.J. O'Grady), gregory.ohare@ucd.ie (G.M.P. O'Hare).
Peer review under responsibility of China Agricultural University.
http://dx.doi.org/10.1016/j.inpa.2017.05.001
2214-3173

1. Introduction

Various initiatives in the domain of smart farming have been documented; examples include SmartAgriFood,[1] the Dutch Smart Dairy Framing project,[2] EU Precision Livestock Farming (EU-PLF),[3] and Cow of the Future.[4] Though particular objectives vary, the overriding objective is that of efficiency. Information and Communication Technologies (ICTs) offers great potential for improving efficiency, effectiveness and productivity; nonetheless, they remain underutilised in agriculture [1]. Small changes in production or efficiency can have a major impact on profitability [2]; from a sustainability perspective, this may, counter-intuitively perhaps, result in a reduction in output. Fundamental to efficiency is the *effective* capture, processing, management and visualisation of many heterogeneous sources of information so as to enable economically-viable and environment-friendly decision-making. Enabling such decision-making is problematic, not only as a consequence of the variety of information available but also due to the dynamic nature of the many variables necessary for strategic planning and optimal decision making.

Ongoing developments in ICT offers significant potential to manage information at the farm level. Sensing technologies, at least in principle, offer farmers the ability to monitor their farms with an unprecedented level of detail, in a multiplicity of dimensions and in near real-time. This offers an intriguing possibility of developing *farm-specific models* that the individual farmer can use to plan their activities in response to changing circumstances, thus enabling the exploration of the various trade-offs inherent in any decision-making process whilst managing the information overload problem. For the remainder of this paper, developments in modelling are explored, and the technologies necessary to enable the construction of farm-specific models considered.

2. Sustainable intensification

Reconciling sustainability with productivity, economic factors, and environmental impact is a formidable challenge; nonetheless, maintaining current agricultural practices will have negative effects on global food production [3]. Three theoretical limits within which agriculture must operate include [4]:

1. quantity of food that can be produced within a given climate;
2. quantity of food demanded by a growing economically changing population, and
3. impact of food production on the environment.

Ultimately, environmental impact depends on how global agriculture expands in response to rising demand [5]. Agricultural intensification has reduced the carbon footprint per agricultural product; this process is expected to continue [6]. Sustainable agriculture seeks to maximize the net benefits that society receives from agricultural production, demanding amongst others, major changes in livestock production practices [7]. Sustainable Intensification, a more recent and fluid construct, seeks to increase food production while minimizing pressure on the environment, and is a specific policy goal for certain institutions [8]. Transition towards more productive livestock production, in combination with other climate policies, for example, represents, potentially, an effective mechanism for delivering desirable climate and food-availability outcomes [9]. Thus, from a practical livestock farming perspective, identification of the most efficient animals and feed systems is a prerequisite for sustainable livestock intensification programs; system modelling is viewed as a key enabling tool [10].

2.1. *Agricultural domain modelling*

Modelling techniques have been harnessed in a wide variety of agricultural domains (Fig. 1); these include high-resolution field maps of soil properties [11], pasture growth rate [12], greenhouse gas emissions [13] amongst others. For animals, basic activity patterns can be quickly derived through the use of GPS-enabled collars [14,15]. More sophisticated models by which to infer behaviour may then be constructed using a variety of machine learning techniques

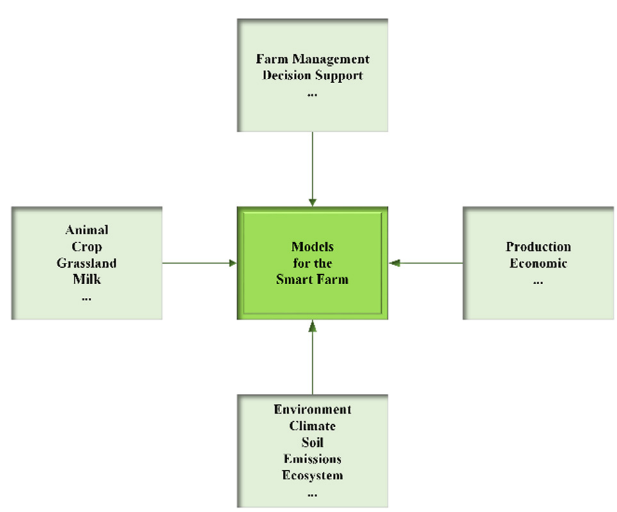

Fig. 1 – Models have been developed for many dimensions of the agricultural enterprise. Incorporating pertinent models whilst managing the trade-offs between complexity and usability is a key challenge for enabling a Smart Farm.

1 http://smartagrifood.com/.
2 http://www.smartdairyfarming.nl/nl/.
3 http://www.eu-plf.eu/.
4 http://www.usdairy.com/sustainability/for-farmers.

Table 1 – Exemplar models for farming enterprises.

Model	Geographic region	Domain
GPFARM (Great Plains Framework for Agricultural Resource Management)	North America	Whole farm
GRAZPLAN	Australia	Grazing enterprises
EcoMod	Australia & New Zealand	Pasture management
APSIM (Agricultural Production Systems sIMulator)	Australia	Crop modelling
NRC (National Research Council)	North America	Nutrition (animal factors)
Norfor (Nordic feed evaluation system)	Scandinavia	Nutrition (animal and feed factors)
TDMI (Total DMI Index)	Finland	Nutrition – Dry Matter Intake (animal and feed factors)
Biopara-Milk	United Kingdom	Impact of feed on rumen pH in dairy cows
Karoline	Scandinavia	Whole dairy cow models for nutrition, milk production, digestion, and CH_4 emissions

[16,17]. Such an approach has also been adopted in the case of feeding behaviour [18]. Multivariate continuous sensing for behaviour and performance monitoring has enabled the construction of models for detecting lameness [19]. In the dairy sector, models have been developed for milk production forecasting [20], predictive feed intake both for Total Mixed Ration (TMR) [21] and for lactating dairy cows [22,23].

