SMARTER FARMING: NEW APPROACHES FOR IMPROVED MONITORING, MEASUREMENT AND MANAGEMENT OF AGRICULTURAL PRODUCTION AND FARMING SYSTEMS

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EDITORIAL
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Editorial: Smarter Farming: New Approaches for Improved Monitoring, Measurement and Management of Agricultural Production and Farming Systems

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Editorial on the Research Topic

Smarter Farming: New Approaches for Improved Monitoring, Measurement and Management of Agricultural Production and Farming Systems

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There is considerable interest and investment in the information that can be derived from new technologies and data to support enhanced monitoring, measurement and management of farming systems for more sustainable food production. At the farm level, information on aspects associated with animals, plants, soil, water, and the farm environment must be in a useful format to enhance management. For example, identifying changes to improve production efficiency (increased outputs and reduced inputs) and profitability of food products is of great interest to farmers, and also has the ability to confer efficiency savings by potentially reducing the environmental impact of production. Nutrient losses from agricultural land negatively impact water and air quality. The papers of Comber et al., McNunn et al. and Preza Fontes et al. discussed tools for enhanced land management to assist with managing nutrient losses from agricultural land. Agriculture is a significant source of water and air pollution. In addition to the environmental benefits of improved nutrient management, the efficacy of any agricultural application is severely reduced if poorly timed and it washes from the crop or the field into watercourses. This reduced efficacy leads to risks of reduced output (i.e., crop yields) and increased input costs (i.e., sprays and fertilizer). McNunn et al. suggest that managing cropping systems for the economic optimum will likely lead to improved environmental outcomes when modeling nitrogen losses from cropping systems. Preza Fontes et al. showed that remote sensing vegetation indices were correlated with nitrous oxide emissions, indicating that new technologies (e.g., unmanned aerial vehicle platform) could represent an integrative tool for linking sustainability outcomes with improved agronomic efficiencies; with lower vegetation index values associated with poor crop performance and higher nitrous oxide emissions. The authors also discovered that the use of an unmanned aerial vehicle to evaluate water quality was limited due to the timing of nutrient losses, which happened prior to early-season crop growth and image collection. Comber et al. provided a modeling framework that can be used to identify hotspots within fields and watercourses, with the aim of supporting informed on-the-ground catchment management by environmental agencies and water companies. Tools that can enhance productivity and reduce environmental impact are of great importance to policy makers and wider society.

Information and data from real-time and automated systems can also help early detection and improve awareness of poor performance, thereby allowing farmers to make timely and informed interventions and changes in practice to enhance the efficiency and sustainability of production. As financial pressures on farmers increase, each farm worker will be expected to allocate their time effectively and toward the tasks that need their attention most. However, the potential usefulness of new technologies, their integration into decision support tools and how such systems may complement other or existing information for food production is still being understood. Bell and Tzimiropoulos discussed how production efficiencies associated with resource utilization and monitoring of animal traits have reduced the environmental impact of cattle systems. Papers of Bell et al. and Miller et al. demonstrate promising imaging technologies to estimate dairy cow body condition (particularly identify low or high body fat) and beef cattle liveweight and carcass characteristics, respectively. Camera monitoring systems have the benefit of providing objective information and not relying on human intervention, transponder attachments, or invasive equipment (e.g., boluses, collars). This can be particularly important for the accuracy of body condition scoring, with digital imaging providing more accuracy compared to manual and subjective scoring methods in cows with a low body condition (Bell et al.). Images can provide lots of opportunities for information (e.g., animal and plant health) at a relatively low cost. Combining tools and sources of digital information may ultimately provide more complete and enhanced monitoring systems for farm use, such as developments in pasture cover (using mobile measures of plant biomass) and pasture nutrient concentrations (using mobile near-infrared spectroscopy) measured in real-time as shown in the paper of Bell et al. Changes in pasture nutrients are typically not monitored but doing so may help land managers improve how effectively they manage forage, which is an important source of nutrients for ruminant livestock and biodiversity in our rural landscape.

While it is acknowledged that there are increasing opportunities to use smart farming technologies and data-driven decision making for improved management of food production systems, the papers of Ingram and Maye, and Eastwood and Renwick, highlighted that we need to better understand the wider issues affecting a farmer's uptake of such smart farming technology and information. Ingram and Maye discussed the "fourth agricultural revolution" of digital agriculture and the implications of digitalization for agricultural knowledge. Digital applications and platforms have the potential to dramatically change the way knowledge is processed, communicated, accessed and utilized as farming processes become increasingly data-driven and data-enabled. The authors proposed that this raises critical questions about how digital agriculture will require new capabilities, support decision-making and interact with, and potentially disrupt, established modes of knowledge processing between people and organizations in these multi-actor knowledge networks i.e., Agricultural Knowledge Innovation Systems. An understanding of the implications of new digital information are important for effective implementation, from support for farmers to data analytics and the linkages between actors. Eastwood and Renwick investigated the impact of innovation uncertainty on adoption of automatic milking systems (AMS) and showed that minimizing the uncertainty around the innovation can influence its success. Eastwood and Renwick highlighted the potential impact of negative experiences associated with new technologies from farmers who struggle with the adaptation process, as such occurrences may act to stall the uptake of smart farming technologies. The authors propose that if public policy organizations are to realize the desired impacts of smart farming technology, there needs to be greater focus on understanding where (and which) technologies can have an actual impact on farm, and greater public and private R&D collaboration is required to foster knowledge development and exchange.

AUTHOR CONTRIBUTIONS

MB wrote the editorial. AC assisted with editing. Both authors contributed to the article and approved the submitted version.

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REVIEW
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Novel Monitoring Systems to Obtain Dairy Cattle Phenotypes Associated With Sustainable Production

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Improvements in production efficiencies and profitability of products from cattle are of great interest to farmers. Furthermore, improvements in production efficiencies associated with feed utilization and fitness traits have also been shown to reduce the environmental impact of cattle systems, which is of great importance to society. The aim of this paper was to discuss selected novel monitoring systems to measure dairy cattle phenotypic traits that are considered to bring more sustainable production with increased productivity and reduced environmental impact through reduced greenhouse gas emissions. With resource constraints and high or fluctuating commodity prices the agricultural industry has seen a growing need by producers for efficiency savings (and innovation) to reduce waste and costs associated with production. New data obtained using fast, in some cases real-time, and affordable objective measures are becoming more readily available to aid farm level monitoring, awareness, and decision making. These objective measures may additionally provide an accurate and repeatable method for improving animal health and welfare, and phenotypes for selecting animals. Such new data sources include image analysis and further data-driven technologies (e.g., infrared spectra, gas analysis), which bring non-invasive methods to obtain animal phenotypes (e.g., enteric methane, feed utilization, health, fertility, and behavioral traits) on commercial farms; this information may have been costly or not possible to obtain previously. Productivity and efficiency gains often move largely in parallel and thus bringing more sustainable systems.

Keywords: cattle, phenotypes, technology, objective assessment, sustainability

INTRODUCTION

New systems that provide automated and real-time information to monitor cattle are being adopted to make meat and milk production more sustainable due to economic, social, and environmental pressures. Changes that improve production efficiencies and profitability of products from cattle are of great interest to farmers, with the added benefit of efficiency savings helping to reduce the environmental impact of production (Bell et al., 2011), which has social importance e.g., air and water quality (Gunton et al., 2016). Increasing animal welfare standards, better quality of life for farm workers, enhanced traceability, and consumer confidence in livestock production are all important social considerations that new technologies can help address for high and low input systems. New tools, technology, and information can provide continuous and repeatable methods for monitoring individual animals, rather than just groups of animals, which may also improve farmer awareness, be used for farm assurance schemes and provide a reliable phenotype measurement for selecting animals. Early detection and awareness of poor health, fertility, and animal welfare will allow farmers to make informed decisions and changes.

The livestock industry has made large improvements to efficiencies over the past 60 years because of changes in breeding, nutrition, and management. However, inefficiencies still exist, for example in dairy cows genetic selection has historically favored production (e.g., milk) rather than fitness traits (e.g., fertility, lameness, mastitis) and ultimately impacting on survival (Pryce et al., 1999; Dillon et al., 2006). Cows bred for high yields are known to mobilize body fat for production in early lactation as they cannot consume enough food to meet the rapid increase in energy demands caused by the onset of lactation, resulting in negative energy balance. While a dilution in animal maintenance requirements with increased average milk yields per cow has reduced greenhouse gas emissions per unit milk (Bell et al., 2011), there is little evidence that improvements in health (e.g., lameness and mastitis) and fertility have been made during the same period (FAWC, 2009); therefore, there is potential to enhance health, fertility, and welfare leading to reduced resource use, input costs, and emissions intensity of production.

Increasing standards for health and welfare of livestock has led to considerable research activity into ways to monitor and measure a wide range of traits (e.g., associated with fertility, legs/feet, metabolism, udder, birth, feeding, behavior, milk composition, body composition) that can be used for management and genetic selection purposes, as well as parameters of public interest (Eggar-Danner et al., 2015). Bell and Wilson (2018) found that regional differences in longevity of cows exists within UK dairy herds, with cows having a shorter life (averaging 2.6 lactations) in the region with the highest milk yields and longest interval between calvings (associated with poor fertility), compared to other regions studied (about 2.8 lactations on average) with lower milk yields and calving intervals; the average number of lactations across the UK was still below three lactations when cows are expected to reach their mature and optimum level of productivity. Ultimately maintaining healthy animals will enhance production, particularly later in life from increased lifetime performance (Bell et al., 2015). Therefore, management and breeding policies should be directed toward not only increasing production but decreasing the causes of involuntary culling (fertility, lameness, and udder health) (Bell et al., 2010). Survival within a herd influences the number of replacement animals needed, which in turn influences the productivity and profitability of the herd, as at a high replacement rate the costs are high but at too low a rate the production, reproduction, or genetic improvement of the herd may be impaired (Hadley et al., 2006). In dairy cows, several countries around the world (France, Italy, Germany, Switzerland, Belgium, Australia, United States, UK, Nordic countries, Ireland, The Netherlands) now give fitness traits more emphasis and weighting in their total economic merit index for ranking cattle for genetic selection purposes (Eggar-Danner et al., 2015) and less weighting than other countries toward milk production traits (milk, fat, and protein yield) at <50% weighting in the index with The Netherlands being the lowest at about 25% weighting on production traits. Therefore, with more weighting given to fitness traits rather than production traits, the health, and fertility of animals is expected to improve in the future. Although heritabilities of fitness traits in cattle can be low compared to production traits, the large coefficient of genetic variation for traits such as mastitis (33%) and lameness (45%) suggests there is considerable potential for breeding (Pritchard et al., 2012) with the effect being permanent and cumulative. Pritchard et al. (2012) found the coefficient of genetic variation to range from 11 to 13% for moderately heritable milk production traits, but to be as little as 3% for calving interval (an indicator of fertility).

As financial pressures on farmers increases (Defra, 2018), each stockperson will be expected to look after more animals. Tools that can assist farmers in monitoring individual animals or groups will be beneficial to the animal and farmer. Enhanced monitoring tools will enable available farm labor to be targeted toward those animals that need it. For example, management at calving plays an important role in the subsequent health and reproductive performance of cattle during their lifetime (Bell and Roberts, 2007). A difficult birth can lead to tissue damage and introduce infectious microorganisms into the uterus leading to a uterine infection (Lewis, 1997; Kim and Kang, 2003). The development of precision monitoring of individual animals that are non-invasive, automated, and produce results in real-time, such as digital image applications and online measurements, are becoming more available as "machine learning" technologies develop and the cost of implementation on farms reduces. Such technologies have the potential to allow welfare and health issues to be detected quickly for more animals compared to more manual methods currently used, thus improving animal health and welfare outcomes. More intensively monitored production systems can provide data to capture a large number of phenotypic measures to manage animals and their environment (e.g., climate, plant, soil) (**Figure 1**). The data can potentially be combined to create monitoring systems that describe animal "wellbeing" or identify abnormal patterns by linking production (e.g., live weight, body composition change, growth rate, milk yield, and composition), fitness or functional (e.g., fertility, lameness, survival, conformation), and behavior (e.g., activity) data. The challenge to society, scientists, and farmers is to improve efficiency of food production by better matching available and appropriate resources to requirements, to optimize profit, production, and minimize pollution (from waste).

The objective of this paper was to discuss selected novel monitoring systems to measure phenotypic traits associated with dairy cows that are considered to bring more sustainable production with increased productivity and reduced environmental impact through reduced greenhouse gas emissions. Bell et al. (2018) identified the phenotypic traits of feed utilization, enteric methane emissions, body condition, health, fertility, and overall survival of dairy cows as important traits for more sustainable production on commercial farms. Novel objective ways to monitor these traits was the focus of this review.

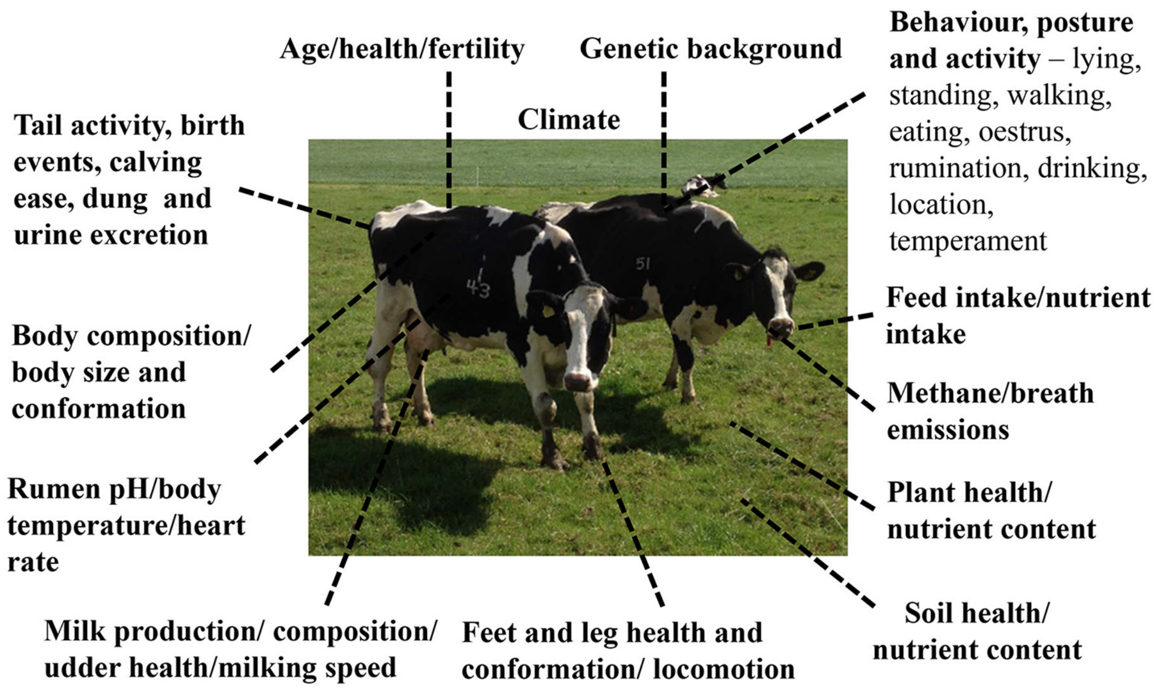

FIGURE 1 | Data sources used to monitor and manage cows and their environment.

PRODUCTION TRAITS

Feed Utilization

With resource constraints and high or fluctuating commodity prices the agricultural industry has seen a growing need by producers to make savings in inputs costs (i.e., feed, health, and fertility). Feed inputs can account for 70% of variable input costs associated with cattle enterprises (Redman, 2015), and with feed intake being high and positively correlated with animal enteric methane emissions (Bell and Eckard, 2012), there has been considerable interest in phenotypic measurements of feed intake (Berry and Crowley, 2013; Pryce et al., 2014) and enteric methane emissions on commercial farms. Improvement in feed efficiency in non-ruminant livestock systems has been remarkable, for example, in broiler chickens the meat produced per ton of feed has nearly doubled from 85 kg/t in the 1960 s to 170 kg/t in 2005 (van der Steen et al., 2005). Optimizing the utilization of available food and its quality is important to the profitability of any production system, as well as helping to minimize the proportion of nutrients consumed by the animal that are lost to the environment. In cattle, about 35% of energy consumed in the diet can be lost in the form of enteric methane, feces, or urine and 77% of nitrogen consumed can be excreted in feces or urine (Bell et al., 2015). Measuring feed intake or feed utilization efficiency (such as residual feed intake, which is the difference between an animal's actual feed intake and its expected feed intake based on its size and growth over a defined period) for a large number of cattle is more costly than for pigs or poultry, due to the equipment needed to measure intakes of a mixed ration. Nieuwhof et al. (1992) found that feed efficiency in growing animals was correlated with feed efficiency in mature breeding and lactating animals, which is important when measuring feed efficiency as younger animals have lower feed intakes and feed consumed is largely used for maintenance and growth.

When formulating a diet to be fed to livestock, the conventional approach is to determine the least-cost ration depending on the estimated nutrient requirement of the average animal in the group based on infrequent determination of diet nutrient concentrations. This means that some animals will be underfed, and others overfed. Typically nutrient concentrations, delivered via concentrate feeds, in the diet are held constant and dependent on how often the feed is analyzed, for example frequency of forage analysis. In reality, considerable temporal variation can exist in quality of feed ingredients and diets, and among animals, and more precise determination of nutrient availability delivered at the level of the individual animal offers considerable productive, financial, and environmental benefits. Specifically, the overall benefits of more precise allocation of nutrients to animals would be to (1) improve production system sustainability by increasing feed utilization efficiency, (2) improve performance of individual animals and the herd, and (3) reduce the environmental impact of food production through less nutrient waste. Near-infrared reflectance (NIR) spectroscopy has been shown to provide a fast and reliable analytical method for analyzing feed and products of digestion (Decruyenaere et al., 2009). Such an approach could provide not only real-time nutrient concentrations in feed and excreta but a prediction of feed intake for housed and grazing animals. Furthermore, poor quality food can impair the production and wellbeing of the animal which leads to an inability to achieve desired intakes of food, therefore resulting in increased land required and reduced nutrient efficiency. Improved utilization of feed by one kilogram per year over a dairy cow's lifetime would amount to about £324,000 in increased profit to the dairy industry per year (assuming a population of 1.8 million cows in the UK), together with a potential reduction of 1.3 kg carbon dioxide equivalent emissions produced per cow per year (Bell et al., 2015).