3. Models for the individual farm

Research in farm simulation and modelling has evolved since the mid-1990s to cover more than one on-farm enterprise; examples include, GPFARM [24], GRAZPLAN [25], and EcoMod [26] (Table 1). In the case of animal models, several important gaps have been highlighted including the need for a more mechanistic representation of the control of feed intake [27]. Yet despite the benefits that should accrue from harnessing sophisticated simulation models, their efficacy for everyday farm management has proven to be somewhat limited [28]. Reasons for this include, but are not limited to, complexity, lack of time and a concern that there will be no increase in profit relative to the effort expended. When considering the lack of take-up of modelling solutions on the farm, the case of APSIM [29] is probably archetypical. APSIM is a well-established platform and has been extensively documented in the literature; yet it was necessary to simplify it for consultants and farmers, resulting in a product called Yield Prophet R.[5] In practice, farmers tend to expect a ready-made solution. However, models do not lend themselves to this; rather they oblige the farmer, and others, to consider alternate production strategies. This raises issues of model perception, understanding and interaction, while always seeking to eliminate the *black box* effect. As using models may be regarded as an exercise in decision support or as an innovation process, it is necessary that the three main components of such a process in agricultural production systems, namely, biological processes, farm management and advisory services, be facilitated [30].

Though the concept of simulation models in agriculture remains compelling, their uptake nonetheless remains disappointing [31]. Traditionally, models almost invariably focus on one particular sub-domain; this may limit their effectiveness. Feed intake models in particular are most valuable when used in conjunction with other models that predict animal responses in terms of milk yield, body weight change, nutrient use efficiency and gaseous emissions [23].

4. Modelling feed intake

Correlations between animal feed characteristics and intake have been studied for decades. Intake and digestibility have been shown to account for the most variation in the productivity of dairy cows; as such, feed intake models have, and continue to be, the focus of intense research efforts. NRC (National Research Council), Norfor (Nordic Feed Evaluation System), and TDMI (Total DMI Index) are amongst the best known for predicting Dry Matter Intake (DMI) in dairy cows fed via TMR; see [21] for an evaluation of each. Relatively simple models such as NRC that only consider animal characteristics and milk yield can be surprisingly effective when compared to more sophisticated models; however, their potential to incorporate additional factors such as diet characteristics is limited [21]. Low rumen pH has a detrimental effect on dairy cows; it is influenced by diet, amongst other factors. Biopara-Milk, is a whole cow model that simulates digestive processes, predicting performance and circadian pH dynamics [32]. Halachmi et al. [33] have developed a feed intake model for individual cows (it can also be used at a macro/herd level), that incorporates feed behaviour in addition to milk yield and live weight; however, it presupposes the availability of low-cost feeding-behaviour sensors. Clearly it is difficult to effectively and accurately sense feeding behaviour in a manner that is not cost prohibitive and that is tolerant of a demanding sensing context. Comparing models is difficult; Tedeschi et al. [34] have concluded that not all models are suitable for predicting milk production and that simpler systems may be more tolerant of variation. Furthermore, it was concluded that the development of mathematical nutrition models is a prerequisite to correctly estimating the contribution of ruminants to Greenhouse Gas Emissions (GHG) emissions.

4.1. *Reducing methane emissions*

Decreasing methane (CH_4) emissions is necessary both environmentally, as CH_4 has a strong greenhouse gas effect, and nutritionally, as CH_4 represents a loss of feed energy [35]. The EU currently encourages voluntary compliance with

[5] http://www.yieldprophet.com.au/yp/Home.aspx

methane emission levels in the farm sector but moves are afoot to include cattle livestock within the Industrial Emissions Directive (IED). Within the EU there are approximately 90 million cattle and they collectively contribute some 41 percent of EU ammonia emissions and 2 percent of methane emissions. Many factors influence ruminant CH_4 production, including level of intake, diet composition, quality of feeds, energy consumption, animal size, growth rate, level of production, and environmental parameters. Broucek [36] suggests that new approaches for measuring emissions from agriculture are needed so as to establish typical emission ranges for dairy (and beef) farms, and to measure the effect of management factors on these emissions. It should be noted that when dairy cows are fed the same diet at the same intake, variation between cows in CH_4 emissions can be substantial [37]. Efforts at modelling methane production of farms have been undertaken. Karoline is a whole dairy cow mechanistic, dynamic model predicting nutrient supply and milk production; this model has been recently revised in terms of its digestion and CH_4 emissions modules [38,35]. A model that predicts CH_4 emissions from an on-farm database, based on intake, digestibility and NDF, has been proposed in [39]; this model improves the estimation of the methane emission factor from both beef and dairy systems. Grainger and Beauchemin [40] have demonstrated that dietary and farm management options can be implemented to reduce CH_4 emissions from beef and dairy cattle without lowering production.

5. Technology-driven models for the smart farm

A broad spectrum of computational intelligence techniques has been harnessed for model development in agriculture. In the case of cattle behaviour inference, Hidden Markov Models [41], regression trees [42] and Support Vector Machines (SVMs) [43] are some examples. Markov Decision Processes (MDPs) are frequently used for decision support [44]. Machine Learning algorithms have been harnessed for predicting conception success in dairy cows [45]. Models based on fuzzy logic have proven effective in detecting general abnormal situations and giving forewarning of abnormalities [46]. A key difficulty with many approaches to inferring behaviour activities is the need for a training dataset. Mixture models supporting unsupervised learning using probability density functions have demonstrated the viability of real-time and automatic monitoring of behaviour with high spatial and temporal resolution [17]. In the dairy domain, a comparison of modelling techniques for milk production forecasting identified a non-linear auto-regressive model as being more accurate than conventional regression modelling techniques [20]. Though the subject of intense research effort, nonetheless, there remains a need for analytic models that are more accurate, robust, and crucially, more reusable [47].