Enteric Methane Emissions

The emissions of enteric methane from ruminant animals follow a diurnal pattern (Crompton et al., 2011; Manafiazar et al., 2017; Bell et al., 2018), with a peak in emissions after feeding followed by a decline until the next consumption of feed. The diurnal pattern is affected by feed allowance and feeding frequency (Crompton et al., 2011), and does not appear to change over time or with a change in diet (Bell et al., 2018). Historically most studies assessing methane emissions from cattle have been done using respiration chambers (Ellis et al., 2007; Yan et al., 2009, 2010), which is impractical for large-scale estimation of methane emissions by individual animals on commercial farms. Approaches to measure enteric methane emissions from individual dairy and beef cattle on commercial farms are being developed (Garnsworthy et al., 2012a,b; Lassen et al., 2012; Manafiazar et al., 2017) due to the availability of more portable gas analysis equipment and the considerable interest in the possibility of identifying high and low methane emitters for benchmarking farms, improving national emissions inventories and/or genetic selection. The frequent "spot" sampling of breath methane emissions when an animal is at a feed bin can provide repeated measurements to allow assessment of between-cow, within-cow, diet, and temporal effects on emissions when sampled over several days. The duration of sampling needed to assess variation among individual animals is dependent on the frequency of spot measurements and visits to the sampling location (Cottle et al., 2015). Garnsworthy et al. (2012a), showed that estimates of methane made during milking were correlated with total daily methane emissions by the same cows when housed subsequently in respiration chambers. Quantifying enteric methane emissions from peaks in concentration whilst feeding (**Figure 2**) has been demonstrated to provide repeatable phenotypic estimates of emissions (Garnsworthy et al., 2012a,b; Lassen et al., 2012).

As with NIR spectra for feed analysis, mid-infrared reflectance (MIR) spectra have gained considerable interest for identifying biomarkers in milk. Standard milk components such as fat, protein, urea, and lactose contents are routinely obtained using MIR spectroscopy. However, the potential exists for a wide range of biomarkers to be monitored using the technique (e.g., fatty acids, lactoferrin, minerals, acetone, and β-hydroxybutyrate) (Gengler et al., 2016). The calibration process for MIR spectra estimates the amount of biomarker based on specific data points within the spectra (**Figure 3**) (Vanlierde et al., 2016). The use of MIR spectra to estimate methane emissions is based on the relationship between changes in rumen fermentation and milk composition. As methane synthesis increases with an increase in the ratio of butyrate to propionate in the rumen, such as with increased forage intake in the diet, this causes a decrease in milk lactose content and an increase in fat content (Miettinen and Huhtanen, 1996). Machine learning on large datasets such as spectral data, accelerometer, or breath sampling can process, refine, or classify, and generate predictions from raw analytical data based on predetermined algorithms to create meaningful outputs for real-time decision making.

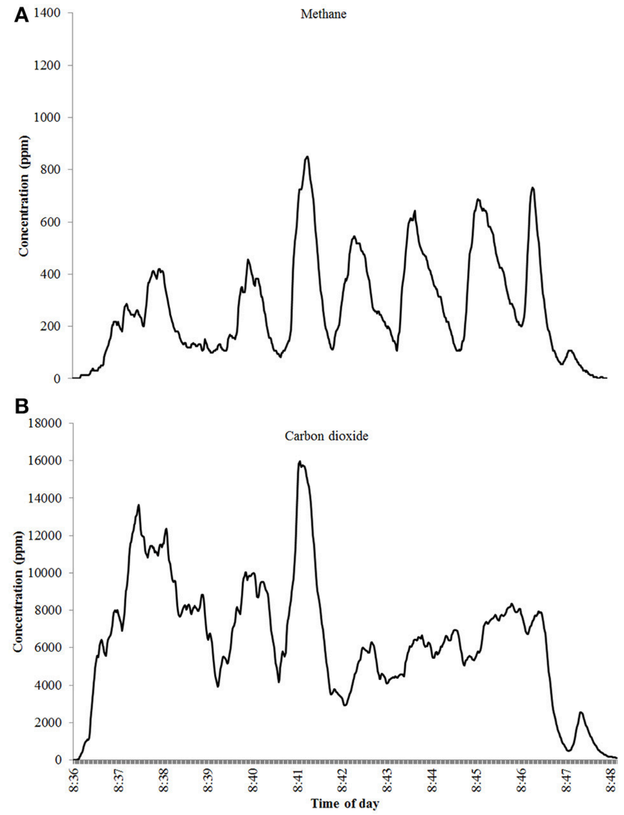

FIGURE 2 | Concentration in parts per million of **(A)** methane and **(B)** carbon dioxide during a single milking showing peaks in breath (Bell et al., 2014).

Body Condition

Body condition scoring has traditionally been done by manual scoring of the amount of body fat reserves associated with a live animal at a given time. The scoring method provided a simiple means for farmers to manually assess the body fat of animals rather than rely on more specialized ultrasound equipment to more accurately measure body fat. This is a subjective scoring measure with potential differences in human interpretation leading to reduced reliability and repeatability. Body condition is scored using a variety of scales and approaches (Bewley et al., 2008a), but typically on a scale of extremely thin (1) to very fat (5 or 9 depending on scale adopted) in quarter intervals. The measure gained prominance as a means of monitoring changes in body fat reserves, which can alter depending on the animal's stage of production (e.g., at calving, conception, and when dried off). Also, in dairy cows, low fat levels and the mobilizing of body fat reserves for milk production has been found to have a deleterious effect on the health and fertility of the cow (Pryce et al., 1999) and lifespan. Modern high milk yielding dairy cows have a high

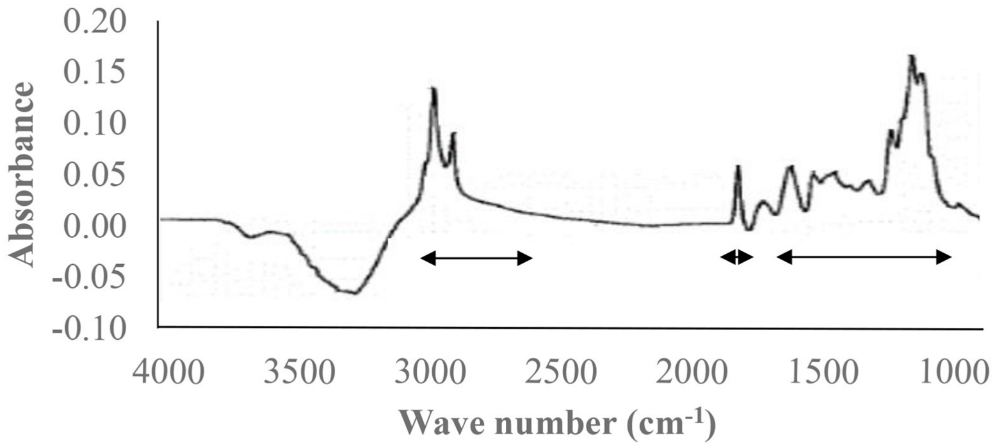

FIGURE 3 | Mid-infrared spectra for milk (Sivakesava and Irudayaraj, 2002) with arrows indicating the three regions of the spectra for estimating enteric methane emissions.

genetic potential for mobilizing body energy reserves for milk. Automated image analysis can be used to objectively assess the body condition (e.g., fat depth) of individual animals in real-time (Bewley et al., 2008b; Halachmi et al., 2008; Azzaro et al., 2011).

FITNESS TRAITS

New technologies are developing that provide new ways to measure fitness traits associated with farmed animals (Day, 2005; Berckmans, 2008; Wathes et al., 2008). A number of sensor technologies (Wathes et al., 2008; Neethirajan, 2017) that can be used on animals exist such as accelerometers, GPS, rumen boluses, and temperature sensors. Other technologies are emerging such as image analysis and online data sources such as spectral data. These technologies benefit from not relying on human intervention, transponder attachments, or invasive equipment (e.g., boluses, collars), and may provide more information compared to other monitoring systems at a relatively low cost. Also, some existing movement or activity sensors, such as accelerometers, are calibrated using video image material. Accelerometers provide information on both body posture (standing, lying, walking) and activity, which are used as descriptors to define behaviors, which can now also be done using live video footage. Accelerometers have provided a useful tool to help farmers to identify estrus activity in cows (Wathes et al., 2008). Data can be acquired from animals when they visit a common location such as milking station, feed, and/or water trough. A disadvantage of video image monitoring is that it is more suited to housed animal environments. Such phenotypes of interest include breath concentrations of biomarkers such as methane (energy lost from rumen fermentation) and carbon dioxide (energy lost by respiration) gas mentioned above (Bell et al., 2014), milk (Gengler et al., 2016), conformation or locomotion (Stock et al., 2017), and behavior recognition (Cangar et al., 2008) systems which filter large amounts of data to produce real-time results. Not only is milk composition affected by the genetic background of cows (e.g., breed), but also the diet they are fed, their health, and environment—therefore providing a means to monitor the status of the animal and potentially subclinical cases such as udder health.

Animal Health and Welfare

The annual cost of common health and welfare challenges in the dairy industry is considerable. With rapid developments in camera surveillance technology, machine learning and processing, and computer vision techniques, new objective methods to monitor animals are possible that can help improve early detection of health, fertility, and welfare problems. The combination of sensors i.e., images with transponder technologies, may ultimately provide a more "complete" approach to monitoring animal wellbeing but further research is needed to determine this. Using camera images to monitor animal behavior manually has been used for decades and automated monitoring of group housed pig and poultry systems is available (Wathes et al., 2008). While still developing, the automatic prediction of individual animal behavior and welfare of animals may be useful for farm assurance schemes as a repeatable, reliable and objective measure across different farm environments. As a management tool, the monitoring of cows at calving is essential to determine if there is a need for intervention, which can be hazardous for the cow, calf and stockperson. Alterations in behavior, such as standing, lying, head, and tail movements, can give an indication of the need for assistance (Hyslop et al., 2008).

Recent technological advances in the field of computer vision based on the technique of deep learning (Krizhevsky et al., 2012; Girshick et al., 2014) have emerged which now makes automated monitoring of video feeds feasible. Deep neural networks can be used for a number of animal monitoring tasks such as recognizing the type of animals (recognition), detecting where the animals (and any other objects of interest) are located in the image (detection), localizing their body parts, and even segmenting their exact shape (silhouette) from the image. See **Figure 4** for an example. Furthermore, adaptations of neural networks for analyzing video can be used for a number of

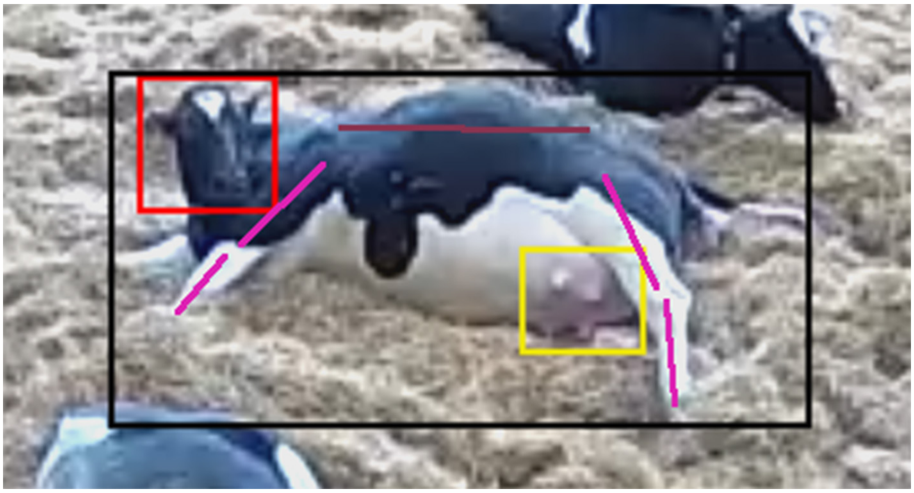

FIGURE 4 | Cow whilst calving with location of the cow, its body parts and the configuration of the cow body (shown in terms of bounding boxes and lines) identified by computer vision from video surveillance.

high level analysis tasks such as recognition of specific animal behaviors (Gkioxari et al., 2015).

A major benefit of automated image analysis is that it allows continuous monitoring for long-periods of time which is not possible for a stockperson, and can complement existing surveillance video footage accessed remotely. Image analysis can not only detect and track individuals but also groups of animals (i.e., herd, flock, or mother with offspring), which is not possible using other monitoring methods.

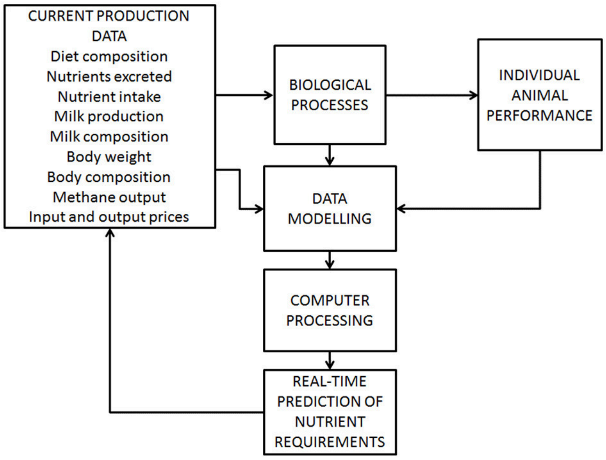

FIGURE 5 | Flow-chart showing animal model used to predict nutrient requirements.

COMBINING DATA SOURCES

Precision management systems that recognize the needs of individual animals could potentially contribute to significant reductions in feed costs and nutrients wasted, but techniques to do this require development. This approach offers increased efficiency in the use of input resources such as feed, by improved predictive capabilities and tools that allow variability among animals to be managed. Farm data, modeling, and computer programs can be integrated (**Figure 5**) to create a real-time system for precise allocation of food (Pomar et al., 2010). The need for testing and practical application of such an approach has been identified by others (Wathes et al., 2008; Pomar et al., 2011), before being implemented on farms. Precision feeding aims to provide a diet tailored to the requirements of an individual animal to enhance overall performance and nutrient utilization. In theory, collated real-time farm information should allow the quantity and composition of the diet to be adjusted daily to the needs of each animal on the farm. Computer-based methods of processing these data will aid the automation of feeding.

In the short-term, recording systems that obtain new information and phenotypes may provide a benchmarking or decision support system for the farmer to improve awareness and management. In the medium to long-term, recording systems may provide customized animal selection indices (Bell et al., 2013, 2015) for herd management or breeding. customized selection indices are appropriate for fitness traits with low heritability (Cottle and Coffey, 2013) or largely influenced by farm environment. A reduction in greenhouse gas emissions per unit product from dairy cows of about 1% per annum has been estimated over the last few decades because of genetic selection alone (Bell et al., 2015), with no change found in the emission intensity of beef cattle (Jones et al., 2008). Due to increasing production per animal over this same period, the emissions per cow are estimated to increase by 1.0% (Bell et al., 2015). Selection on body maintenance requirements (or live weight as an approximation for maintenance) or feed efficiency/methane could help reduce the increase in emissions per cow and per unit product.

Furthermore, automated and objective farm level recording systems may capture the effect of environment and its interaction with the genetic background of the animal. Evaluating progeny for production and fitness traits across breeds and environments fails to fully account for the effect of environment on different genotypes, and therefore there is potential for better genetic progress to be made within different production systems using customized indices. Strandberg et al. (2009) found a genotype by environment interaction for fertility traits, with days to first insemination and calving interval explaining the majority of the genotype by environment variation observed. It could be that these objective fertility traits are more accurately acquired than traits that rely on a subjective pregnancy diagnosis. Haskell et al. (2007) studied Holstein-Friesian herds and found production intensity (age at first calving, kilograms milk, milk fat, and protein production) and climate (temperature and rainfall) were the factors explaining the majority of the variation seen in production systems across the UK. Several of these variables were also common variables identified in a study on Holstein-Friesian cows across countries by Zwald et al. (2003). Zwald et al. (2003) found climatic temperature, herd size, sire for milk, percentage of North American Holstein genes, peak milk yield, fat to protein ratio in milk, and standard deviation of milk yield to be the main variables explaining the majority of variation between a genotype and its environment. Sires vary in the sensitivity of their daughters to different farm environments, with a small proportion of sires producing daughters that are less affected by their farm environment (Haskell et al., 2007) i.e., more robust animals. Therefore, identifying progeny that are more robust to a certain production system or farm environment would be beneficial to the efficiency of the system.

CONCLUDING REMARKS

This study discussed selected novel monitoring systems that have the potential to increase productivity and reduce the environmental impact of commercial cattle systems. Improvements in the production efficiency and utilization of resources needed to produce meat and milk from cattle is of great interest to farmers, policy makers, and society. New technologies are providing opportunities to objectively monitor and measure phenotypes using non-invasive methods associated with cattle that were previously seen as difficult or costly to obtain (e.g., enteric methane, feed utilization, and behavioral traits). This potentially brings new information or data sources for enhanced farm level monitoring, awareness, and decision making. For any new monitoring system it needs to easily integrate into the farm system, as well as be accurate and reliable for longevity of use. Adoption by the farmer is reliant on the perceived benefits and investment needed, which may be influenced by the production system i.e., high versus low input system. Whatever the farmers' needs might be depending on their production system, new ways of monitoring performance can complement the existing work of the farmer, especially with regard to traits that are difficult to continually monitor (e.g., feed utilization, methane emissions, body condition, animal behavior, health, and welfare).

AUTHOR CONTRIBUTIONS

MB conducted the literature survey, collated the relevant information, and wrote the paper with GT.

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REFERENCES

Azzaro, G., Caccamo, M., Ferguson, J. D., Battiato, S., Farinella, G. M., Guarnera, G. C., et al. (2011). Objective estimation of body condition score by modelling cow body shape from digital images. *J. Dairy Sci.* 94, 2126–2137. doi: 10.3168/jds.2010-3467

Bell, M. J., Craigon, J., Saunders, N., Goodman, J. R., and Garnsworthy, P. C. (2018). Does the diurnal pattern of enteric methane emissions from dairy cows change over time? *Animal* doi: 10.1017/S1751731118000228. [Epub ahead of print].

Bell, M. J., and Eckard, R. J. (2012). "Reducing enteric methane losses from ruminant livestock – its measurement, prediction and the influence of Diet," in *Livestock Production*, ed K. Javed (Rijeka: InTech), 135–150.

Bell, M. J., Eckard, R. J., Haile-Mariam, M., and Pryce, J. E. (2013). The effect of changing cow production and fitness traits on net income and greenhouse gas emissions from Australian Dairy systems. *J. Dairy Sci.* 96, 7918–7931. doi: 10.3168/jds.2012-6289

Bell, M. J., Garnsworthy, P. C., Stott, A. W., and Pryce, J. E. (2015). The effect of changing cow production and fitness traits on profit and greenhouse gas emissions from UK Dairy systems. *J. Agric. Sci.* 153, 138–151. doi: 10.1017/S0021859614000847

Bell, M. J., and Roberts, D. J. (2007). The impact of uterine infection on a dairy cow's performance. *Theriogenology* 68, 1074–1079. doi: 10.1016/j.theriogenology.2007.08.010

Bell, M. J., Saunders, N., Wilcox, R., Homer, E., Goodman, J. R., Craigon, J., et al. (2014). Methane emissions among individual dairy cows during milking quantified by eructation peaks or ratio with carbon dioxide. *J. Dairy Sci.* 97, 6536–6546. doi: 10.3168/jds.2013-7889

Bell, M. J., Wall, E., Russell, G., Roberts, D. J., and Simm, G. (2010). Risk factors for culling in Holstein-Friesian dairy cows. *Vet. Record* 167, 238–240. doi: 10.1136/vr.c4267

Bell, M. J., Wall, E., Russell, G., Simm, G., and Stott, A. (2011). The effect of improving cow productivity, fertility, and longevity on the global warming potential of dairy systems. *J. Dairy Sci*. 94, 3662–3678. doi: 10.3168/jds.2010-4023

Bell, M. J., and Wilson, P. (2018). Estimated differences in economic and environmental performance of forage-based dairy herds across the UK. *Food Energy Secur.* 7:e00127. doi: 10.1002/fes3.127

Berckmans, D. (2008). Precision livestock farming. *Comput. Electron. Agric.* 62:1. doi: 10.1016/j.compag.2007.09.002

Berry, D. P., and Crowley, J. J. (2013). Genetics of feed efficiency in dairy and beef cattle. *J. Anim. Sci.* 91, 1594–1613. doi: 10.2527/jas.2012-5862

Bewley, J. M., and M. M., Schutz (2008a). Review: an interdisciplinary review of body condition scoring for dairy cattle. *Profess. Anim. Sci.* 24, 507–529. doi: 10.15232/S1080-7446(15)30901-3

Bewley, J. M., Peacock, A. M., Lewis, O., Boyce, R. E., Roberts, D. J., Coffey, M. P., et al. (2008b). Potential for estimation of body condition scores in dairy cattle from digital images. *J. Dairy Sci.* 91, 3439–3453. doi: 10.3168/jds.2007-0836

Cangar, Ö., Leroy, T., Guarino, M., Vranken, E., Fallon, R., Lenehan, J., et al. (2008). Automatic real-time monitoring of locomotion and posture behaviour of pregnant cows to calving using online image analysis. *Comput. Electron. Agric.* 64, 53–60. doi: 10.1016/j.compag.2008.05.014

Cottle, D. J., and Coffey, M. P. (2013). The sensitivity of predicted financial and genetic gains in Holsteins to changes in the economic value of traits. *J. Anim. Breed. Genet.* 130, 41–54. doi: 10.1111/j.1439-0388.2012.01002.x

Cottle, D. J., Velazco, J., Hegarty, R. S., and Mayer, D. G. (2015). Estimating daily methane production in individual cattle with irregular feed intake patterns from short-term methane emission measurements. *Animal* 9, 1949–1957. doi: 10.1017/S1751731115001676

Crompton, L. A., Mills, J. A. N., Reynolds, C. K., and France, J. (2011). "Fluctuations in methane emission in response to feeding pattern in lactating dairy cows," in *Modelling Nutrient Digestion and Utilization in Farm Animals*, eds D. Sauvant, J. Van Milgen, P. Faverdin, and N. Friggens (Wageningen: Wageningen Academic Publishers), 76–180.

Day, W. (2005). Engineering precision into variable biological systems. *Ann. Appl. Biol.* 146, 155–162. doi: 10.1111/j.1744-7348.2005.040064.x

Decruyenaere, V., Lecomte, P. H., Demarquilly, C., Aufrere, J., Dardenne, P., Stilmant, D., et al. (2009). Evaluation of green forage intake and digestibility in ruminants using near infrared reflectance spectroscopy (NIRS): developing a global calibration. *Anim. Feed Sci. Technol.* 148, 138–156. doi: 10.1016/j.anifeedsci.2008.03.007

Defra (2018). *The Future Farming and Environment Evidence Compendium.* Available online at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/683972/future-farming-environment-evidence.pdf (Accessed April 13, 2018).

Dillon, P., Berry, D. P., Evans, R. D., Buckley, F., and Horan, B. (2006). Consequences of genetic selection for increased milk production in European seasonal pasture based systems of milk production. *Livest. Sci.* 99, 141–158. doi: 10.1016/j.livprodsci.2005.06.011

Eggar-Danner, C., Cole, J. B., Pryce, J. E., Gengler, N., Heringstad, B., Bradley, A., et al. (2015). Invited review: overview of new traits and phenotyping strategies in dairy cattle with a focus on functional traits. *Animal* 9, 191–207. doi: 10.1017/S1751731114002614

Ellis, J. L., Kebreab, E., Odongo, N. E., McBride, B. W., Okine, E. K., and France, J. (2007). Prediction of methane production from dairy and beef cattle. *J. Dairy Sci.* 90, 3456–3467. doi: 10.3168/jds.2006-675

FAWC (2009). *Opinion on the Welfare of the Dairy Cow.* London: Farm Animal Welfare Council (FAWC).

Garnsworthy, P. C., Craigon, J., Hernandez-Medrano, J. H., and Saunders, N. (2012a). Variation among individual dairy cows in methane measurements made on farm during milking. *J. Dairy Sci.* 95, 3181–3189. doi: 10.3168/jds.2011-4606

Garnsworthy, P. C., Craigon, J., Hernandez-Medrano, J. H., and Saunders, N. (2012b). On-farm methane measurements during milking correlate with total methane production by individual dairy cows. *J. Dairy Sci.* 95, 3166–3180. doi: 10.3168/jds.2011-4605

Gengler, N., Soyeurt, H., Dehareng, F., Bastin, C., Colinet, F., Hammami, H., et al. (2016). Capitalizing on fine milk composition for breeding and management of dairy cows. *J. Dairy Sci.* 99, 4071–4079. doi: 10.3168/jds.2015-10140

Girshick, R., Donahue, J., Darrell, T., and Malik, J. (2014). "Rich feature hierarchies for accurate object detection and semantic segmentation," in *IEEE Conference on Computer Vision and Pattern Recognition* (Columbus, OH).

Gkioxari, G., Girshick, R., and Malik, J. (2015). "Actions and attributes from wholes and parts," *IEEE International Conference on Computer Vision.* arXiv:1412.2604v2. Available online at: https://arxiv.org/abs/1412.2604v2

Gunton, R. M., Firbank, L. G., Inman, A., and Winter, D. M. (2016). 0How scalable is sustainable intensification? *Nat. Plants* 2, 1–4. doi: 10.1038/nplants.2016.65

Hadley, G. L., Wolf, C. A., and Harsh, S. B. (2006). Dairy cattle culling patterns, explanations, and implications. *J. Dairy Sci.* 89, 2286–2296. doi: 10.3168/jds.S0022-0302(06)72300-1

Halachmi, I., Polak, P., Roberts, D. J., and Klopcic, M. (2008). Cow body shape and automation of condition scoring. *J. Dairy Sci.* 91, 4444–4451. doi: 10.3168/jds.2007-0785

Haskell, M. J., Brotherstone, S., Lawrence, A. B., and White, I. M. S. (2007). Characterization of the dairy farm environment in Great Britain and the effect of the farm environment on cow life span. *J. Dairy Sci.* 90, 5316–5323. doi: 10.3168/jds.2006-865

Hyslop, J., Ross, D., Bell, M., and Dwyer, C. (2008). "Observations on the time course of calving events in unassisted multiparous spring calving suckler cows housed in a straw bedded yard," in *BSAS proceedings* (Scarborough), 158.

Jones, H. E., Warkup, C. C., Williams, A., and Audsley, E. (2008). "The effect of genetic improvement on emission from livestock systems," in *Proceedings of the European Association of Animal Production* (Vilnius), 24–27.

Kim, I. H., and Kang, H. G. (2003). Risk factors for endometritis and the effect of endometritis on reproductive performance in dairy cows in Korea. *J. Reprod. Develop.* 49, 485–491. doi: 10.1262/jrd.49.485

Krizhevsky, A., Sutskever, I., and Hinton, G. (2012). "Imagenet classification with deep convolutional neural networks," in *Proceedings 25th International Conference on Neural Information Processing Systems* (Lake Tahoe, CA), 1097–1105. Available online at: https://dl.acm.org/citation.cfm?id=2999257

Lassen, J., Løvendahl, P., and Madsen, J. (2012). Accuracy of noninvasive breath methane measurements using fourier transform infrared methods on individual cows. *J. Dairy Sci.* 95, 890–898. doi: 10.3168/jds.2011-4544

Lewis, G. S. (1997). Uterine health and disorders. *J. Dairy Sci.* 80, 984–994. doi: 10.3168/jds.S0022-0302(97)76024-7

Manafiazar, G., Zimmerman, S., and Basarab, J. A. (2017). Repeatability and variability of short-term spot measurement of methane and carbon dioxide emissions from beef cattle using GreenFeed emissions monitoring system. *Can. J. Anim. Sci.* 97, 118–126. doi: 10.1139/cjas-2015-0190

Miettinen, H., Huhtanen, P. (1996). Effects of the ration of ruminal propionate to butyrate on milk yield and blood metabolites in dairy cows. *J. Dairy Sci.* 79, 851–861.

Neethirajan, S. (2017). Recent advances in wearable sensors for animal health management. *Sens. Bio-Sensing Res.* 12, 15–29. doi: 10.1016/j.sbsr.2016.11.004

Nieuwhof, G. J., van Arendonk, J. A. M., and Vos, H., Korver, S. (1992). Genetic relationships between feed intake, efficiency and production traits in growing bulls, growing heifers and lactating heifers. *Livest. Prod. Sci.* 32, 189–202.

Pomar, C., Hauschild, L., Zhang, G. H., Pomar, J., and Lovatto, P. A. (2010). "Precision feeding can significantly reduce feeding cost and nutrient excretion in growing animals," in *Modelling Nutrition Digestion and Utilization in Farm Animals,* eds D. Sauvant, J. van Milgen, P. Faverdin, and N. Friggens (Wageningen: Wageningen Academic Publishers), 327–334.

Pomar, J., Lopez, V., and Pomar, C. (2011). Agent-based simulation framework for virtual prototyping of advanced livestock precision feeding systems. *Comput. Electron. Agric.* 78, 88–97. doi: 10.1016/j.compag.2011.06.004

Pritchard, T., Coffey, M., Mrode, R., and Wall, E. (2012). Genetic parameters for production, health, fertility and longevity traits in dairy cows. *Animal* 7, 34–46. doi: 10.1017/S1751731112001401

Pryce, J. E., Nielson, B. L., Veerkamp, R. F., and Simm, G. (1999). Genotype and feeding system effects and interactions for health and fertility traits in dairy cattle. *Livest. Prod. Sci.* 57, 193–201. doi: 10.1016/S0301-6226(98)00180-8

Pryce, J. E., Wales, W. J., de Haas, Y., Veerkamp, R. F., and Hayes, B. J. (2014). Genomic selection for feed efficiency in dairy cattle. *Animal,* 8, 1–10. doi: 10.1017/S1751731113001687

Redman, G. (2015). *The John Nix Farm Management Pocketbook 2016.* Melton Mowbray: Agro Business Consultants Ltd.

Sivakesava, S., and Irudayaraj, J. (2002). Rapid determination of tetracycline in milk by FT-MIR and FT-NIR spectroscopy. *J. Dairy Sci.* 85, 487–493. doi: 10.3168/jds.S0022-0302(02)74099-X

Stock, J. D., Calderón Díaz, J. A., Abell, C. E., Baas, T. J., Rothschild, M. F., Mote, B. E., et al.J (2017). Development of an objective feet and leg conformation evaluation method using digital imagery in swine. *J. Anim. Sci. Livestock. Prod.* 1, 1–7. Available online at: http://www.imedpub.com/articles/development-of-an-objective-feet-and-leg-conformation-evaluation-method-using-digital-imagery-in-swine.php?aid=19291

Strandberg, E., Brotherstone, S., Wall, E., and Coffey, M. P. (2009). Genotype by environment interaction for first-lactation female fertility traits in UK dairy cattle. *J. Dairy Sci.* 92, 3437–3446. doi: 10.3168/jds.2008-1844

van der Steen, H. A. M., Prall, G. F. W., and Plastow, G. S. (2005). Applications of genomics to the pork industry. *J. Anim. Sci.* 83, E1–E8. doi: 10.2527/2005.8313_supplE1x

Vanlierde, A., Vanrobays, M.-L., Gengler, N., Dardenne, P., Froidmont, E., Soyeurt, H., et al. (2016). Milk mid-infrared spectra enable prediction of lactation-stage-dependent methane emissions of dairy cattle within routine population-scale milk recording schemes. *Anim. Prod. Sci.* 56, 258–264. doi: 10.1071/AN15590

Wathes, C. M., Kristensen, H. H., Aerts, J.-M., and Berckmans, D. (2008). Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Comput. Electron. Agric.* 64, 2–10. doi: 10.1016/j.compag.2008.05.005

Yan, T., Mayne, C. S., Gordon, F. G., Porter, M. G., Agnew, R. E., Patterson, D. C., et al. (2010). Mitigation of enteric methane emissions through improving efficiency of energy utilization and productivity in lactating dairy cows. *J. Dairy Sci.* 93, 2630–2638. doi: 10.3168/jds.2009-2929

Yan, T., Porter, M. G., and Mayne, C. S. (2009). Prediction of methane emission from beef cattle using data measured in indirect open-circuit respiration calorimeters. *Animal* 3, 1455–1462. doi: 10.1017/S175173110900473X

Zwald, N. R., Weigel, K. A., Fikse, W. F., and Rekaya, R. (2003). Identification of factors that cause genotype by environment interaction between herds of Holstein cattle in seventeen countries. *J. Dairy Sci.* 86, 1009–1018. doi: 10.3168/jds.S0022-0302(03)73684-4

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The Use of Mobile Near-Infrared Spectroscopy for Real-Time Pasture Management

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Changes in pasture nutrients over the growing season are typically not monitored but doing so may help farmers improve how effectively they utilize forage. The aim of this research was to assess the use of real-time near-infrared spectroscopy (NIRS) for monitoring seasonal changes in nutrient concentrations of different pasture types used for grazing and silage production. Three permanent pastures and three temporary ley pastures (3 years old) grazed by cattle or sheep and/or used for silage production were monitored weekly for 20 weeks from April to August 2017 in the UK. Five pasture samples per field were obtained per week for NIRS analysis and estimation of fresh and dry matter herbage cover (both kg per hectare). Herbage height was also measured each week. Permanent pastures included a diverse range of native UK grass species, and temporary ley pastures were predominantly perennial ryegrass (*Lolium perenne*) with either white (*Trifolium repens*) or red clover (*Trifolium pretense*). Effects of pasture type (permanent or temporary), phase of production (grazed or rested for regrowth) and month of year (April to August) on pasture nutrients [dry matter, crude protein, acid detergent fiber (ADF), neutral detergent fiber (NDF), water soluble carbohydrate (WSC), ash, digestible organic matter (DOMD), and dry matter digestibility (DMD)] were assessed by fitting a linear mixed model. Considerable variation was observed in pasture production and in the concentrations of dry matter, crude protein and WSC in pastures. This study suggests that grazing pastures to a mean height of below 7 cm results in a significantly reduced concentration of crude protein, DOMD, and DMD, which may be detrimental to the grass intake and protein intake of the grazing animal. The DOMD and DMD of pasture were positively correlated with herbage height and herbage cover crude protein concentration. An approach of real-time nutrient monitoring will facilitate more timely adaptive pasture management than currently feasible for farmers. This should lead to productivity gain.

Keywords: grasslands, technology, spectral data, predictions, management

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INTRODUCTION

Grassland is the dominant agricultural land use type in the UK, covering 12.3 million ha (66% of total agricultural area). The UK grassland area can be subdivided into 1.4 million ha of temporary grassland, 5.8 million ha of permanent pasture, and 5.1 million ha of rough grazing (Defra, 2018). The diversity of grasslands and their spatial arrangement within a farm, and the landscape, have major importance for the sustainability of the environment and ruminant livestock systems (Gibon, 2005). Grass provides a cheap and affordable source of nutrients for

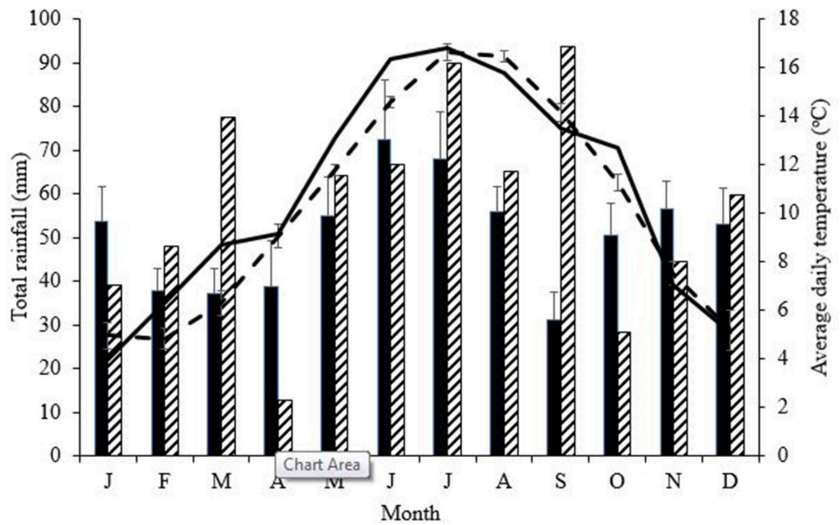

FIGURE 1 | Total rainfall and average daily temperatures for the months January to December during the years 2007 to 2016 (solid column and line respectively) and during the study year of 2017 (dashed column and line respectively). Standard error bars are ahown for months during years 2007 to 2016.

ruminants, with pasture providing approximately 70% of the 42 million tons of forage dry matter consumed by ruminants (Wilkinson, 2011). Furthermore, feed costs can represent as much as 70% of the variable costs of livestock production (Redman, 2016), and therefore ways to manage forage efficiently will enhance the use of this valuable resource. Grazed pasture can supply over half of the protein and energy needed by ruminants (Waghorn and Clark, 2004; Hopkins and Wilkins, 2006). Understanding seasonal changes in pasture nutrient concentrations can enhance ruminant production systems and management. The poor matching of nutrient supply with animal requirements can reduce livestock performance (Dillon, 2006), increase the demand for land and reduce nutrient use efficiency. Timely information on supply and nutrient concentrations of pasture, and its associated variability, will allow farmers to better match nutrient supply with animal demand.