Feeding, in addition to standing and lying behaviour, is an important indicator of the comfort and psychological status of cows [48]; it has been demonstrated to be an important indicator of the onset of oestrus [49]. Rumination time is a promising predictor of calving [50] and risk of disease in early lactation [51]. Acoustic monitoring [52], jaw movement augmented with sensor data [53], bite counters [54], noseband pressure sensors [55] and electromyography (EMG) [56] have all been demonstrated as potential enablers of feed intake measurement. In housing situations, computer vision-based systems enable the automatic detection of feeding and standing behaviours [57]. A precision feeding system (concentrates) for singular cows, using passive transponders for cow identification and RFID readers, has been developed [58]. Though viable, the cost effectiveness of such a system for the average commercial dairy farm is questionable. Cattle require optimum nutrition and management during their life time, demanding a coordinated approach between all stakeholders. Yet despite considerable research into the management and nutrition of dairy cows, there remains much on-farm variability in its application [59].

5.1. *Sensing for the smart farm*

Animal modelling, machine learning and feed monitoring are invariably underpinned by sensors and sensor networks. Sensing technologies has proven fundamental to precision agriculture since its earliest days, evolving from ground-based sensor deployments for speciality crops, for example, citrus fruit production [60] to UAVs for vineyards [61] to harnessing multi-purpose satellite systems to aid cotton farming [62]. In the case of cattle health, Helwatkar et al. [63] have identified a number of common diseases in dairy cattle that can be identified through the use of non-invasive, cheap sensor technologies. More complex sensor platforms exist; camera systems to detect back posture [64], and ingestible pills for heart rate determination [65] for instance. However, RFID is one of the most generic and popular technologies in multiple agri-food domains, including dairy farms [66]. Both Caja et al. [67] and Rutten et al. [68] have considered the literature in terms of the documented use of sensors for managing the health of dairy herds. Sensors that measure arbitrary aspects of a cow, or summarise sensor data to provide information (e.g., estrus), are predominant. Cases where sensor information is augmented with data from other sources so as to enable decision-making were non-existent; this reinforces observations made by other researchers. Pesonen et al. [69] observed that though there was (and indeed still is) much information available from sensors and as a result of manual record keeping, this information is not used as the time incurred often outweighs the economic benefits.

Sensor networks, particularly Wireless Sensor Networks (WSNs), have been widely deployed in agriculture [70,71] and the food industry [72,73]. Application domains include crop management [74], phenotype measurement [75], rustling prevention [76] and greenhouse management [77]. Wireless Sensor and Actuator Networks (WSANs) are receiving increased attention in domains such as irrigation control [78,79]. Mobile sensing [80], usually realised through drones, is still very much in its infancy. Moosense [81] is a WSN that incorporates both ground-based and animal-mounted sensors that manages multiple animal parameters including ambient environment parameters, and nutrient intake (customised food auger and fluid kiosk). González et al. [14] demonstrated the viability of a heterogeneous WSN to provide data in real-time so as to aid in the understanding of animal behaviour and enable effective herd management.

5.2. Enabling the smart farm

The Smart Farm [82] is predicated on large-scale heterogeneous sensing. Heterogeneous sensors can measure a range of modalities, and be instantiated in practice using platforms from different manufacturers comprising different hardware, protocols and algorithms. Though of great potential, managing heterogeneity is challenging. A common approach is that of middleware which offers sufficient levels of abstractions such that the heterogeneity in its various dimensions can be mitigated and effectively managed [83–85]. SIXTH [86], a distributed, intelligent middleware solution is an exemplar of this genre of sensor network. Global Sensor Network, an open-source sensor middleware, has been demonstrated as an enabler of the smart farm [87]. To ensure interoperability and scalability, standards such as Sensor Web Enablement (SWE),[6] an Open Geospatial Consortium (OGC)[7] initiative, must be adopted; this has been prototyped successfully in multiple domains including precision farming [88]. Such standards must co-exist with pre-existing agricultural standardisation activities including agroXML[8] and ISOAgriNET.[9] Deploying technologies on a farm can be problematic [89]. In the case of a cattle monitoring WSN, specific challenges must be overcome [90]. These include the unforgiving nature of the environment, namely animals in close proximity and, in a rural context, mobility, radio interference caused by the animal itself, data storage limitations and data transmission difficulties. Energy limitations are an omnipresent problem [91] often thwarting network longevity; likewise cost becomes a factor in remote monitoring scenarios [92].

5.3. The Internet of Things (IoTs)

Internet of Things (IoTs) points to the promise of a framework through which diverse data from the farm, including sensor networks, can be captured and managed [93–96]. Likewise, a Web of Things (WoTs) approach has been demonstrated in an experimental smart farm in Australia [97]. Both approaches, IoTs and WoTs, mirror the relationship between the WWW and the Internet within the context of real-world objects.