Tools that measure herbage height and cover have been used for a long time, such as a rising plate meter or cut and weigh methods (French et al., 2015). The value of pasture is a combination of not only pasture production but its nutrient quality. The maximizing of forage utilization in ruminant production systems is associated with reduced operating costs, such as inputs of supplementary feed as mentioned above (Dillon, 2006; Ramsbottom et al., 2015). In recent years the principal method of wet chemistry analysis in the laboratory for obtaining nutrient levels in forage has been replaced by NIRS analysis (Stergiadis et al., 2015), which is calibrated using wet chemistry data. The NIRS technique measures the spectrum of infrared energy reflected from a sample illuminated by white light. This approach to estimating nutrient levels in products has reduced the time taken for analysis (from about 16 h to less than a minute) and its cost (Stuth et al., 2003). Even with this quicker and lower cost approach, forage analysis is often done infrequently by farmers. Developments in NIRS devices that are smaller and more mobile (Malley et al., 2005; Pullanagari et al., 2012) with data processing and storage, now allow real-time analysis on farms. The benefit of this mobile approach is that the technology allows frequent nutrient analysis and timelier decision making at a lower cost to sending samples for laboratory analysis, which should encourage more adoption on farms.

The objective of this study was to assess the use of real-time NIRS for monitoring seasonal changes in nutrient concentrations of different pasture types used for grazing and silage production. During this study, three permanent pastures and three temporary ley pastures were monitored during spring and summer months in the UK.

MATERIALS AND METHODS

Field Data

The study was carried out at the University of Nottingham farm at Sutton Bonington over a 20-week period from April to August 2017. During the study, the lowest amount of rainfall (13 mm) and lowest average daily temperatures (9°C) were in April, and highest amount of rainfall (90 mm) and highest average daily temperatures (17°C) in July (17°C; **Figure 1**). During the study the average daily temperatures in May and June were noticeably higher than the average for the same months during the previous 10 years from 2007 to 2016. Total rainfall was also noticeably lower in April and higher in July during the study compared to the previous 10 years.

Grassland at the farm consisted of permanent and temporary ley pastures used for cattle or sheep grazing and/or silage production. Six fields were selected for this study, with three being permanent pastures and three being temporary ley pastures. The permanent pastures (Fields A, B and C; **Table 1**) have never been cultivated and contain a diverse botanical composition of native UK grass species of perennial ryegrass

TABLE 1 | Characteristics of fields assessed in the study.

Field	Pasture type	Soil type	Predominant pasture species	Nutrient applications	Use during study
A	Permanent and never cultivated	Sandy loam	Perennial ryegrass, timothy, Yorkshire fog, cocksfoot, common bent and meadow grass	1 × 30m^3/ha (0.7 kg N/m^3) of dirty water	Cattle grazing
B	Permanent and never cultivated	Sandy loam	Perennial ryegrass, timothy, Yorkshire fog, cocksfoot, common bent and meadow grass	1 × 30m^3/ha (0.7 kg N/m^3) of dirty water	Cattle grazing
C	Permanent and never cultivated	Sandy loam	Perennial ryegrass, timothy, Yorkshire fog, cocksfoot, common bent and meadow grass	None	Sheep grazing
D	Temporary ley, 3 years old	Sandy loam	Perennial ryegrass and white clover	Inorganic fertilizer (50 kg of ammonium nitrate of 34% N: 0% P:0% K) plus 3 × 30m^3/ha (0.7 kg N/m^3) of dirty water	Sheep grazing and silage harvested
E	Temporary ley, 3 years old	Clay loam	Perennial ryegrass and red clover	Inorganic fertilizer (60 kg of ammonium nitrate of 34% N: 0% P:0% K) plus 3 × 30m^3/ha (0.7 kg N/m^3) of dirty water	Silage harvested
F	Temporary ley, 3 years old	Sandy loam	Perennial ryegrass and white clover	Inorganic fertilizer (50 kg of ammonium nitrate of 34% N: 0% P:0% K) plus 1 × 30m^3/ha (0.7 kg N/m^3) of dirty water	Sheep grazing and silage harvested

(*Lolium perenne*), timothy (*Phleum pretense*), Yorkshire fog (*Holcus lanatus*), cocksfoot (*Dactylis glomerata*), common bent (*Agrostis capillaris*), and meadow grass (*Poa annua*). The temporary ley pastures were part of a crop rotation and are cultivated after 3 to 5 years of production. The temporary leys consisted of predominantly perennial ryegrass, with either white clover (*Trifolium repens*, Fields D and F; **Table 1**) or red clover (*Trifolium pretense*, Field E).

Prior to commencement of the study all six fields were rested for four or more weeks, as prior to this fields were intermittently grazed by sheep over the winter months. During this period the temporary pasture fields of D, E and F received an application of inorganic fertilizer, and fields A and B received dirty water, which is produced after removing solid organic material from cattle slurry (the amount of nutrient inputs are shown in **Table 1**). Field C didn't have any nutrients applied during the study. Fields D, E and F had dirty water applied after each harvest of silage, and during this week no grass measurements were taken. During the study, ewes and their lambs intermittently grazed fields C and F and dairy heifers grazed fields A and B. Management of each field during the weeks of the study are shown in **Table 2**, with periods highlighted when pasture is rested for regrowth, grazed and harvested for silage.

MEASUREMENTS

The herbage height, fresh and dry matter herbage cover and nutrient concentrations of each field were measured during the study. No grass measurements were taken during weeks when silage was harvested and dirty water was applied, as the application of dirty water prevented accurate NIRS analysis of nutrient concentrations. Grass measurements avoided dung, urine and dense weed patches when taken.

Pasture Sampling

Pasture measurements were conducted on the same day each week. In each field 5 grass samples were cut to ground level and within a 36 cm diameter wire ring (0.1 m^2) randomly placed on the ground. To ensure representative coverage of each field, the 5 grass samples were taken in a W-pattern (Wilkinson et al., 2014). The total weight (grams) of pasture within the ring was multiplied by 100 (i.e., 1 hectare = 10,000 m^2) to estimate the fresh herbage cover (kg fresh weight/hectare). The fresh pasture cover value was then multiplied by the percentage of dry matter measured by NIRS to derive the dry matter herbage cover (kg DM/hectare).

A rising plate meter (F400; Farmworks Precision Farming Systems Ltd, Feilding, NZ) was used to measure sward height (**Figure 2**). The pasture height of each field was estimated from the average of 30 "spot" measurements taken in a W-pattern across the field.

Nutrient Analysis

A mobile NIRS device (NIR4; Aunir, Towcester, UK) was used to scan cut pasture samples for their nutrient concentrations (**Figure 2**). The NIR4 takes four replicate scans, consisting of a spectrum of infrared energy reflected from the pasture sample illuminated by the scanner, from which nutrient concentrations are estimated from the average of the four scans. The scan results are uploaded to a tablet and secure server for further

TABLE 2 | Illustration showing periods of pasture regrowth (black), grazing (gray), and silage harvest (white) for each field (A to F) during the 20 weeks of the study.

	Month/week of study																			
	April				May				June				July				August			
Field	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
A																				
B																				
C																				
D																				
E																				
F																				

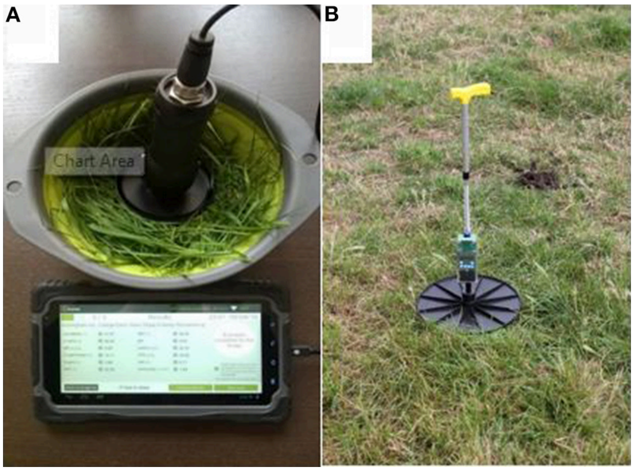

FIGURE 2 | Pasture measurement devices of **(A)** Tablet near-infrared spectroscopy scanner and tablet for nutrient analysis and **(B)** rising plate meter for herbage height.

analysis. The nutrient concentrations measured were: dry matter, crude protein, acid detergent fiber (ADF), neutral detergent fiber (NDF), water soluble carbohydrate (WSC), ash, digestible organic matter (DOMD), and dry matter digestibility (DMD; all expressed as grams per kilogram of dry matter).

Statistical Analysis

The mean value for the 5 weekly measurements of herbage cover and nutrient concentrations per field was used for further analysis. This produced a total of 112 weekly records for all fields (20 weeks × 6 fields with the 8 weekly values when silage was harvested not included). Data were analyzed using a linear mixed model in Genstat software (version 18.1; VSN International Ltd., Hemel Hempstead, UK). Equation (1) was used to assess the effect of pasture type (permanent or temporary), phase of production (grazed or rested for regrowth) and month of year (April to August) on pasture nutrients:

$$y_{ijkl} = \mu + \mathrm{M}_i \times \mathrm{P}_j \times \mathrm{S}_k + \mathrm{F}_l + e_{ijkl} \tag{1}$$

where y_{ijkl} is the dependent variable; μ = overall mean; M_i = fixed effect of month of year (i = April to August); P_j = fixed effect of pasture type (j = permanent or temporary); S_k = fixed effect of phase of production (k = grazed or regrowth); F_l = fixed effect of field (l = A to F); e_{ijkl} = random error term.

Equation (1) was also used to assess differences in fresh pasture cover, dry matter cover and herbage height without the fixed effect of field. Predicted means for pasture type (permanent or temporary), phase of production (grazed or rested for regrowth), month of year (April to August) and field (A to F; for analysis of nutrient concentrations) and pasture type × phase of production were presented. The interaction between pasture type × phase of production and month of year are not presented since influenced by field management (i.e., grazing, silage cut or regrowth; **Table 2**). Pearson correlation coefficient (r) was used to test the association between herbage height, herbage cover (fresh and dry matter per hectare) and pasture nutrient concentrations. Significant differences were attributed at $P < 0.05$.

RESULTS

Differences in Pasture Height, Herbage Cover, and Pasture Nutrients

There was considerable variation in herbage height (coefficient of variation = 46%), and fresh and dry matter herbage cover (coefficient of variation = 78 and 71%, respectively) across fields studied (**Table 3**). For pasture nutrients, there was more variability in measured dry matter, crude protein and WSC concentrations in pasture (coefficient of variation ranging from 18 to 23%) than observed for NDF, DOMD and DMD concentrations (coefficient of variation ranging from 2 to 5%).

On average, herbage height and cover (fresh and dry matter) were lower during periods of grazing (all $P < 0.001$) and declined from April/May to June/July/August ($P < 0.05$ or greater; **Table 4**). An interaction was found between temporary ley pastures that were grazed, with lower herbage height and cover (fresh and dry matter) than other combinations of pasture type × phase of production (all $P < 0.05$). There was no effect of pasture type on herbage height and herbage cover (both $P > 0.05$).

Permanent pastures were associated with significantly higher concentrations of dry matter, WSC (both $P < 0.001$) and NDF ($P < 0.05$) but lower crude protein, ADF (both $P < 0.05$) and ash ($P < 0.001$) than temporary ley pastures (**Table 5**). Periods when pastures were grazed were associated with higher dry matter, NDF and WSC (all $P < 0.001$) but lower crude protein, ash

TABLE 3 | Average pasture height, herbage cover, and nutrient concentrations across fields, and weeks of the study.

Variable	Units	Mean (s.d)	Range	Coefficient of variation (%)
Pasture height	cm	8.6 (4.0)	3.3–24.3	46
Herbage cover	kg FW/ha	7416 (5784)	780–30400	78
Herbage cover	kg DM/ha	1413 (1000)	136–5073	71
Dry matter	g/kg DM	205 (48)	118–390	23
Crude protein	g/kg DM	198 (39)	45–247	20
ADF[1]	g/kg DM	267 (28)	219–444	10
NDF[1]	g/kg DM	431 (21)	382–565	5
WSC[1]	g/kg DM	74 (13)	49–137	18
Ash	g/kg DM	90 (12)	47–110	13
DOMD[1]	g/kg DM	710 (17)	615–745	2
DMD[1]	g/kg DM	758 (20)	645–800	3

[1]*ADF is Acid detergent fiber, NDF is neutral detergent fiber, WSC is water soluble carbohydrate, DOMD is digestible organic matter and DMD is dry matter digestibility.*

(all $P < 0.001$), DOMD, and DMD (both $P < 0.05$). During July, the concentrations of dry matter, ADF and NDF were at their highest and concentrations of crude protein, DOMD and DMD at their lowest, and significantly different to the months of April/May (all $P < 0.001$). The concentrations of WSC varied from April to August ($P < 0.05$). With adjustment for fixed effects, the permanent pasture fields of B and C had higher ash concentrations, and Field C had lower DOMD and DMD compared to other fields (all $P < 0.05$). An interaction was found between temporary ley pastures that were grazed, which had a higher mean NDF concentration ($P < 0.001$) and lower DOMD and DMD concentrations (both $P < 0.05$) than other combinations of pasture type × phase of production.

Relationship Between Pasture Height, Herbage Cover, and Pasture Nutrients

Fresh and dry matter herbage cover were highly correlated (r = 0.969) and both were highly correlated with pasture height (r = 0.870 and 0.842 respectively, both $P < 0.001$; **Table 6**). Pasture height and fresh herbage cover were positively correlated with concentrations of crude protein, ash (both $P < 0.05$), DOMD and DMD (both $P < 0.001$), and negatively correlated with concentrations of dry matter ($P < 0.001$), ADF, NDF (both $P < 0.05$) and WSC ($P < 0.05$ for pasture height only). Dry matter herbage cover was positively correlated with DOMD and DMD concentrations (both $P < 0.001$), and negatively correlated with ADF concentration ($P < 0.001$). The correlation between fresh herbage cover, pasture height and different pasture nutrients were of similar magnitude. The concentration of dry matter in the pasture was positively correlated with ADF, NDF and WSC, and negatively correlated with crude protein, ash, DOMD and DMD (all $P < 0.001$). The concentration of crude protein in the pasture was positively correlated with ash, DOMD and DMD, and negatively correlated with ADF, NDF and WSC (all $P < 0.001$). Concentrations of ADF and NDF were positively correlated ($P < 0.001$), and both were negatively correlated with DOMD and DMD (which are highly correlated; all $P < 0.001$). The concentration of WSC was positively correlated with concentration of ADF ($P < 0.05$) and negatively correlated with concentration of ash ($P < 0.001$).

TABLE 4 | Effect of pasture type (permanent or temporary), phase of production (grazed or rested for regrowth), and month of year (April to August) on herbage height, and fresh weight (FW) and dry matter (DM) herbage cover.

		Herbage height	Herbage cover	Herbage cover
Variable		cm	kg FW/ha	kg DM/ha
Type	Permanent	9.2	6757	1498
	Temporary	8.3	6759	1169
	SED[3]	0.7	1012	183
	P value	0.926	0.173	0.469
Phase	Grazed	6.6	4866	1019
	Regrowth	10.9	8650	1648
	SED[3]	0.7	1012	183
	P value	<0.001	<0.001	<0.001
Month[2]	April	10.1^{a}	11705^{a}	2148^{a}
	May	9.8^{a}	8600^{b}	1643^{a}
	June	8.1^{ab}	5017^{c}	1055^{b}
	July	7.9^{b}	4860^{c}	1050^{b}
	August	7.8^{b}	3608^{c}	772^{b}
	SED[3]	1.1	1588	288
	P value	<0.05	<0.001	<0.001
Permanent[2]	Grazed	7.8^{b}	6262^{bc}	1383^{a}
	Regrowth	10.6^{a}	7252^{b}	1613^{a}
Temporary	Grazed	5.3^{c}	3470^{c}	655^{b}
	Regrowth	11.3^{a}	10048^{a}	1684^{a}
	SED[3]	1.0	1428	259
	P value	<0.05	<0.05	<0.05

[1]*ADF is acid detergent fiber, NDF is neutral detergent fiber, WSC is water soluble carbohydrate, DOMD is digestible organic matter and DMD is dry matter digestibility.*
[2]*Means for month of year and pasture type × phase of production and within a column and with different superscript letters differ significantly.*
[3]*SED means standard errors of differences.*

DISCUSSION

Precision Monitoring

As shown in this study, the use of real-time data on pasture dry matter concentration measured by NIRS can be combined with a measure of pasture production to determine the dry matter herbage cover. The alternative would be to dry the pasture samples in a microwave or oven to calculate the mass of dry plant material. Removing pasture samples from the field may allow the plant material to degrade and affect analysis results, as well as taking additional time to process the sample. The analysis of other pasture nutrient concentrations is typically done in the laboratory after being sent in the postal system, with results received after the grazing event. Unlike ensiled forages

TABLE 5 | Effect of pasture type (permanent or temporary), phase of production (grazed or rested for regrowth), month of year (April to August) and field (A to F) on pasture nutrient concentrations.

		Dry matter	Crude protein	ADF[1]	NDF[1]	WSC[1]	Ash	DOMD[1]	DMD[1]
Variable		**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**
Type	Permanent	235	177	262	437	79	80	714	763
	Temporary	183	206	282	429	67	97	700	746
	SED[3]	14	14	10	7	5	4	5	6
	P value	<0.001	<0.05	<0.05	<0.05	<0.001	<0.001	0.104	0.104
Phase	Grazed	221	178	279	440	76	86	701	748
	Regrowth	197	205	264	426	71	91	713	761
	SED[3]	8	8	6	4	3	3	3	4
	P value	<0.001	<0.001	0.054	<0.001	<0.001	<0.001	<0.05	<0.05
Month[2]	April	189[b]	214[b]	251[c]	421[b]	73[ab]	92	723[a]	773[a]
	May	195[b]	205[b]	253[c]	429[b]	70[b]	91	717[a]	767[a]
	June	227[a]	168[a]	288[ab]	444[a]	72[ab]	87	698[b]	744[bc]
	July	232[a]	166[a]	297[a]	449[a]	78[a]	88	691[b]	736[c]
	August	201[b]	204[b]	271[b]	424[b]	73[ab]	85	705[b]	753[b]
	SED[3]	11	11	8	6	4	3	4	5
	P value	<0.001	<0.001	<0.001	<0.001	<0.05	0.058	<0.001	<0.001
Field[2]	A	214	185	271	433	75	86[b]	707[a]	755[a]
	B	201	196	273	434	73	95[a]	706[a]	754[a]
	C	204	215	283	444	67	96[a]	694[b]	739[b]
	D	214	185	271	433	75	86[b]	707[a]	755[a]
	E	199	183	274	428	70	84[b]	709[a]	757[a]
	F	223	185	260	428	78	84[b]	718[a]	767[a]
	SED[3]	15	16	11	8	5	5	6	7
	P value	0.232	0.343	0.451	0.595	0.246	<0.05	<0.05	<0.05
Permanent[2]	Grazed	241[a]	169	269	434[b]	82	78	710[a]	758[a]
	Regrowth	228[ab]	184	256	432[b]	76	82	718[a]	768[a]
Temporary	Grazed	201[b]	186	290	447[a]	70	95	693[b]	737[b]
	Regrowth	166[c]	226	273	420[b]	65	99	707[a]	755[a]
	SED[3]	14	15	10	8	5	5	6	7
	P value	<0.05	0.168	0.374	<0.001	0.702	0.569	<0.05	<0.05

[1]*ADF is Acid detergent fiber, NDF is neutral detergent fiber, WSC is water soluble carbohydrate, DOMD is digestible organic matter and DMD is dry matter digestibility.*
[2]*Means for month of year, field and pasture type × phase of production within a column and with different superscript letters differ significantly.*
[3]*SED means standard errors of differences.*

both oxidative degradation of carbohydrates and hydrolysis of peptides continues post-harvest in fresh grass (Binnie et al., 1997; Dale et al., 2016). Dale et al. (2016) suggested nutrient analysis should occur within 24 h to minimize degradation to plant material and changes in nutrient concentrations. This is unlikely to occur within a small country such as the UK, let alone larger countries, where the distance to analytical laboratories may be greater. Therefore, for perishable plant material, the implementation of real-time NIRS is better suited.

Monitoring Pasture Variability

Temporal and spatial changes in nutrient concentrations of pasture are important to the productivity of grazing animals and forage production (Miller et al., 2001; Wilkins and Humphreys, 2003; Colmenero and Broderick, 2006). Herbage digestibility (DOMD and DMD) has a major effect on herbage intake, with early-season management one of the overriding factors determining herbage digestibility (Ferris, 2007). Poor nutrient intake can impair the production and wellbeing of the animal, due to an inability to achieve required nutrient intakes.

As shown in this study on a small number of fields used for grazing and silage production and observed by others studying thousands of pasture samples from farms across the UK (Wilkinson et al., 2014), considerable temporal and spatial variation in quality and quantity of pasture biomass exists, which is currently poorly understood particularly in the case of nutrient

TABLE 6 | Pearson correlation coefficients and significance of the relationship between pasture height, herbage cover (fresh and dry matter) and pasture nutrient concentrations.

		Pasture height	Herbage cover	Herbage cover	Dry matter	Crude protein	ADF	NDF	WSC	Ash	DOMD	DMD
Variable[1]	**Units**	**cm**	**kg FW/ha**	**kg DM/ha**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**	**g/kg DM**
Pasture height	cm	1										
Herbage cover	kg FW/ha	0.870	1									
Significance		(<0.001)										
Herbage cover	kg DM/ha	0.842	0.969	1								
Significance		(<0.001)	(<0.001)									
Dry matter	g/kg DM	−0.315	−0.323	−0.141	1							
Significance		(<0.001)	(<0.001)	(0.141)								
Crude protein	g/kg DM	0.248	0.261	0.132	−0.881	1						
Significance		(<0.05)	(<0.05)	(0.167)	(<0.001)							
ADF	g/kg DM	−0.253	−0.361	−0.364	0.421	−0.630	1					
Significance		(<0.05)	(<0.001)	(<0.001)	(<0.001)	(<0.001)						
NDF	g/kg DM	−0.237	−0.272	−0.168	0.554	−0.610	0.541	1				
Significance		(<0.05)	(<0.05)	(0.079)	(<0.001)	(<0.001)	(<0.001)					
WSC	g/kg DM	−0.207	−0.140	−0.009	0.791	−0.675	0.240	0.135	1			
Significance		(<0.05)	(0.143)	(0.926)	(<0.001)	(<0.001)	(<0.05)	(0.158)				
Ash	g/kg DM	0.212	0.200	0.062	−0.751	0.683	−0.151	−0.127	−0.587	1		
Significance		(<0.05)	(<0.05)	(0.519)	(<0.001)	(<0.001)	(0.114)	(0.184)	(<0.001)			
DOMD	g/kg DM	0.381	0.464	0.460	−0.353	0.496	−0.853	−0.722	−0.017	0.087	1	
Significance		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.864)	(0.366)		
DMD	g/kg DM	0.381	0.463	0.460	−0.353	0.496	−0.853	−0.722	−0.016	0.087	1	1
Significance		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.865)	(0.366)	(<0.001)	

[1] *ADF is Acid detergent fiber, NDF is neutral detergent fiber, WSC is water soluble carbohydrate, DOMD is digestible organic matter and DMD is dry matter digestibility.*

concentrations in different pasture types. In the current study, the coefficient of variation for fresh herbage cover was 78% and dry matter herbage cover was 71% across fields and weeks of the study (**Table 3**). The nutrient concentrations of dry matter, crude protein and WSC showed more variability across fields and weeks (coefficient of variation ranging from 18 to 23%) than other nutrient concentrations (coefficient of variation ranging from 2 to 13%). The mean and range of pasture nutrient concentrations observed in the current study were similar to values in other studies in the UK (Wilkinson et al., 2014). Wilkinson et al. (2014) found similar coefficients of variation for nutrient concentrations of dry matter, crude protein and WSC in pre-grazed pasture ranging from 22 to 27%, but greater variability in ADF and NDF (coefficient of variation ranging from 14 to 19% compared to 5 to 10% in the current study). Several factors can influence pasture quality including sward management (Curran et al., 2010; Crosse et al., 2015), maturity and season (Binnie et al., 1997; Frame and Laidlaw, 2011; Wilkinson et al., 2014), grass variety, sward botanical composition and soil properties (Frame and Laidlaw, 2011). During the wettest and warmer summer month of July (**Figure 1**), the concentrations of dry matter, ADF and NDF were higher and concentrations of crude protein, DOMD and DMD lower compared to the driest and coolest spring month of April. Seasonal changes in climate, pasture production and sward maturity may explain the seasonal changes observed for the majority of pasture nutrients measured; no seasonal effect on ash concentration was observed. Frame and Laidlaw (2011) reported no seasonal effect on ADF, NDF and WSC in the cooler and wetter climate of Northern Ireland for a dairy grazing system.

The use of real-time nutrient analysis in the current study allowed differences in pasture nutrients to be assessed under different management practices. Grazed pastures, and a decline in herbage height and cover, were associated with lower concentrations of crude protein, DOMD and DMD as the composition of the sward is more stem and residual plant material than vegetative leaf material. The seasonal decline in crude protein and digestibility are consistent with other studies over the same months (Frame and Laidlaw, 2011; Wilkinson et al., 2014). The current study found grazed (mean height of 6.6 cm) and temporary ley pastures that were grazed (mean height of 5.3 cm) had significantly lower DOMD and DMD and higher NDF concentrations than non-grazed and other combinations of pasture type × phase of production respectively. The higher mean herbage height of 7.8 cm for grazed permanent pastures (6.2 tons fresh herbage and 1.4 tons of dry matter herbage cover) had no significant impact on pasture digestibility (DOMD or DMD). This finding is supported by Hodgson (1990) who found the dry matter intake of cattle and sheep was reduced below about 7 cm, presumably due to similar changes in pasture digestibility. In the current study, due to availability of grazing for cattle and sheep at the farm studied it was not possible to assess differences between pastures grazed by different livestock species due to the lack of replication in the design of the study. Even with reduced nutrient intake due to herbage height (e.g., Hodgson, 1990), physical differences in muzzle size, mechanics of their bite, and body size mean that sheep are better able to graze shorter sward heights than cattle (Frame and Laidlaw, 2011) and therefore sheep grazing systems may benefit more from real-time nutrient analysis. Intensive grazing management has been found to reduce crude protein and DOMD concentrations (Hopkins and Holmes, 2000; McDonald et al., 2011). A review by Ferris (2007) highlighted that a number of studies have advocated grazing swards to a residual height of below 6 cm, which the current study suggests would be detrimental to pasture quality and animal performance due to a potentially restricted nutrient intake for intensively grazed systems. Further, research could use real-time NIRS to explore within-day variability in pasture species nutrients, timing of optimum grazing for cattle and sheep, and silage management. Orr et al. (2001) observed that dairy cows grazing after evening milking had a significantly longer evening meal compared to when grazing after morning milking, which they attributed to a higher dry matter (197 vs. 178 g/kg) and WSC (204 vs. 175 g/kg DM) concentration in herbage grazed in the evening. However, the authors found no overall improvement in milk production. Younger and genetically superior temporary pastures are supposed to be more productive, with better nutrient qualities and greater persistency than older pastures (Miller et al., 2001; Shalloo et al., 2011). The younger temporary ley pastures in the current study had higher crude protein, ADF and ash concentrations than permanent pastures, which had higher concentrations of dry matter, WSC and NDF. The higher concentrations of crude protein and minerals in the temporary ley pastures is possibly due to the presence of clover, which is rich in protein (due to its ability to fix atmospheric nitrogen into the soil) and minerals, and clover also helps increase these nutrients in the grass (Frame and Laidlaw, 2011). Surprisingly, there was no difference in overall digestibility (i.e., DOMD or DMD) between the predominantly perennial ryegrass temporary ley pastures and the permanent pastures, as perennial ryegrass is known to have a higher digestibility than grass species in the permanent pastures (e.g., timothy and cocksfoot), especially as they mature (Frame and Laidlaw, 2011). This lack of difference is presumably due to the grazing management of the pasture types. Reseeding is used to improve the overall productivity from grasslands, with fields selected for reseeding based typically on poor grass production or low perennial ryegrass quantity (Shalloo et al., 2011). Pastures containing high sugar grass varieties have become increasingly common, and were present in the temporary ley swards studied (Fields D to F), but interestingly the permanent pastures had a significantly higher mean concentration of WSC. The aim of high sugar varieties is to increase pasture palatability (with a reduced ADF content; **Table 6**) and overall animal productivity, which has been found to have variable success and this may be due to a marginal increase in actual overall WSC concentrations in the pasture (Ferris, 2007).

When formulating a diet to be fed to livestock, the conventional approach is to determine the least-cost ration depending on the estimated nutrient requirement of the average animal in the group based on infrequent determination of diet nutrient concentrations. This means that some animals will be underfed, and others overfed. As highlighted in this study, in reality considerable variation can exist in quality of forage, and more precise and current determination of nutrient availability offers considerable productive, financial and environmental benefits from this timely information. Adoption of pasture NIRS analysis will presumably be greater if done on farms, and help improve pasture nutrient management, reduce production costs and reduce the potential for waste at the farm level with better practice. For ruminants, about 35% of energy consumed in the diet is lost in the form of enteric methane, feces or urine and 77% of nitrogen consumed is excreted in feces or urine (Bell et al., 2015). More precise feeding of animals to meet their requirements will improve utilization of consumed forage resources from available land, leading to less nutrients lost per unit product (Bell et al., 2015). The use of NIRS has been shown to provide a fast and reliable analytical method for analyzing forages, products of digestion and potentially provide a prediction of feed intake in grazing situations (Decruyenaere et al., 2009). Eastwood and Dela Rue (2017) found the important factors for adoption of grazing software by farmers were (1) the alignment of data for monitoring key performance indicators, (2) using data for benchmarking and reporting and (3) enabling farm team communication. Eastwood et al. (2013) proposed that the value proposition for farmers of using precision farming tools needs to be clear to encourage farmers to invest time and money toward the equipment and learning how to use the new information effectively. It is envisaged that the reduced analytical cost, speed, improved reliability of current NIRS analysis should encourage greater uptake of pasture analysis with more timely information for farm level decision making. Potentially, you could obtain 20 times more NIRS nutrient analysis results for the equivalent cost of forage wet chemistry nutrient analysis (assuming £0.60 per sample for NIRS and £12 per sample for wet chemistry analysis). Mobile NIRS offers not only the potential of more frequent analysis for farmers to monitor a wide range of key nutrients in forage when they need the information, but also soil and manure nutrients within a soil-plant-animal system. While aerial imaging can provide useful information on biomass production and nutrient concentrations of crude protein and metabolisable energy of grassland (Pullanagari et al., 2018), the proposed ground level analysis in the current study can be used to measure spatial and temporal variation in biomass and nutrient concentrations of dry matter, crude protein, fiber, WSC, ash, and the digestibility of pasture. Detailed information on the diversity in botanical composition of swards and replication in grazing livestock species would add to the study and provide further practical insight for adaptive management of pastures. This study assessed the use of mobile NIRS analysis for monitoring pasture nutrients in real-time. Considerable variation existed in herbage production and concentrations of dry matter, crude protein and WSC in pastures studied. When combined with a measure of herbage height or herbage cover, the measured real-time NIRS nutrient concentrations can help identify temporal (i.e., seasonal) or spatial (i.e., within or between fields) changes that may impact on grazing or silage production. Pastures grazed to a height of below 7 cm had significantly lower concentrations of crude protein, DOMD and DMD compared to taller and greater herbage covers, which may be detrimental to the productivity of the land. More precise monitoring of pastures will (1) improve production system sustainability by enhancing feed utilization efficiency, (2) improve productivity of livestock and conserved forages and (3) reduce the potential for wasted resources.

AUTHOR CONTRIBUTIONS

MB, LM, and JD carried out the data collection and analysis, with JD and MB writing the paper.

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REFERENCES

Bell, M. J., Garnsworthy, P. C., Stott, A. W., and Pryce, J. E. (2015). The effect of changing cow production and fitness traits on profit and greenhouse gas emissions from UK Dairy systems. *J. Ag. Sci.* 153, 138–151. doi: 10.1017/S0021859614000847

Binnie, R. C., Kilpatrick, D. J., and Chestnutt, D. M. B. (1997). Effect of altering the length of the regrowth interval in early, mid and late season on the productivity of grass swards. *J. Ag. Sci.* 128, 303–309. doi: 10.1017/S0021859696004224

Colmenero, J. O., and Broderick, G. A. (2006). Effect of dietary crude protein concentration on milk production and nitrogen utilization in lactating dairy cows. *J. Dairy Sci.* 89, 1704–1712. doi: 10.3168/jds.S0022-0302(06)72238-X

Crosse, M., O'Donovan, M., Boland, T. M., Delaby, L., Ganche, E., and Kennedy, E. (2015). Using post-grazing sward height to impose dietary restrictions of varying duration in early lactation: its effects on spring-calving dairy cow production. *J. Anim. Sci.* 9, 592–603. doi: 10.1017/S1751731114002948

Curran, J., Delaby, L., Kennedy, E., Murphy, J. P., Boland, T. M., and O'Donovan, M. (2010). Sward characteristics, grass dry matter intake and milk production performance are affected by pre-grazing herbage mass and pasture allowance. *Livest. Sci.* 127, 144–154. doi: 10.1016/j.livsci.2009.09.004

Dale, A., Gordon, A. W., Archer, J., and Ferris, C. P. (2016). Impact of sampling and storage technique, and duration of storage, on the composition of fresh grass when analysed using near-infrared reflectance spectroscopy. *Grass For. Sci.* 72, 614–625. doi: 10.1111/gfs.12266

Decruyenaere, V., Lecomte, P.h., Demarquilly, C., Aufrere, J., Dardenne, P., Stilmant, D., et al. (2009). Evaluation of green forage intake and digestibility in ruminants using near infrared reflectance spectroscopy (NIRS): Developing a global calibration. *Anim. Feed Sci. Technol.* 148, 138–156. doi: 10.1016/j.anifeedsci.2008.03.007

Defra (2018). *Annual Statistics About Agriculture in the United Kingdom to 2017*. Available online at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/741062/AUK-2017-18sep18.pdf (Accessed august 2, 2018).

Dillon, P. (2006). "Achieving high dry-matter intake from pasture with grazing dairy cows," in *Fresh Herbage for Dairy Cattle, the Key to a Sustainable Food Chain*, eds A. Elgersma, J. Dijkstra and S. Tamminga, (Dordrecht: Wageningen UR Frontis Series Volume 18. Springer), 1–26.

Eastwood, C., and Dela Rue, B. (2017). "Precision grazing management-understanding farmer uptake of grazing software," in *Proceedings of the 1st Asian-Australasian Conference on Precision Pastures and Livestock Farming*, (Hamilton), October 16–18, 2017.

Eastwood, C., Trotter, M., and Scott, N. (2013). Understanding the user: learning from on-farm application of precision farming technologies in the australian livestock sector. *Aust. J. Multi Discipl. Eng.* 10, 41–50. doi: 10.7158/N12-AE04.2013.10.1

Ferris, C. P. (2007). Sustainable pasture based dairy systems–meeting the challenges. *Can. J. Plant Sci.* 87, 723–738. doi: 10.4141/CJPS06011

Frame, J., and Laidlaw, A. S. (2011). *Improved Grassland Management*. Marlborough: The Crowood Press.

French, P., O'Brien, B., and Shalloo, L. (2015). Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. *Anim. Prod. Sci.* 55, 931–935. doi: 10.1071/AN14896

Gibon, A. (2005). Managing grassland for production, the environment and the landscape. Challenges at the farm and the landscape level. *Livest. Prod. Sci.* 96, 11– 31 doi: 10.1016/j.livprodsci.2005.05.009

Hodgson, J. (1990). *Grazing Management: Science Into Practice*. Harlow: Longman Scientific and Technical.