Developments in the IoTs and WoTs space cannot be treated in isolation from that of the Internet itself. Future Internet (FI) is seen as a mechanism through which a diverse series of systems and services can be seamlessly integrated within an arbitrary domain, including that of agriculture [98]. A prerequisite for such systems will be an ability to:

1. gracefully handle ever-increasing and diverse real-time data streams;
2. handle noisy, incomplete and sometimes contradictory data;
3. capture, correlate and conflate data in real-time;
4. dynamically affect network behaviour to opportunistically alter data capture, data routing or data recording regimes;
5. facilitate orchestrated sensing activity through the ability of individual network nodes to reason, operate and collaborate within a collective, recognising the coexistence of both individual and collective goals. This demands the embracing of distributed intelligence and multi-agent approaches [99–102].

Though IoTs will be an indispensable technology for the smart farm itself, their use in conjunction with FI offers a basis for a new generation of Farm Management Information Systems [103–105] enabling smart farms become active nodes in Business to Business (B2B) solutions and agricultural value chains.

6. Future developments

Though many of the technologies for delivering the smart farm exist, their adoption by individual farmers and agricultural enterprises depends on a number of additional factors. Foremost amongst these are the issues of usability and the identification of best practice; such issues are also common to the adoption of smart technologies in other domains. Both farm and farmer-centric approaches are needed; only in this way will the smart farm concept prove sustainable going forward.

6.1. User centricity

User-centered design envisages the end-user being integral to the design, development and evaluation of innovative technologies. The rational for this is irrefutable; however, ensuring this happens in practice can prove challenging, resulting in products that fail to meet needs, and may even be deficient in terms of usability and functionality. Technologies for the smart farm are not immune to these kind of problems; effective solutions to such problems demands a detailed understanding of farmers' needs, interactions and operational contexts. This difficulty is accentuated when it is considered that technologies fundamental to the smart farm may be regarded as disruptive by the farming community; thus conventional acceptance models, for example the Technology Acceptance Model (TAM) may need revision. Overcoming such perceptions may indeed pose a grand challenge not just for those actively involved in farming, but all stakeholders including agribusiness and government.

Given the indispensable nature of IoTs to the smart farm enterprise, issues of business cases, sustainability and innovation must be considered if acceptance is to be achieved. One approach to this may be that of the Living Lab. Such labs seek to integrate research and innovation processes into real communities, resulting in open, user-centered innovative systems. They are characterised by co-creation, active user involvement, real-life setting, multi-stakeholder participation and multi-method approaches.[10] Uptake in the agri-food

6 http://www.opengeospatial.org/ogc/markets-technologies/swe.

7 http://www.opengeospatial.org.

8 http://www.agroxml.de.

9 http://www.isoagrinet.org.

10 http://www.openlivinglabs.eu/.

domain has been limited to date; however, Wolfert et al. have utilised the construct in the Dutch arable farming sector [106].

6.2. Sustainable Decision-making

A key determinant in motivating the adoption of modelling techniques as an indispensable tool for the management of the smart farm will be the efficacy of the resultant decision-making. It has been suggested that the volume and heterogeneity of the data will demand a cloud-based analytics approach to derive meaningful information [107]. Web 2.0 and cloud computing have been successfully harnessed for livestock management [108]; however, to gain a deeper understanding of the contextual relationships between the diverse elements, an ontological approach is required [109]. This necessitates an open standards-based approach such as that proposed by Chen et al. [110], for example. In so far as the smart farm is viewed as a cyber-physical infrastructure for precision farming, opportunities for autonomous decision-making exist. However, to fully exploit the potential of new technologies, it is necessary to design for Human-in-the-Loop. Many technologies claim to be human-centric; nonetheless, in the case of control and decision making, the human is often regarded as an external element. Reconciling the desire to reduce the burden on the user, in this case the farmer, whilst ensuring the effectiveness of any necessary decision-making present particular challenges. Establishing best practice principles, through the utilisation of individual farms as Living Labs for example, offer one avenue through which these challenges can be addressed going forward.

7. Conclusion

Significant research effort has been expended in the development of models in the broad agricultural domain. Applying models on individual farms has been for the most part sporadic despite the potential advantages that could ensue. Why this is the case may be debated; however, the monolithic nature of many models, lack of business cases for adopting such models, as well as the difficulties that arise for individual farmers in applying such models in practice all contribute. Benefits that could potentially accrue from smart farming are multiple; how these might be realised within the dimensions of productivity, profitability and sustainability remains less than clear. Technologies underpinning smart farms offer an opportunity for enabling the construction and application of *farm-specific models*. This objective is attainable, and offers a radical innovation for farming management practice.