Hopkins, A., and Holmes, W. (2000). *Grass: Its production and utilization*. Oxford: Blackwell Science.

Hopkins, A., and Wilkins, R. J. (2006). Temperate grassland: key developments in the last century and future perspectives. *J. Ag. Sci*. 144, 503–523. doi: 10.1017/S0021859606006496

Malley, D., McClure, C., Martin, P. D., Buckley, K., and McCaughey, W. P. (2005). Compositional analysis of cattle manure during composting using a field-portable NIRS. *Commun. Soil Sci. Plant Anal.* 36, 455–475. doi: 10.1081/CSS-200043187

McDonald, P., Edwards, R. A., Greenhalgh, J. F. D., Morgan, C. A., Sinclair, L. A., and Wilkinson, R. G. (2011). *Animal Nutrition, 5th edn*. Harlow: Longman Press.

Miller, L. A., Moorby, J. M., Davies, D. R., Humphrey, M. O., Scollan, N. D., MacRae, J. C., et al. (2001). Increased concentration of water-soluble carbohydrate in perennial ryegrass (*Lolium perenne* L.): milk production from late-lactation dairy cows. *Grass For. Sci.* 56, 383–394. doi: 10.1046/j.1365-2494.2001.00288.x

Orr, R. J., Rutter, S. M., Penning, P. D., and Rook, A. J. (2001). Matching grass supply to grazing patterns for dairy cows. *Grass For. Sci.* 56, 352–361. doi: 10.1046/j.1365-2494.2001.00284.x

Pullanagari, R. R., Kereszturi, G., and Yule, I. J. (2018). Integrating airborne hyperspectral, topographic, and soil data for estimating pasture quality using recursive feature elimination with random forest regression. *Remote. Sens.* 10:1117. doi: 10.3390/rs10071117

Pullanagari, R. R., Yule, I. J., Tuohy, M. P., Hedley, M. J., Dynes, R. A., and King, W. M. (2012). In-field hyperspectral proximal sensing for estimating quality parameters of mixed pasture. *Precis. Agric.* 13, 351–369. doi: 10.1007/s11119-011-9251-4

Ramsbottom, G., Horan, B., Berry, D. P., and Roche, J. R. (2015). Factors associated with the financial performance of spring-calving, pasture-based dairy farms. *J. Dairy Sci.* 98, 3526–3540. doi: 10.3168/jds.2014-8516

Redman, G. (2016). *John Nix Farm Management Pocketbook*. Melton Mowbray: Agro Business Consultants Ltd.

Shalloo, L., Creighton, P., and O'Donovan, M. (2011). The economics of reseeding on a dairy farm. *Irish J. Agr. Food Res.* 50, 113–122. doi: 10.2307/41348159

Stergiadis, S., Allen, M., Chen, X. J., Wills, D., and Yan, T., (2015). Prediction of nutrient digestibility and energy concentrations in fresh grass using nutrient composition. *J. Dairy Sci.* 98, 3257–3273. doi: 10.3168/jds.2014-8587

Stuth, J., Jama, A., and Tolleson, D. (2003). Direct and indirect means of predicting forage quality through near infrared reflectance spectroscopy. *Field Crops Res.* 84, 45–56. doi: 10.1016/S0378-4290(03)00140-0

Waghorn, G. C., and Clark, D. A. (2004). Feeding value of pastures for ruminants. *NZ Vet. J.* 52, 320–331. doi: 10.1080/00480169.2004.36448

Wilkins, P. W., and Humphreys, M. O. (2003). Progress in breeding perennial forage grasses for temperate agriculture. *J. Ag. Sci.* 140, 129–150. doi: 10.1017/S0021859603003058

Wilkinson, J. M. (2011). Re-defining efficiency of feed use by livestock. *Animal* 5, 1014–1022. doi: 10.1017/S175173111100005X

Wilkinson, J. M., Allen, J. D., Tunnicliffe, R., Smith, M., and Garnsworthy, P. C. (2014). Variation in composition of pre-grazed pasture herbage in the United Kingdom, 2006– 2012. *Anim. Feed Sci. Technol.* 196, 139–144. doi: 10.1016/j.anifeedsci.2014.07.001

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Comparison of Methods for Monitoring the Body Condition of Dairy Cows

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Dairy cows are known to mobilize body fat to achieve their genetic potential for milk production, which can have a detrimental impact on the health, fertility and survival of the cow. Better monitoring of cows with poor body condition (low or high body fat) will lead to improvements in production efficiencies and less wasted resources when producing milk from dairy cows. The aim of this study was to compare different methods for monitoring the body condition (body fat) of dairy cows. The methods used to measure body condition were: ultrasound scanner, manual observation, and a still digital image of the cow. For comparison, each measure was expressed as a body condition score (BCS) on a scale of extremely thin (1) to very fat (5) in quarter intervals. A total of 209 cows at various stages of lactation were assessed. Lin's concordance correlation coefficient (*CCC*) and the root mean square prediction error (RMSPE) were used to compare the accuracy of methods. The average BCS across cows was 2.10 for ultrasound, 2.76 for manual and 2.41 for digital methods. The study found that both manual ($r = 0.790$) and digital ($r = 0.819$) approaches for monitoring cow body condition were highly correlated with ultrasound BCS measurements. After adjusting correlation coefficients for prediction bias relative to a 45° line through the origin, the digital BCS had a higher CCC of 0.789 when compared to the ultrasound BCS than the manual BCS with a CCC of 0.592. The digital BCS also had a lower prediction error (RMSPE = 28.3%) when compared with ultrasound BCS than the manual BCS (RMSPE = 42.7%). The prediction error for digital and manual BCS methods were similar for cows with a BCS of 2.5 or more (RMSPE = 20.5 and 19.0%, respectively) but digital BCS was more accurate for cows of <2.5 BCS (RMSPE = 35.5 and 63.8%, respectively). Digital BCS can provide a more accurate assessment of cow body fat than manual BCS observations, with the added benefit of more automated and frequent monitoring potentially improving the welfare and sustainability of high production systems.

Keywords: cattle, body fat, objective assessment, health, wellbeing

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INTRODUCTION

Originally body condition scoring was developed for management in sheep during the 1960s, before being adopted for use with cattle in the 1970s (Earle, 1976; Bewley and Schutz, 2008). The approach was developed to help farmers monitor the body fat composition of animals at key stages in production i.e., parturition, mating, lactation. Furthermore, assessment of animal body condition is used to inform decisions on appropriate feed allocation at an animal's given stage of production (Keady et al., 2005). This is therefore a valuable tool to manage animal productivity and feed utilization (Roche et al., 2009).

Garnsworthy (2007) suggests that cows have a physiological target level for body reserves in early lactation, and cows will try to reach a target BCS of 2.5 at around 12–15 weeks post-partum. Target BCS is influenced by genetics. Given the importance of body condition at different stages of production and their physiological target, a reliable phenotypic measure of BCS would be extremely beneficial. Typically, body condition is managed by appropriate nutrition, and Garnsworthy and Jones (1987) proposed that cows with low BCS (2.0) should be fed a high protein diet which maintains BCS by using excess protein for gluconeogenesis rather than body reserves, whereas fatter cows (BCS 3.5) had a greater loss of condition. Alternatively, high BCS cows can be fed a low fiber, high starch diet to reduce BCS loss, and this type of diet will also increase BCS in cows with a low BCS (Garnsworthy and Jones, 1993). The need to frequently monitor changes in body condition and prevent excessive body condition loss (more than 0.5 BCS) is further supported by studies highlighting associations with poor health, fertility, and ultimately survival. Research has shown that cows with a (high) BCS of 3.5 are twice more likely to develop ketosis than cows with a (low) BCS of 2.0 (Reid et al., 1986); and a 2–4 times higher risk of having ketosis in the next lactation (Rasmussen et al., 1999). Other health risks include increased chance of a retained placenta and/or metritis, and oestrus not being observed if cows have a low BCS (Markusfeld et al., 1997). It is estimated that conception rate decreases by 10% for every 0.5 BCS lost (Butler, 2005) and cows losing >1.0 BCS post-partum take on average 11 days longer to conceive than those that maintained or only lost a 0.5 BCS (Lopez-Gatius et al., 2003). Oestrus in cattle occurs when they are also lactating. For high milk yielding dairy cows this can pose a challenge, as the metabolic demands of milk production, and the mobilizing of body fat to produce milk, tend to take priority over reproduction, and can lead to conception failure due to a low negative energy balance (Collard et al., 2000). Therefore, monitoring individual cow body fat and maintaining adequate body condition is essential to maintain a productive animal that has appropriate nutrition and fertility, whilst also producing acceptable amounts of milk. While Holstein dairy cows are a popular breed for producing high volumes of milk, they are also characterized by having lower body condition score (BCS), and reduced fertility and survival compared to other breeds (Dillon et al., 2006). Bell and Wilson (2018) identified body condition as an important phenotypic trait, along with feed utilization, enteric methane emissions, health, fertility, and survival, associated with more sustainable milk production in UK dairy herds. The authors found that the cost of poor fertility in the UK (each day over the optimal calving interval length of 365 days) is about £2.80 per day with an associated increase in emissions of greenhouse gases for each extra day of about 15 kg of carbon dioxide equivalent (CO_2-eq.) emissions per cow and 23 kg CO_2-eq. emissions per kilogram milk solids. Ultimately poor health and fertility can lead to poor survival. The cost of poor survival in the UK (each percentage increase in cows culled or died within a herd) is estimated at about £13.50 per percentage of cows lost from a herd, with each percentage change resulting in an increase in CO_2-eq. emissions of about 50 kg per cow and 91 kg per kilogram milk solids due to resources required by replacement animals (Bell and Wilson, 2018).

The most widely used and traditional method of body condition scoring is by manual observation and/or physical examination of the animal to form an assessment of overall body condition (Edmonson et al., 1989; Roche et al., 2004). Body condition is scored using a variety of scales and approaches (Bewley and Schutz, 2008), but typically on a scale of extremely thin (1) to very fat (5 or 9 depending on scale adopted) in quarter intervals. To reduce the subjective nature of scoring, manual observers require training to ensure a consistent, and reliable measure. The approach also requires labor time and is therefore generally done once per week or only at key stages of production, if at all. The scoring method provides a simple means for people to manually monitor the body fat of animals. In recent years the expectation has been for each stockperson to look after more animals, as input costs (such as labor and feed) have increased. Also, finding skilled farm workers has become more difficult. With these developments has come new and more mobile technologies such as ultrasound for measuring body composition (fat and muscle) and digital image analysis software. These new technologies provide the potential to produce more objective measures for monitoring body condition (body fat) of livestock. While the use of ultrasound scanners requires a trained operator and can be an expensive device, the opposite is true of camera surveillance systems with digital image analysis software. Rather than rely on more specialized ultrasound equipment to accurately measure body fat and obtain a BCS (Domecq et al., 1995; Hussein et al., 2013; Singh et al., 2015), digital camera systems provide the opportunity for continuous and automated monitoring in real-time and potentially requires no prior training by the user other than interpreting the output. Several commercially available digital BCS tools exist (Bewley et al., 2008; Halachmi et al., 2008; Azzaro et al., 2011) and take images from above the animal to relate body shape angles around the hook bones and caudal area to BCS. Due to the images being taken from directly above the animal, the curvature around the hook bones has proved more useful in predictions than when including the tail head (Bewley et al., 2008). However, this is partly a function of the camera angle used to obtain the digital image. Also, the body curvature around the hook bones can be influenced by gut fill and pregnancy, and stage of production.

The objective of this study was to compare three different methods for measuring the body condition of dairy cows using an ultrasound scanner, manual observation, and a still digital image of the cow. An objective measure (i.e., still digital image) may provide a more accurate approach to identify animals that are too thin or too fat compared to a subjective measure (i.e., manual observations).

MATERIALS AND METHODS

Approval for this study was obtained from the University of Nottingham animal ethics committee before commencement of the study.

Data

Data were obtained from a total of 209 cows from two Holstein dairy herds, with 87 cows from Farm A, and 122 cows from Farm B. The cows used in this study represented a range of stages of production from early, mid and late lactation, and prior to calving. Farms were visited between May and July 2017, and cows were randomly selected from each herd. Lactating cows at Farm A were milked twice per day using a traditional herringbone parlor and had access to grazing, whereas cows at Farm B used an automatic milking station and were housed throughout lactation. Whilst lactating, cows at Farm A were grouped and fed according to stage of production (i.e., early, mid, or late lactation), whereas at Farm B cows were of various stages of production within a group of about 40 cows allocated to three automatic milking stations and fed the same diet. Both farms had a similar average daily milk yield of 30.1 L/day at Farm A and 32.1 L/day at Farm B.

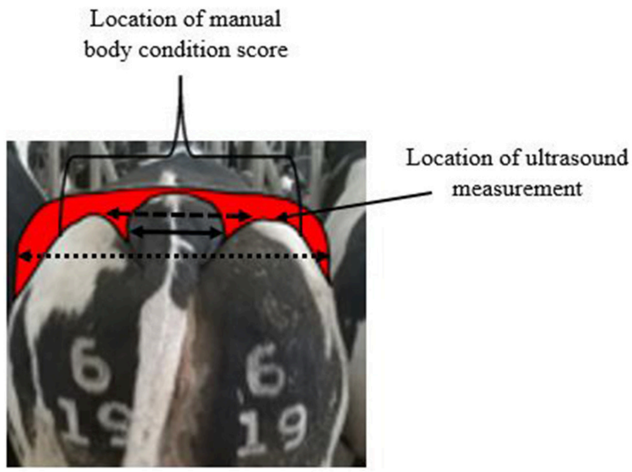

FIGURE 1 | Example of a digital image taken of the caudal area of the cow showing annotation for measurement of tail head width (solid line), distance between hook bones (dotted line), and pin bones (dashed line), and location of manual observed body condition and ultrasound measurement.

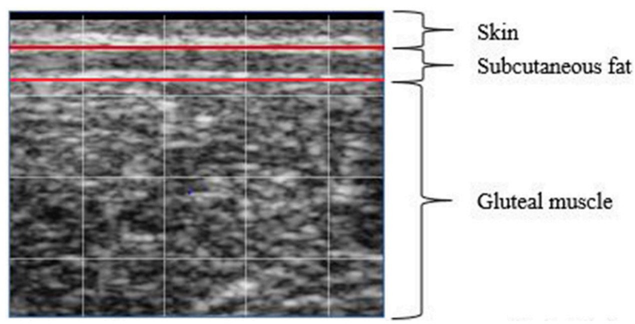

FIGURE 2 | Example of an ultrasound image used to measure subcutaneous fat depth (mm) between the red lines.

Body Fat and Body Condition Measurements

There were three methods used to measure the body condition of each cow, which were (1) manual observation, (2) ultrasound scanner, and (3) a still digital image. The body condition and fat depth measurements for all cows were assessed by the same operator with experience and training in assessment of body condition and ultrasound measurements. For the purpose of comparing different BCS methods, all measurements were taken in the same caudal area.

Manually Observed Body Condition

A combination of a visual observation and physical examination of the cow's body fat around its tail head was carried out following the condition scoring method of Edmonson et al. (1989). The amount of subcutaneous fat of each animal is assessed by a combination of manual palpation by hand of the tail head and observing from directly behind the cow the shape of the loins (e.g., spinous processes), pelvis (e.g., hook and pin bones), and tail head (e.g., tail and depression beneath the tail) areas. Based on the assessment an overall BCS was then attributed on a scale of extremely thin (1) to very fat (5) in quarter intervals (Edmonson et al., 1989).

Ultrasound Fat Depth

After the manual body condition assessment, an Easy-scan 4 (BCF, Livingstone, UK) ultrasound scanner was used to measure body fat on the rump of each cow, as illustrated in **Figure 1**. The rump of the cow was cleaned, and ultrasound gel was applied to the area prior to obtaining an ultrasound image (**Figure 2**) showing skin, subcutaneous fat, and muscle depths. The scanner has a linear multi-frequency (4.5–8.5 MHz) probe, and the body composition mode with inbuilt manual caliper function was used to measure subcutaneous fat depth in millimeters. The examination site was specifically located in front of the tuber ischia (pin bone) and following a line to the tuber coxae (hook bone). This location has been found by others to be the most appropriate (Schroder and Staufenbiel, 2006) and also ensuring suitable contact between the ultrasound probe head and the cow's body for better image quality.

Digital Photo Measurements

After obtaining the manual score and ultrasound measurement, a handheld 5 megapixel camera (Vodafone Smart Tab 4G, Newbury, UK) of 2,592 × 1,944 pixel resolution was used to obtain a still digital photo of the caudal area of each cow (**Figure 2**), and the area where manual and ultrasound measurements had been obtained. The image photo was taken from directly behind the cow at a 10° angle above the tail head and from 2 m behind the cow. No adjustment for lighting was required. Digital software (Inkscape 0.91, Boston, US) was subsequently then used to measure the tail head width distance, distance between the hook bones and distance between the pin bones of each cow. The distances were measured in pixels and the width of the tail head was expressed as a percentage of the distance between the pin bones or the distance between the hook bones.

The ultrasound body fat measurement was used to test the accuracy of manual and digital body condition measures. The ultrasound fat depth measurement was converted to a linear BCS from 1 to 5 with quarters by attributing the fat depth value to one of 17 categories, as shown in **Figure 3**.

Statistical Analysis

Pearson correlation coefficient (r) was multiplied by Lin's bias correction factor (C_b), which determines how far the best-fit line deviates from the 45° line through the origin, to derive the concordance correlation coefficient (CCC) (Lin, 1989). The coefficient CCC was used to test the association between ultrasound BCS and manual or digital BCS. Ultrasound (O_i) and manual or digital BCS (P_i) were also compared by their overall prediction error, and prediction error associated with cows <2.5 BCS and cows 2.5 BCS or more, using the square root of the mean square prediction error (RMSPE) expressed as a percentage of the observed mean ultrasound BCS. The mean square prediction error (MSPE) was calculated (Equation 1) for all 209 observations (n):

$$\text{MSPE} = \sum\nolimits_{\text{i}=1}^{n} (Oi - Pi)^2/n \tag{1}$$

RESULTS

Farm Data

On average cows at Farm A had less body fat (5.28 mm) than cows at Farm B (11.32 mm) (**Table 1**). The coefficient of variation for measured fat depth was greater at 81% for Farm A compared to 68% for Farm B.