REFERENCES

[1] Milovanovic S. The role and potential of information technology in agricultural improvement. Ekonomika Poljoprivrede 2014;61(2):471.
[2] Bewley JM, Russell RA, Dolecheck KA, Borchers MR. Precision dairy monitoring: what have we learned? In: Halachmi I, editor. Precision livestock farming applications - Making sense of sensors to support farm management. Wageningen: Wageningen Academic Publishers; 2015. p. 13–24.
[3] Liu Y, Pan X, Li J. Current agricultural practices threaten future global food production. J Agric Environ Ethics 2015;28 (2):203–16.
[4] Beddington JR, Asaduzzaman M, Clark ME, Bremauntz AF, Guillou MD, Howlett DJ, et al. What next for agriculture after Durban? Science 2012;335(6066):289–90.
[5] Tilman D, Balzer C, Hill J, Befort BL. Global food demand and the sustainable intensification of agriculture. Proc Natl Acad Sci 2011;108(50):20260–4.
[6] Bennetzen EH, Smith P, Porter JR. Decoupling of greenhouse gas emissions from global agricultural production: 1970–2050. Glob Change Biol 2016;22(2):763–81.
[7] Tilman D, Cassman KG, Matson PA, Naylor R, Polasky S. Agricultural sustainability and intensive production practices. Nature 2002;418(6898):671–7.
[8] Garnett T, Appleby MC, Balmford A, Bateman IJ, Benton TG, Bloomer P, et al. Sustainable intensification in agriculture: premises and policies. Science 2013;341 (6141):33–4.
[9] Havlík P, Valin H, Herrero M, Obersteiner M, Schmid E, Rufino MC, et al. Climate change mitigation through livestock system transitions. Proc Natl Acad Sci 2014;111 (10):3709–14.
[10] Tedeschi LO, Muir JP, Riley DG, Fox DG. The role of ruminant animals in sustainable livestock intensification programs. Int J Sustain Develop World Ecol 2015;22 (5):452–65.
[11] Knadel M, Thomsen A, Schelde K, Greve MH. Soil organic carbon and particle sizes mapping using vis–NIR, EC and temperature mobile sensor platform. Comp Electron Agric 2015;114:134–44.
[12] Rahman MM, Lamb DW, Stanley JN, Trotter MG. Use of proximal sensors to evaluate at the sub-paddock scale a pasture growth-rate model based on light-use efficiency. Crop and Pasture Sci 2014;65(4):400–9.
[13] Salcedo G. DairyCant: a model for the reduction of dairy farm greenhouse gas emissions. Adv Animal Biosci 2015;6 (1):26.
[14] González LA, Bishop-Hurley G, Henry D, Charmley E. Wireless sensor networks to study, monitor and manage cattle in grazing systems. Anim Prod Sci 2014;54 (10):1687–93.
[15] Umemura K. Technical note: monitoring grazing bites and walking activity with pedometers. J Dairy Sci 2013;96 (2):1090–3.
[16] Smith D, Dutta R, Hellicar A, Bishop-Hurley G, Rawnsley R, Henry D, et al. Bag of class posteriors, a new multivariate time series classifier applied to animal behaviour identification. Expert Syst Appl 2015;42(7):3774–84.
[17] González LA, Bishop-Hurley GJ, Handcock RN, Crossman C. Behavioral classification of data from collars containing motion sensors in grazing cattle. Comp Electron Agric 2015;110:91–102.
[18] Bishop-Hurley G, Henry D, Smith D, Dutta R, Hills J, Rawnsley R, et al. An investigation of cow feeding behavior using motion sensors. In: Proc. I2 MTC Proceedings of the 2014 IEEE International Instrumentation and Measurement Technology Conference. Montevideo, Uruguay; 2014. p. 1285-90.
[19] Van Hertem T, Maltz E, Antler A, Romanini CE, Viazzi S, Bahr C, et al. Lameness detection based on multivariate continuous sensing of milk yield, rumination, and neck activity. J Dairy Sci 2013;96(7):4286–98.
[20] Murphy MD, O'Mahony MJ, Shalloo L, French P, Upton J. Comparison of modelling techniques for milk-production forecasting. J Dairy Sci 2014;97(6):3352–63.

[21] Jensen LM, Nielsen NI, Nadeau E, Markussen B, Nørgaard P. Evaluation of five models predicting feed intake by dairy cows fed total mixed rations. Livestock Sci 2015;176:91–103.
[22] Krizsan SJ, Sairanen A, Höjer A, Huhtanen P. Evaluation of different feed intake models for dairy cows. J Dairy Sci 2014;97(4):2387–97.
[23] Zom RL, André G, Van Vuuren AM. Development of a model for the prediction of feed intake by dairy cows: 1. Prediction of feed intake. Livestock Science 2012;143(1):43–57.
[24] Shaffer MJ, Bartling PN, Ascough JC. Object-oriented simulation of integrated whole farms: GPFARM framework. Comp Electron Agric 2000;28(1):29–49.
[25] Moore AD, Donnelly JR, Freer M. GRAZPLAN: decision support systems for Australian grazing enterprises. III. Pasture growth and soil moisture submodels, and the GrassGro DSS. Agric Syst 1997;55(4):535–82.
[26] Johnson IR, Chapman DF, Snow VO, Eckard RJ, Parsons AJ, Lambert MG, et al. DairyMod and EcoMod: biophysical pasture-simulation models for Australia and New Zealand. Anim Prod Sci 2008;48(5):621–31.
[27] Black JL. Brief history and future of animal simulation models for science and application. Anim Prod Sci 2014;54 (12):1883–95.
[28] Sempore AW, Andrieu N, Nacro HB, Sedogo MP, Le Gal PY. Relevancy and role of whole-farm models in supporting smallholder farmers in planning their agricultural season. Environ Modelling Softw 2015;68:147–55.
[29] Holzworth DP, Huth NI, Zurcher EJ, Herrmann NI, McLean G, Chenu K, et al. APSIM–evolution towards a new generation of agricultural systems simulation. Environ Modelling Softw 2014;62:327–50.
[30] Le Gal PY, Dugué P, Faure G, Novak S. How does research address the design of innovative agricultural production systems at the farm level? A Rev Agric Syst 2011;104 (9):714–28.
[31] McCown RL, Carberry PS, Hochman Z, Dalgliesh NP, Foale MA. Re-inventing model-based decision support with Australian dryland farmers. 1. changing intervention concepts during 17 years of action research. crop and pasture. Science 2009;60(11):1017–30.
[32] Ambriz-Vilchis V, Fawcett RH, Shaw DJ, Macrae AI, Jessop NS. Biopara-Milk: a whole cow simulation model for the prediction of rumen pH. In: Halachmi I, editor. Precision livestock farming applications - Making sense of sensors to support farm management. Wageningen: Wageningen Academic Publishers; 2015. p. 299–306.
[33] Halachmi I, Meir YB, Miron J, Maltz E. Feeding behavior improves prediction of dairy cow voluntary feed intake but cannot serve as the sole indicator. Animal 2016;10 (09):1501–6.
[34] Tedeschi LO, Herrero M, Thornton PK. An Overview of Dairy Cattle Models for Predicting Milk Production: Their Evolution, Evaluation, and Application for the Agricultural Model Intercomparison and Improvement Project (AgMIP) for Livestock. Link: <https://cgspace.cgiar.org/rest/bitstreams/40330/retrieve>.
[35] Huhtanen P, Ramin M, Udén P. Nordic dairy cow model Karoline in predicting methane emissions: 1. Model description and sensitivity analysis. Livestock Sci 2015;178:71–80.
[36] Broucek J. Production of methane emissions from ruminant husbandry: a review. J Environ Protection 2014;5 (15):1482.
[37] Bell MJ, Potterton SL, Craigon J, Saunders N, Wilcox RH, Hunter M, et al. Variation in enteric methane emissions among cows on commercial dairy farms. Animal 2014;8 (09):1540–6.
[38] Ramin M, Huhtanen P. Nordic dairy cow model Karoline in predicting methane emissions: 2. Model Eval Livestock Sci 2015;178:81–93.
[39] Jaurena G, Cantet JM, Arroquy JI, Palladino RA, Wawrzkiewicz M, Colombatto D. Prediction of the Ym factor for livestock from on-farm accessible data. Livestock Sci 2015;177:52–62.
[40] Grainger C, Beauchemin KA. Can enteric methane emissions from ruminants be lowered without lowering their production? Anim Feed Sci Technol 2011;166:308–20.
[41] Guo Y, Poulton G, Corke P, Bishop-Hurley GJ, Wark T, Swain DL. Using accelerometer, high sample rate GPS and magnetometer data to develop a cattle movement and behaviour model. Ecol Model 2009;220(17):2068–75.
[42] Ungar ED, Henkin Z, Gutman M, Dolev A, Genizi A, Ganskopp D. Inference of animal activity from GPS collar data on free-ranging cattle. Rangeland Ecol Manag 2005;58 (3):256–66.
[43] Martiskainen P, Järvinen M, Skön JP, Tiirikainen J, Kolehmainen M, Mononen J. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. Appl Anim Behav Sci 2009;119 (1):32–8.
[44] Nielsen LR, Kristensen AR. Markov decision processes to model livestock systems. In: Plà-Aragonés LM, editor. Handbook of operations research in agriculture and the agri-food industry. New York: Springer; 2015. p. 419–54.
[45] Hempstalk K, McParland S, Berry DP. Machine learning algorithms for the prediction of conception success to a given insemination in lactating dairy cows. J Dairy Sci 2015;98(8):5262–73.
[46] Liberati P, Zappavigna P. Improving the automated monitoring of dairy cows by integrating various data acquisition systems. Comp Electron Agric 2009;68(1):62–7.
[47] Dutta R, Smith D, Rawnsley R, Bishop-Hurley G, Hills J, Timms G, et al. Dynamic cattle behavioural classification using supervised ensemble classifiers. Comp Electron Agric 2015;111:18–28.
[48] Bava L, Tamburini A, Penati C, Riva E, Mattachini G, Provolo G, et al. Effects of feeding frequency and environmental conditions on dry matter intake, milk yield and behaviour of dairy cows milked in conventional or automatic milking systems. Italian J Anim Sci 2012;11(3):e42.
[49] Halli K, Koch C, Romberg FJ, Hoy S. Investigations on automatically measured feed intake amount in dairy cows during the oestrus period. Archiv fuer Tierzucht 2015;58 (1):93.
[50] Clark CE, Lyons NA, Millapan L, Talukder S, Cronin GM, Kerrisk KL, et al. Rumination and activity levels as predictors of calving for dairy cows. Animal 2015;9 (04):691–5.
[51] Calamari LU, Soriani N, Panella G, Petrera F, Minuti A, Trevisi ER. Rumination time around calving: an early signal to detect cows at greater risk of disease. J Dairy Sci 2014;97 (6):3635–47.
[52] Andriamandroso A, Lebeau F, Bindelle J. Accurate monitoring of the rumination behaviour of cattle using IMU signals from a mobile device. In: Hopkins A, Collins RP, Fraser MD, King VR, Lloyed DC, Moorby JM, Robson PRH, editors. Grassland Science in Europe. Wales: Gomer Press; 2014. p. 631–4.
[53] Tani Y, Yokota Y, Yayota M, Ohtani S. Automatic recognition and classification of cattle chewing activity by an acoustic monitoring method with a single-axis acceleration sensor. Comp Electron Agric 2013;92:54–65.
[54] Umemura K, Wanaka T, Ueno T. Technical note: estimation of feed intake while grazing using a wireless system requiring no halter. J Dairy Sci 2009;92(3):996–1000.