For the analysis, the data from both farms was combined into a single dataset with animals of BCS from extremely thin (1) to very fat (5).

Body Condition Score Measures

The ultrasound BCS was compared to the digital measurements of tail head to pin bones and hook bones dimensions. There was a strong positive relationship between ultrasound BCS and the tail head to pin bones width (**Figure 4**). There was a poor relationship between the ultrasound BCS and the tail head to hook bones width (**Figure 5**).

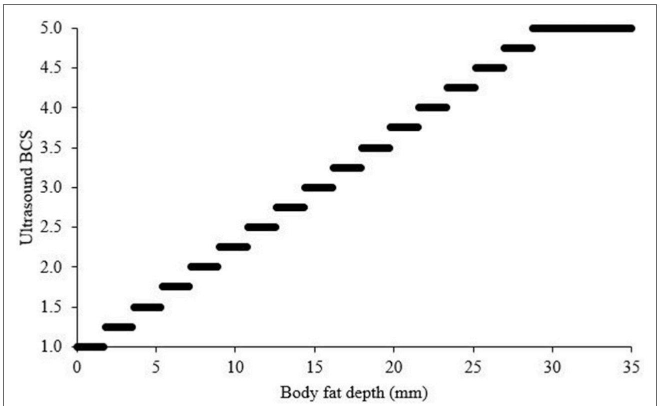

FIGURE 3 | Classification of ultrasound body fat depth into 17 body condition scores (BCS).

Given the relationship between the tail head to pin bones width and ultrasound BCS (**Figure 4**), the values for tail head to pin bones (ranging from 22.2 to 63.2%) were converted to a linear digital BCS with 17 classifications for comparison with other scoring methods, as shown in **Figure 6**.

The manual BCS had a high and positive correlation with the ultrasound BCS (r = 0.790) and had a high Lin's bias correction factor (C_b = 0.749), resulting in a moderate CCC of 0.592. However, the manual BCS tended to over predict the body fat of cows when compared to the ultrasound fat depth measure (**Figure 7**), and particularly at lower body condition scores. The manual BCS had a relatively high prediction error (RMSPE = 42.7%) when compared with the ultrasound BCS, with the error being lower for cows of 2.5 BCS or more (RMSPE = 19.0%) compared to cows of <2.5 BCS (RMSPE = 63.8%).

The digital BCS had a high and positive correlation with the ultrasound BCS (r = 0.819) and had a high Lin's bias correction factor (C_b = 0.964), resulting in a high CCC of 0.789. The prediction error of the digital BCS was moderately low (RMSPE = 28.3%) when compared with the ultrasound BCS (**Figure 8**) and was even lower for cows of 2.5 BCS or more (RMSPE = 20.5%) compared to cows of <2.5 BCS (RMSPE = 35.5%).

DISCUSSION

The current study compared manual observations of BCS and digital BCS methods with detailed body fat depth measurements using an ultrasound scanner, taken in the same caudal area for each cow. The dataset provided the necessary range of animals with body condition scores from extremely thin (1) to very fat (5) for the analysis and comparison of scoring methods (Edmonson et al., 1989; Schroder and Staufenbiel, 2006). The linear classification of ultrasound measured subcutaneous fat into 17 BCS categories from 1 to 5, and subcutaneous body fat values ranging from 0.9 to 33.2 mm, was comparable in the current study (**Figure 3**) to that found by Schroder and Staufenbiel (2006). Both herds used in the current study consisted of high milk yielding Holstein dairy cows, with a similar average daily milk yield (30.1 L/day at Farm A and 32.1 L/day at Farm B), however, the herds were managed differently with cows at Farm A grouped and fed according to stage of production whereas at Farm B cows were of various stages of production within a group using an automatic milking station. The difference in management meant that at farm B the cows had a higher average body fat (11.3 mm) than the cows at Farm A (5.3 mm). The methods assessed all measured subcutaneous fat depth, expressed as a BCS, and assumed that this provided an appropriate assessment to the animal's subcutaneous fat and overall body fat reserves (Domecq et al., 1995; Schroder and Staufenbiel, 2006; Hussein et al., 2013). The data obtained in the current study would suggest that optimum BCS of 2.5 at about 50 days postpartum to 3.0 at calving and toward the end of lactation (Chagas et al., 2007) is often not achieved for modern high milk yielding dairy cows. This is considered the optimum range, with

TABLE 1 | Mean (s.d.) body fat depth, tail head to pin and hook bone widths, ultrasound, manual, and digital body condition scores at Farm A and B and across farms.

		Farm				
		A		B		
Farm	Units	Mean (s.d.)	Range	Mean (s.d.)	Range	Overall
Fat depth	mm	5.28 (4.25)	1.01–23.02	11.32 (7.69)	0.91–33.20	8.81 (7.12)
Tail head to pin bones[a]	%	32.56 (6.06)	24.04–47.40	38.91 (9.18)	22.15–63.22	36.67 (8.74)
Tail head to hook bones[a]	%	23.78 (4.25)	15.87–34.71	21.22 (4.53)	13.16–30.62	22.12 (4.59)
Ultrasound BCS	1–5	1.60 (0.59)	1.00–4.00	2.45 (1.05)	1.00–5.00	2.10 (0.98)
Manual BCS	1–5	2.40 (0.68)	1.00–4.50	3.02 (0.69)	1.25–5.00	2.76 (0.75)
Digital BCS	1–5	1.99 (0.64)	1.00–3.50	2.63 (0.95)	1.00–5.00	2.41 (0.91)

[a] *The width of the tail head was expressed as a percentage of the distance between the pin bones or the distance between the hook bones.*

an acceptable change of 0.5 BCS, so dairy cows can minimize the impact of mobilizing body reserves for milk production and negative energy balance on health, fertility, and well-being, whilst still allowing cows to achieve adequate milk production (Roche et al., 2009). Across all cows, the manual BCS produced the highest average BCS of 2.76, compared to 2.41 for digital BCS and 2.10 for ultraound BCS. The ultrasound and digital methods were below the recommended "ideal" range of 2.5–3.0 (Chagas et al., 2007). On average, the manual BCS overpredicted body condition when compared to ultrasound measurements by 31%. This over prediction of manual BCS was greater in low BCS cows at 57% higher than ultrasound measurements (**Figure 7**). A limitation of visual assessment of body condition is that it is unlikely to accurately detect subtle changes in body composition change at a BCS of <2.5 (low), which equates to a subcutaneous fat depth of <13 mm (**Figure 3**). Also, at very low subcutaneous fat depths, the decrease in BCS may represent protein loss and not changes in body fat reserves (MacDonald et al., 1999). The cows in the current study had high genetic potentials for milk, which is known to result in greater loss of BCS over a longer period postpartum and a failure to repartition significant amounts of energy toward body reserves until later in lactation or when lactation ceases (Roche et al., 2006). The main benefit of better monitoring of cow body condition is to improve awareness of animals that are too thin or too fat, and consequently of higher risk from poor health, fertility, and survival (Reid et al., 1986; Markusfeld et al., 1997; Lopez-Gatius et al., 2003). There is little evidence to suggest that improvements have been made with regard to health and fertility in recent decades (Farm Animal Welfare Council (FAWC), 2009), and therefore supporting the case for enhanced monitoring of animals and their body condition. With less wastage of resources such as feed, a 1-kg improvement in feed utilization per cow per year would mitigate 1.3 kg of CO_2-eq. emissions each year, which for the UK dairy cow population of 1.8 million cows would equate to a reduction of 2,340 t CO_2-eq. emissions and more profit of £324,000 to the dairy industry (Bell et al., 2015). Improving health, fertility, and survival of cows will increase profitability and reduce greenhouse gas emissions intensity of milk production (Bell and Wilson, 2018), leading to more sustainable milk production systems.

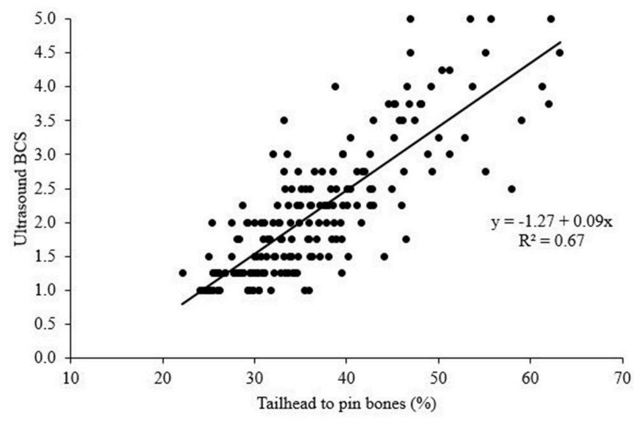

FIGURE 4 | Relationship between the tail head to pin bones width and ultrasound body condition score (BCS).

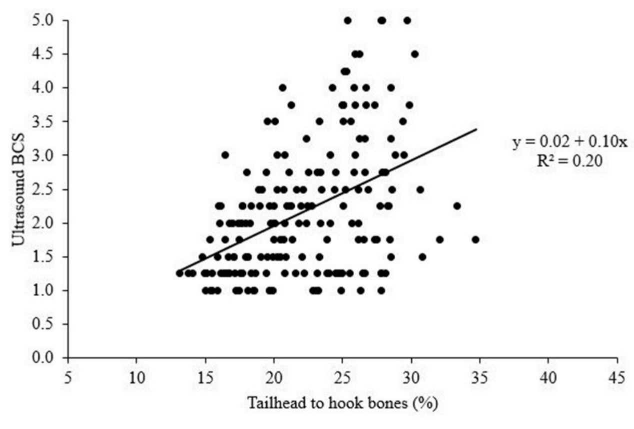

FIGURE 5 | Relationship between the tail head to hook bones width and ultrasound body condition score (BCS).

To address the need for better and frequent monitoring of cow body condition, there has been considerable interest in the use and application of digital technologies to predict body condition. Taking digital images of the rear or caudal area has also been shown to provide a reliable measure of

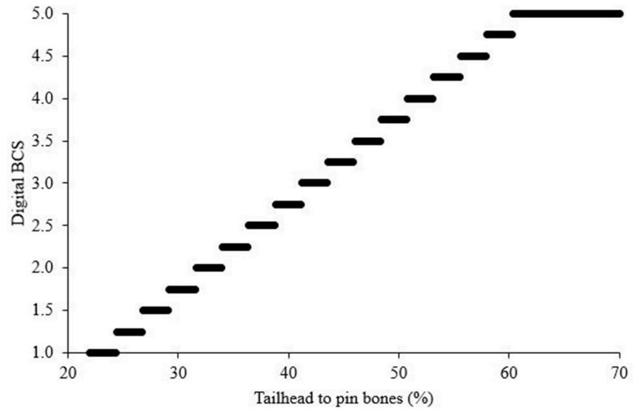

FIGURE 6 | Classification of digital measure of tail head to pin bones width into 17 body condition scores (BCS).

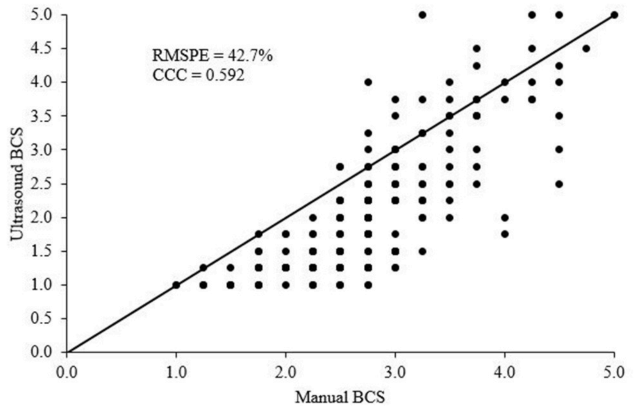

FIGURE 7 | Relationship between manual observed and ultrasound body condition score (BCS). Root mean square prediction error (RMSPE) expressed as a percentage of the observed mean for ultrasound BCS and Lin's concordance correlation coefficient *(CCC)* are shown, and the 45° line through the origin.

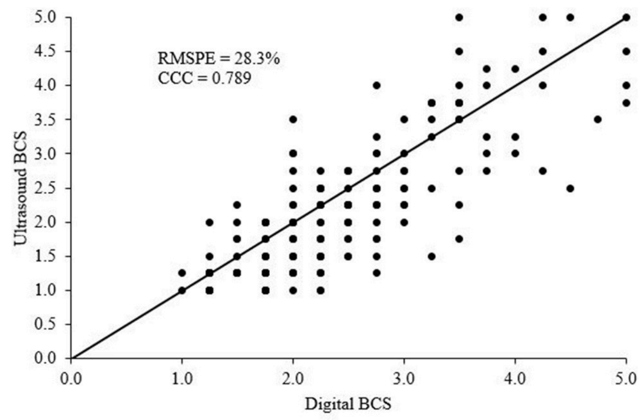

FIGURE 8 | Relationship between digital and ultrasound body condition score (BCS). Root mean square prediction error (RMSPE) expressed as a percentage of the observed mean for ultrasound BCS and Lin's concordance correlation coefficient *(CCC)* are shown, and the 45° line through the origin.

body condition (Ferguson et al., 2006). Therefore, the current study focused on measuring caudal subcutaneous fat and body condition, which are not influenced by gut fill or pregnancy or stage of production and have been shown to provide a reliable measure of body fat (Schroder and Staufenbiel, 2006). In the current study a digital BCS of cows was also estimated from the tail head to pin bones width, which had a similar accuracy to manual BCS for cows of 2.5 BCS or more (RMSPE of 20.5 and 19.0%, respectively) but higher accuracy for thinner cows of <2.5 BCS (RMSPE of 35.5 and 63.8%, respectively). This suggests that digital images from tail head dimensions can be used to monitor cows with a broad range of body conditions. The accuracy of the digital BCS prediction can be further refined using computer vision techniques to automatically extract image measurements and can also be estimated by Equation (2) (**Figure 4**):

$$\text{Ultasound BCS (1to5)} = -1.27 + 0.09 \times \text{tail head to pin bones (\%)} \quad (2)$$

There are several factors that can reduce the reliability of digital BCS predictions and therefore need to be considered. The current study supports the finding of Ferguson et al. (2006) that the image photo needs to be taken at a 0–20° angle above the tail head to get an optimum image for assessment. Also, the influence of changing light, cow posture and color, and tail movement may be causes of error, however, they were not a problem when conducting measurements in the current study.

If an accurate method was developed that could detect low body fat changes and monitor animals frequently, then impacts on the well-being of a cow can be minimized and managed better than current practice. The different methods (ultrasound, manual, or digital) assessed can all provide an easy, quick, and practical measure for monitoring body condition on farms. For large numbers of animals, the use of an ultrasound scanner can be more time consuming than manual or digital camera methods. Ultrasound measurements are more expensive, but accurate, and can be used for other tasks such as pregnancy diagnosis of animals. Both ultrasound and manual BCS methods can be done infrequently whilst performing other routine animal husbandry tasks, while automated digital analysis may provide the "ideal" cow BCS profile based on frequent measurements.

The methods assessed all provide a useful and easily implemented tool for monitoring cow BCS on commercial farms to improve farm level decision making and awareness of cow body condition. The approaches compared offer different levels of complexity to monitoring cow body condition, with manual and ultrasound methods requiring operator training, whereas digital photos require minimal user input and provide an automated objective measure. Across a wide range of BCS, digital BCS was found to provide a more accurate assessment of cow body condition than manual BCS observations when compared to ultrasound body fat measurements. The digital BCS can remove operator error and provide frequent monitoring to allow detection of short-term changes in body condition, which will ultimately improve cow performance and well-being, and enhance the sustainability of high milk production systems.

AUTHOR CONTRIBUTIONS

MB, MM, MS, and RP collected the data. MB and RP carried out the analysis and wrote the paper.

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REFERENCES

Azzaro, G., Caccamo, M., Ferguson, J. D., Battiato, S., Farinella, G. M., Guarnera, G. C., et al. (2011). Objective estimation of body condition score by modelling cow body shape from digital images. *J. Dairy Sci.* 94, 2126–2137. doi: 10.3168/jds.2010-3467

Bell, M. J., Garnsworthy, P. C., Stott, A. W. and Pryce, J. E. (2015). The effect of changing cow production and fitness traits on profit and greenhouse gas emissions from UK Dairy systems. *J. Ag. Sci.* 153, 138–151. doi: 10.1017/S0021859614000847

Bell, M. J., and Wilson, P. (2018). Estimated differences in economic and environmental performance of forage-based dairy herds across the UK. *Food Energy Secur.* 7:e00127. doi: 10.1002/fes3.127

Bewley, J. M., Peacock, A. M., Lewis, O., Boyce, R. E., Roberts, D. J., Coffey, M. P., et al. (2008). Potential for estimation of body condition scores in dairy cattle from digital images. *J. Dairy Sci.* 91, 3439–3453. doi: 10.3168/jds.2007-0836

Bewley, J. M., and Schutz, M. M. (2008). Review: an interdisciplinary review of body condition scoring for dairy cattle. *Prof. Anim. Sci.* 24, 507–529. doi: 10.15232/S1080-7446(15)30901-3

Butler, W. R. (2005). Nutrition, negative energy balance and fertility in the postpartum dairy cow. *Cattle Pract.* 13, 13–18. Available online at: https://www.bcva.eu/cattle-practice/documents/1754

Chagas, L. M., Bass, J. J., Blache, D., Burke, C. R., Kay, J. K., Lindsay, D. R., et al. (2007). Invited review: new perspectives on the roles of nutrition and metabolic priorities in the subfertility of high-producing dairy cows. *J. Dairy Sci.* 90, 4022–4032. doi: 10.3168/jds.2006-852

Collard, B. L., Boettcher, P. J., Dekkers, J. C., Petitclerc, D., and Schaeffer, L. R. (2000). Relationships between energy balance and health traits of dairy cattle in early lactation. *J. Dairy Sci.* 83, 2683–2690. doi: 10.3168/jds.S0022-0302(00)75162-9

Dillon, P., Berry, D. P., Evans, R. D., Buckley, F., and Horan, B. (2006). Consequences of genetic selection for increased milk production in European seasonal pasture based systems of milk production. *Livest. Sci.* 99, 141–158. doi: 10.1016/j.livprodsci.2005.06.011

Domecq, J. J., Skidmore, A. L., Lloyd, J. W., and Kaneene, J. B. (1995). Validation of body condition scores with ultrasound measurements of subcutaneous fat of dairy cows. *J. Dairy Sci.* 78, 2308–2313. doi: 10.3168/jds.S0022-0302(95)76857-6

Earle, D. F. (1976). A guide to scoring dairy cow condition. *J. Agric.* 74:228.