[55] Braun U, Zürcher S, Hässig M. Eating and rumination activity in 10 cows over 10 days. Res Vet Sci 2015;101:196–8.
[56] Büchel S, Sundrum A. Technical note: evaluation of a new system for measuring feeding behavior of dairy cows. Comp Electron Agric 2014;108:12–6.
[57] Porto SM, Arcidiacono C, Anguzza U, Cascone G. The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. Biosys Eng 2015;133:46–55.
[58] Yan Y, Wang R, Song Z, Yan S. Study on intelligent multi-concentrates feeding system for dairy cow. In: Li D, Zhao C, editors. Int Conf Comp Comput Technol Agric. Beijing: China; 2009. p. 275–82.
[59] Logue DN, Mayne CS. Welfare-positive management and nutrition for the dairy herd: a European perspective. Vet J 2014;199(1):31–8.
[60] Lee WS, Ehsani R. Sensing systems for precision agriculture in Florida. Comp Electron Agric 2015;112:2–9.
[61] Candiago S, Remondino F, De Giglio M, Dubbini M, Gattelli M. Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. Remote Sens 2015;7(4):4026–47.
[62] Huang Y, Thomson SJ. Remote sensing for cotton farming. Cotton 2015;57:439–64.
[63] Helwatkar MA, Riordan D, Walsh J. Sensor technology for animal health monitoring. In: ICST 2014 Proceedings of the 8th International Conference on Sensor Technology. Liverpool, UK. p. 266–71.
[64] Viazzi S, Bahr C, Van Hertem T, Schlageter-Tello A, Romanini CE, Halachmi I, et al. Comparison of a three-dimensional and two-dimensional camera system for automated measurement of back posture in dairy cows. Comp Electron Agric 2014;100:139–47.
[65] Warren S, Martinez A, Sobering T, Andresen D. Electrocardiographic pill for cattle heart rate determination. In: 30th annual international conference of the IEEE engineering in medicine and biology society. BC: Vancouver; 2008. p. 4852–5.
[66] Trevarthen A, Michael K. The RFID-enabled dairy farm: towards total farm management. In: Proc. ICMB'08 Proceedings of the 7th international conference on mobile business. Spain: Barcelona; 2008. p. 241–50.
[67] Caja G, Castro-Costa A, Knight CH. Engineering to support wellbeing of dairy animals. J Dairy Res 2016;83(02):136–47.
[68] Rutten CJ, Velthuis AG, Steeneveld W, Hogeveen H. Invited review: sensors to support health management on dairy farms. J Dairy Sci 2013;96(4):1928–52.
[69] Pesonen L, Sørensen CAG, Nikkilä R, Rydberg A, Green O. Information and communication technology in agriculture. Link: https://www.researchgate.net/publication/252326254_NJF_Seminar_411_Information_and_Communication_Technology_in_Agriculture.
[70] Ojha T, Misra S, Raghuwanshi NS. Wireless sensor networks for agriculture: the state-of-the-art in practice and future challenges. Comp Electron Agric 2015;118:66–84.
[71] Abbasi AZ, Islam N, Shaikh ZA. A review of wireless sensors and networks' applications in agriculture. Comp Standards Interfaces 2014;36(2):263–70.
[72] Wang J, Wang H, He J, Li L, Shen M, Tan X, et al. Wireless sensor network for real-time perishable food supply chain management. Comp Electron Agric 2015;110:196–207.
[73] Ruiz-Garcia L, Lunadei L, Barreiro P, Robla I. A review of wireless sensor technologies and applications in agriculture and food industry: state of the art and current trends. Sensors 2009;9(6):4728–50.
[74] Juul JP, Green O, Jacobsen RH. Deployment of wireless sensor networks in crop storages. Wireless Pers Commun 2015;81(4):1437–54.
[75] Greenwood PL, Valencia P, Overs L, Paull DR, Purvis IW. New ways of measuring intake, efficiency and behaviour of grazing livestock. Anim Prod Sci 2014;54(10):1796–804.
[76] Nkwari PK, Rimer S, Paul BS. Cattle monitoring system using wireless sensor network in order to prevent cattle rustling. In: Proceedings of the IST-Africa Conference and Exhibition. Mauritius. p. 1–10.
[77] Srbinovska M, Gavrovski C, Dimcev V, Krkoleva A, Borozan V. Environmental parameters monitoring in precision agriculture using wireless sensor networks. J Cleaner Prod 2015;88:297–307.
[78] Nikolidakis SA, Kandris D, Vergados DD, Douligeris C. Energy efficient automated control of irrigation in agriculture by using wireless sensor networks. Comp Electron Agric 2015;113:154–63.
[79] Chikankar PB, Mehetre D, Das S. An automatic irrigation system using zigbee in wireless sensor network. In: Proc. ICPC Proceedings of the 2015 International Conference on Pervasive Computing (ICPC)Maharashtra, India. p. 1–5.
[80] Zecha CW, Link J, Claupein W. Mobile sensor platforms: categorisation and research applications in precision farming. J Sens Sens Syst 2013;2(1):51–72.
[81] Sarangi S, Bisht A, Rao V, Kar S, Mohanty TK, Ruhil AP. Development of a wireless sensor network for animal management: experiences with Moosense. In: Proc. ANTS proceedings of the 2014 IEEE International Conference on Advanced Networks and Telecommunications Systems. New Delhi, India. p. 1–6.
[82] Wark T, Corke P, Sikka P, Klingbeil L, Guo Y, Crossman C, et al. Transforming agriculture through pervasive wireless sensor networks. IEEE Pervasive Comput 2007;6(2):50–7.
[83] Bhuyan B, Sarma HK, Sarma N. A survey on middleware for wireless sensor networks. J Wireless Network Commun 2014;4(1):7–17.
[84] Lee J, Park GL, Kang MJ, Kwak HY, Lee SJ, Han J. Middleware integration for ubiquitous sensor networks in agriculture. In: Proc. ICCSA'12 Proceedings of the 12th international conference on Computational Science and Its Applications - Volume Part III. Salvador de Bahia, Brazil. p. 217–22.
[85] Wang MM, Cao JN, Li J, Dasi SK. Middleware for wireless sensor networks: A survey. J Comp Sci Technol 2008;23(3):305–26.
[86] O'Hare GMP, Muldoon C, O'Grady MJ, Collier RW, Murdoch O, Carr D. Sensor web interaction. Int J Artif Intell Tools 2012;21(02):1240006.
[87] Gaire R, Lefort L, Compton M, Falzon G, Lamb D, Taylor K. Demonstration: Semantic web enabled smart farm with GSN. Link: http://ceur-ws.org/Vol-1035/iswc2013_demo_11.pdf..
[88] Geipel J, Jackenkroll M, Weis M, Claupein W. A sensor web-enabled infrastructure for precision farming. ISPRS Int J Geo-Inf 2015;4(1):385–99.
[89] Banhazi T, Vranken E, Berckmans D, Rooijakkers L, Berckmans D. Word of caution for technology providers; practical problems associated with large scale deployment of PLF-technologies on commercial farms. In: Halachmi I, editor. Making sense of sensors to support farm management. Wageningen: Wageningen Academic Publishers; 2015. p. 2–10.
[90] Kwong KH, Wu TT, Goh HG, Sasloglou K, Stephen B, Glover I, et al. Practical considerations for wireless sensor networks in cattle monitoring applications. Comp Electron Agric 2012;81:33–44.
[91] Anisi MH, Abdul-Salaam G, Abdullah AH. A survey of wireless sensor network approaches and their energy consumption for monitoring farm fields in precision agriculture. Precision Agric 2015;16(2):216–38.

[92] Xu X, Liang W, Xu Z. Remote monitoring cost minimization for an unreliable sensor network with guaranteed network throughput. Inf Proc Agric 2014;1(2):83–94.
[93] Jayaraman PP, Palmer D, Zaslavsky A, Salehi A, Georgakopoulos D. Addressing information processing needs of digital agriculture with OpenIoT platform. In: Podnar Žarko I, Pripužić K, Serrano M, editors. Proceedings of the International Workshop, FP7 OpenIoT Project, Held in Conjunction with SoftCOM. Split: Croatia; 2015. p. 137–52.
[94] Ma J, Zhou X, Li S, Li Z. Connecting agriculture to the internet of things through sensor networks. In: Proc. iThings/CPSCom Proceedings of the 2011 International Conference on Internet of Things and 4th International Conference on Cyber, Physical and Social Computing. Dalian, China. p. 84–7.
[95] Yan-e D. Design of intelligent agriculture management information system based on IoT. In: Proc. ICICTA Proceedings of the 4th International Conference on Intelligent Computation Technology and Automation. Shenzhen, China. p. 1045–9.
[96] Ilapakurti A, Vuppalapati C. Building an IoT framework for connected dairy. In: Proc. BigDataService 2015 Proceedings of the First International Conference on Big Data Computing Service and Applications.San Francisco, USA. p. 275–85.
[97] Taylor K, Griffith C, Lefort L, Gaire R, Compton M, Wark T, et al. Farming the web of things. IEEE Intell Syst 2013;28 (6):12–9.
[98] Lehmann RJ, Reiche R, Schiefer G. Future internet and the agri-food sector: State-of-the-art in literature and research. Comp Electron Agric 2012;89:158–74.
[99] Tynan R, O'Hare GMP, Marsh D, O'Kane D. Interpolation for wireless sensor network coverage. In: Proc. EmNetS-II Proceedings of the Second IEEE Workshop on Embedded Networked Sensors.Sydney, Australia. p. 123–31.
[100] Tynan R, Marsh D, O'Kane D, O'Hare, GMP. Intelligent agents for wireless sensor networks. In: Proc. AAMAS'05 Proceedings of the fourth international joint conference on autonomous agents and multiagent systems. Utrecht, The Netherlands. p. 1179–80.
[101] Muldoon C, O'Hare GMP, O'Grady MJ, Tynan R. Agent migration and communication in WSNs. In: Proceedings of the Ninth International Conference on Parallel and Distributed Computing, Applications and Technologies. Dunedin, New Zealand. p. 425–30.
[102] Marsh D, Tynan R, O'Kane D, O'Hare GMP. Autonomic wireless sensor networks. Eng Appl Artif Intell 2004;17 (7):741–8.
[103] Barmpounakis S, Kaloxylos A, Groumas A, Katsikas L, Sarris V, Dimtsa K, et al. Management and control applications in Agriculture domain via a future internet business-to-business platform. Inf Proc Agric 2015;2(1):51–63.
[104] Fountas S, Carli G, Sørensen CG, Tsiropoulos Z, Cavalaris C, Vatsanidou A, et al. Farm management information systems: Current situation and future perspectives. Comp Electron Agric 2015;115:40–50.
[105] Kaloxylos A, Eigenmann R, Teye F, Politopoulou Z, Wolfert S, Shrank C, et al. Farm management systems and the Future Internet era. Comp Electron Agric 2012;89:130–44.
[106] Wolfert J, Verdouw CN, Verloop CM, Beulens AJ. Organizing information integration in agri-food—A method based on a service-oriented architecture and living lab approach. Comp Electron Agric 2010;70(2):389–405.
[107] Waga D, Rabah K. Environmental conditions' big data management and cloud computing analytics for sustainable agriculture. World J Comp Appl Technol 2014;2(3):73–81.
[108] Teng CC, Brown K, Caro C, Nielsen W, Wells J. A service oriented livestock management system using occasionally connected mobile-cloud architecture. In: Proc. SysCon 2012 Proceedings of the 2012 IEEE International Systems Conference. Vancouver, Canada. p. 1–5.
[109] Sivamani S, Park J, Shin C, Cho K, Park D, Cho Y. Towards an intelligent livestock farm management using OWL-based ontology model. Int J Smart Home 2015;9(4):251–66.
[110] Chen N, Zhang X, Wang C. Integrated open geospatial web service enabled cyber-physical information infrastructure for precision agriculture monitoring. Comp Electron Agric 2015;111:78–91.