Edmonson, A. J., Lean, I. J., Weaver, L. D., Farver, T., and Webster, G. (1989). A body condition scoring chart for Holstein dairy cows. *J. Dairy Sci.* 72, 68–78. doi: 10.3168/jds.S0022-0302(89)79081-0

Farm Animal Welfare Council (FAWC) (2009). *Opinion on the Welfare of the Dairy Cow*. London: Farm Animal Welfare Council.

Ferguson, J. D., Azzaro, G., and Licitra, G. (2006). Body condition assessment using digital images. *J. Dairy Sci.* 89, 3833–3841. doi: 10.3168/jds.S0022-0302(06)72425-0

Garnsworthy, P. C. (2007). "Body condition score in dairy cows: targets for production and fertility," in *Recent Advances in Animal Nutrition 2006*, eds P. C. Garnsworthy and J. Wiseman (Nottingham: Nottingham University Press), 61–86.

Garnsworthy, P. C., and Jones, G. P. (1987). The influence of body condition at calving and dietary protein supply on voluntary food intake and performance in dairy cows. *Anim. Prod.* 44, 347–353. doi: 10.1017/S0003356100012277

Garnsworthy, P. C., and Jones, G. P. (1993). The effects of dietary fibre and starch concentrations on the response by dairy cows to body condition at calving. *Anim. Prod.* 57, 15–21. doi: 10.1017/S0003356100006553

Halachmi, I., Polak, P., Roberts, D. J., and Klopcic, M. (2008). Cow body shape and automation of condition scoring. *J. Dairy Sci.* 91, 4444–4451. doi: 10.3168/jds.2007-0785

Hussein, H. A., Westphal, A., and Staufenbiel, R. (2013). Relationship between body condition score and ultrasound measurement of backfat thickness in multiparous Holstein dairy cows at different production phases. *Aust. Vet. J.* 91, 185–189. doi: 10.1111/avj.12033

Keady, T. W. J., Mayne, C. S., Kilpatrick, D. J., and McCoy, M. A. (2005). Effect of level and source of nutrients in late gestation on subsequent milk yield and composition and fertility of dairy cows. *Livest. Prod. Sci.* 94, 237–248. doi: 10.1016/j.livprodsci.2004.12.001

Lin, L. I. (1989). A concordance correlation coefficient to evaluate reproducibility. *Biometrics* 45, 255–268. doi: 10.2307/2532051

Lopez-Gatius, F., Yaniz, J., and Madriles-Helm, D. (2003). Effects of body condition score and score change on the reproductive performance of dairy cows: a meta-analysis. *Theriogenology* 59, 801–812. doi: 10.1016/S0093-691X(02)01156-1

MacDonald, K. A., Verkerk, G. A., and Penno, J. W. (1999). Validation of body condition scoring by using ultrasound measurements of subcutaneous fat. *Proc. N. Z. Soc. Anim. Prod.* 59, 177–179.

Markusfeld, O., Galon, N., and Ezra, E. (1997). Body condition score, health, yield and fertility in dairy cows. *Vet. Record.* 141, 67–72. doi: 10.1136/vr.141.3.67

Rasmussen, L. K., Nielsen, B. L., Pryce, J. E., Mottram, T. T., and Veerkamp, R. F. (1999). Risk factors associated with the incidence of ketosis in dairy cows. *Anim. Sci.* 68, 379–386. doi: 10.1017/S1357729800050372

Reid, I. M., Roberts, C. J., Treacher, R. J., and Williams, L. A. (1986). Effect of body condition at calving on tissue mobilisation, development of fatty liver and blood chemistry of dairy cows. *Anim. Prod.* 43, 7–15. doi: 10.1017/S0003356100018298

Roche, J. R., Berry, D. P., and Kolver, E. S. (2006). Holstein-friesian strain and feed effects on milk production, body weight, and body condition score profiles in grazing dairy cows. *J. Dairy Sci.* 89, 3532–3543. doi: 10.3168/jds.S0022-0302(06)72393-1

Roche, J. R., Dillon, P. G., Stockdale, C. R., Baumgard, L. H., and VanBaale, M. J. (2004). Relationships among international body condition scoring systems. *J. Dairy Sci.* 87, 3076–3079. doi: 10.3168/jds.S0022-0302(04)73441-4

Roche, J. R., Friggens, N. C., Kay, J. K., Fisher, M. W., Stafford, K. J., and Berry, D. P. (2009). *Invited review:* body condition score and its association with dairy cow productivity, health, and welfare. *J. Dairy Sci.* 92, 5769–5801. doi: 10.3168/jds.2009-2431

Schroder, U. J., and Staufenbiel, R. (2006). Invited review: methods to determine body fat reserves in the dairy cow with special regard to ultrasonographic measurement of backfat thickness. *J. Dairy Sci.* 89, 1–14. doi: 10.3168/jds.S0022-0302(06)72064-1

Singh, R., Randhawa, S. N. S., and Randhawa, C. S. (2015). Body condition score and its correlation with ultrasonographic back fat thickness in transition crossbred cows. *Vet. World.* 8, 290–294. doi: 10.14202/vetworld.2015.290-294

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frontiers in Sustainable Food Systems

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Combining Environmental Monitoring and Remote Sensing Technologies to Evaluate Cropping System Nitrogen Dynamics at the Field-Scale

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Nitrogen (N) losses from cropping systems in the U.S. Midwest represent a major environmental and economic concern, negatively impacting water and air quality. While considerable research has investigated processes and controls of N losses in this region, significant knowledge gaps still exist, particularly related to the temporal and spatial variability of crop N uptake and environmental losses at the field-scale. The objectives of this study were (i) to describe the unique application of environmental monitoring and remote sensing technologies to quantify and evaluate relationships between artificial subsurface drainage nitrate (NO_3-N) losses, soil nitrous oxide (N_2O) emissions, soil N concentrations, corn (*Zea mays* L.) yield, and remote sensing vegetation indices, and (ii) to discuss the benefits and limitations of using recent developments in technology to monitor cropping system N dynamics at field-scale. Preliminary results showed important insights regarding temporal (when N losses primarily occurred) and spatial (measurement footprint) considerations when trying to link N_2O and NO_3-N leaching losses within a single study to assess relationship between crop productivity and environmental N losses. Remote sensing vegetation indices were significantly correlated with N_2O emissions, indicating that new technologies (e.g., unmanned aerial vehicle platform) could represent an integrative tool for linking sustainability outcomes with improved agronomic efficiencies, with lower vegetation index values associated with poor crop performance and higher N_2O emissions. However, the potential for unmanned aerial vehicle to evaluate water quality appears much more limited because NO_3-N losses happened prior to early-season crop growth and image collection. Building on this work, we encourage future research to test the usefulness of remote sensing technologies for monitoring environmental quality, with the goal of providing timely and accurate information to enhance the efficiency and sustainability of food production.

Keywords: nitrogen dynamics, nitrous oxide emissions, nitrate leaching, remote sensing, environmental monitoring, sustainable food production

INTRODUCTION

The installation of artificial subsurface drainage (tile drainage) played an important role in the development of the U.S. Midwestern Corn Belt, with the drainage improved in this way on more than 17 million ha across the region today (USDA-NASS, 2012). This region is one of the most productive agricultural areas in the world. In 2017, the states of Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin produced ∼232 million metric tons of corn (*Zea mays* L.) on 19.4 million ha of land (USDA-NASS, 2018), accounting for ∼35% of the world's total corn production (USDA-ERS, 2018). As global demand for food, fiber, and energy is expected to continue increasing throughout the second half of the twenty first century (Godfray, 2014), agricultural producers are facing the dual challenge of further increasing crop production while conserving natural resources and enhancing environmental sustainability. Nitrogen (N) fertilizer inputs, in particular, are essential to maximize production and sustain soil quality in high-yielding cropping systems (Mueller et al., 2012; EU Nitrogen Expert Panel, 2015). However, applied N fertilizer is susceptible to environmental losses, with approximately only half of N inputs recovered by harvested crop products globally (Lassaletta et al., 2014; Zhang et al., 2015).

In the U.S. Midwest, N losses from croplands represent a major environmental and economic concern, negatively impacting water and air quality. The naturally N-rich soils in this region are extremely well-suited for highly productive cropping systems, but these soils also require artificial tile drainage to meet productivity potential. The combination of cropping systems composed of annual row crops, some of which are N-intensive, naturally N-rich soils, and tile drainage is a key driver of elevated nitrate (NO_3-N) concentrations in the upper Mississippi River Basin (David et al., 2010). High N loads from this region contribute significantly to the seasonal hypoxic zone (oxygen-depleted area) in the Northern Gulf of Mexico each year (USEPA, 2007). Meanwhile, soil nitrous oxide (N_2O) emissions are a potent greenhouse gas (GHG) contributing to stratospheric ozone depletion (Ravishankara et al., 2009). In 2016, soil management activities (including N fertilizer application) accounted for 77% of the total anthropogenic N_2O sources in the U.S., with the agriculture sector contributing around 9% of total GHG emissions overall (USEPA, 2018). A recent economic analysis estimated N losses (air/deposition, surface freshwater, groundwater, and coastal zones) related to agricultural N use in the U.S. have corresponding environmental damage costs of $157 billion year^{-1} (Sobota et al., 2015).

Management of N fertilizer to meet both production and environmental goals is challenging, in part because cropping system N dynamics are based on complex relationships that are difficult to monitor and cannot be easily predicted. Ammonium (NH_4-N) and NO_3-N are the main forms of inorganic soil N, with NH_4-N being rapidly converted to NO_3-N through the process of nitrification in warm, well-aerated soil (Norton, 2008). However, NO_3-N is susceptible to losses through leaching (the downward movement of dissolved nutrients through the soil profile with flowing water) (Mulla and Strock, 2008) and denitrification (the biological reduction of NO_3-N into N_2O gas under anaerobic conditions and microbial respiratory metabolism) (Coyne, 2008). Due to interactions among weather, soil properties, crop growth, and soil N transformations, the fate of applied N fertilizer is highly variable and there are unanswered questions about how much N not recovered by the crop is susceptible to N leaching and gaseous losses (Scharf, 2015). Adding to this complexity is that relationships between soil N availability, crop N uptake, and environmental losses vary across temporal and spatial scales. While considerable research has investigated processes and controls of N losses in this region, individual studies are often focused on only one or two components of the system, leading to an incomplete understanding. Thus, significant knowledge gaps still exist, particularly related to how the spatial and temporal variability of soil-plant-water relationships collectively drive environmental N losses at the field-scale.

The ability to simultaneously measure crop N dynamics and environmental loss pathways using recent developments in monitoring technologies could be an important step in improving crop production efficiencies to maximize grain yields while reducing N losses. For instance, it is well-documented in separate studies that increased N inputs correspond to greater N_2O and tile drainage N losses in corn-based systems, especially when the N rate exceeds plant N demand (Decock, 2014; Christianson and Harmel, 2015a). Therefore, one would expect that conditions leading to high N leaching losses would also result in high N_2O losses. However, a recent meta-analysis evaluating the effects of N fertilizer management practices on corn yields and N losses highlighted the lack of paired N_2O emission and drainage N leaching data collected from the same fields in the same cropping year (Eagle et al., 2017b). With only one study out of 27 in the U.S. and Canada measuring both N_2O and N leaching losses, these authors concluded the lack of information is impeding our understanding of N cycling tradeoffs and synergies (Eagle et al., 2017b). Similarly, understanding potential tradeoffs between crop productivity and environmental N losses is a key issue in reducing the N footprint of agriculture (Zhang et al., 2015). Nevertheless, few studies have evaluated whether increased crop yields and N uptake within a field correspond with lower N_2O emissions and N leaching losses, likely because individual studies are often focused on only limited parameters due to disciplinarily of researches often combined with funding limitations.

Investigating the potential usefulness of enhanced monitoring technologies requires field-scale research approaches to identify benefits and limitations for specific crop production contexts. In addition to spatial variability of N cycling processes within a field, there is also variation between different measurement methods. Nitrous oxide emissions are often measured following the static closed-chamber method in small areas (∼0.7 × 0.4 m) (Parkin and Venterea, 2010). This observational footprint is significantly smaller than many drainage studies where the nature of drainage hydrology integrates N leaching losses over several ha (Christianson et al., 2016). Crop response to N fertilizer has also been shown to be highly variable within-field due to differences in soil properties (Scharf et al., 2005; Schmidt et al., 2011). At broader spatial scales, remote sensing technologies [e.g., satellite imagery, unmanned aerial vehicles (UAV)] have increasingly been used for crop monitoring and yield forecasting in the recent decades (Rembold et al., 2013). These new technologies allow improved data collection capability over large areas with finer temporal and spatial resolution, and these technologies are becoming more readily available at the farm-level to aid monitoring, awareness, and decision-making (Atzberger, 2013; Bell and Tzimiropoulos, 2018). However, we are unaware of efforts to combine recently available technologies with the goal of shedding new insights into how fundamental N cycling processes are correlated at the field-scale, while also exploring the limitations of such approaches.

The objective of this investigation was to describe the unique application of environmental monitoring and remote sensing technologies to quantify cropping system N dynamics (i.e., artificial subsurface drainage N losses, soil N_2O emissions, soil N concentrations, corn yield, and remote sensing vegetation indices) at a new research site established in central Illinois, U.S. The purpose of this manuscript was to interpret preliminary results from 2017 (corresponding to the baseline year of a long-term field experiment) to illustrate how this research approach can help inform the development of high-yielding crop production systems with a low environmental footprint.

MATERIALS AND METHODS

Site Description and Experimental Design

Sixteen individually subsurface drained plots (hydrologically isolated using border tiles) were established in fall 2016 at the University of Illinois Dudley Smith Farm in Christian County, IL, U.S. (39° 27' N, 89° 6' W). Each plot was approximately 0.85 ha, containing three tile laterals at 18 m spacing (**Figure 1**). The drainage system was design using a drainage design coefficient of 9.5 mm day^{-1} (i.e., the rate at which water is to be removed from the field). The soils were generally silty clay loam and silt loam series, classified as somewhat poorly drained (Herrick, Oconee, and Oconee-Darmstadt-Coulterville series), poorly drained (Virden series), and moderately well-drained (Harrison series) (Web Soil Survey, 2018). The region has a hot humid continental climate (Köppen Climate Classification System: Dfa), with long term annual rainfall of 1,043 mm and annual mean temperature of 11.6°C (30-year average). Daily temperature and precipitation were recorded using an on-site weather station (HOBO RX3000, Onset Computer Corporation, Bourne, MA, U.S.) (**Figure 2**).

Drainage Water Monitoring

Each plot drained to an inline control structure (Agridrain™, Adair, IA, U.S.). Beginning in late spring 2017 (April/May), flow was continuously monitored using a water level data logger (HOBO U20L-04, Onset Corporation, Bourne, MA, U.S.; water depth recorded every 15 min) at six of the 16 plots (plots 3, 7, 9, 10, 13, and 15). These initial six plots were selected from across the site to trial potential monitoring equipment during this baseline year; all plots were eventually instrumented during the treatment period (data not presented here). Drainage flow rates were calculated using a calibrated v-notch weir equation or a compound weir equation at greater flow depths (AgriDrain™, personal communication; Chun and Cooke, 2008). Drainage water samples (~100 mL) were collected weekly from all 16 plots, filtered within 24 h (0.45 µm, S-Pak® Membrane Filters, Millipore Sigma, Darmstadt, Germany), and stored frozen until analysis for NO_3-N (within 20 days; method 10-107-106-1-J, Lachat QuickChem 8500 series, Loveland, CO, U.S.). Nitrate-N loads for this period were estimated by multiplying NO_3-N concentrations by discharge volumes for each sampling event and summing across the growing season. Yield-scaled NO_3-N leaching losses ($YSNO_3$, in kg NO_3-N per Mg of grain) were estimated by dividing NO_3-N loads by grain yield for each plot.

Soil N_2O Emission and Inorganic N Measurements

Measurements of N_2O were performed following the closed-static chamber method according to USDA-ARS GraceNET Project Protocols (see details in Parkin and Venterea, 2010). The chamber consisted of two parts: a chamber base (67.3 cm length × 40.6 cm width × 14 cm height) and a vented closed chamber lid (same dimensions as base) that was covered with reflective double bubble foil insulation (Ecofoil, Urbana, IA, U.S.) to minimize temperature changes during gas sampling. The lids also contained a layer of weather stripping (Lundell Manufacturing Corporation, Minneapolis, MN, U.S.) lining the connection between lids and base to create an air-tight seal during gas sampling and prevent ambient mixing. The chamber bases were inserted 5 cm into the soil on May 15, ~4.5 m beside the center tile lateral to obtain representative drainage conditions. This location was the midpoint between the plot area furthest from the lateral (9 m) and directly over the lateral. Chamber bases were left in place during the entire growing season (**Figure 1**).

Gas samples were collected weekly from side-dress N application until August, and twice a month thereafter. On each sampling date, the chamber lid was placed on top of the chamber base and secured in place with clamps. Each chamber lid had an airtight septum at the top through which samples were withdrawn. Individual gas samples of 20 mL were taken at 0, 16, 32, and 48 min following chamber deployment using a 20 mL syringe. After withdrawing a sample, 5 mL of gas was ejected, and 15 mL was immediately transferred into a 10 mL previously evacuated glass vial sealed with butyl rubber stoppers (Voigt Global Distribution Inc., Lawrence, KS, U.S.). Rubber stoppers were covered with clear RTV silicone adhesive sealant (Dow Corning, Midland, MI, U.S.) to prevent leakage. Gas samples were stored in glass vials until analyzed by gas chromatography (Shimadzu GC-2017, Canby, OR, U.S.). Nitrous oxide fluxes were calculated from the linear increase in gas concentration in the chamber headspace vs. time, as described by Parkin and Venterea (2010). Cumulative area-scaled N_2O emissions (cN_2O) were estimated using trapezoidal integration of flux vs. time, as described by Venterea et al. (2011). Yield-scaled N_2O emissions (YSNE, in kg N_2O per Mg of grain) were estimated for each plot by dividing cN_2O by the respective grain yield (van Groenigen et al., 2010).

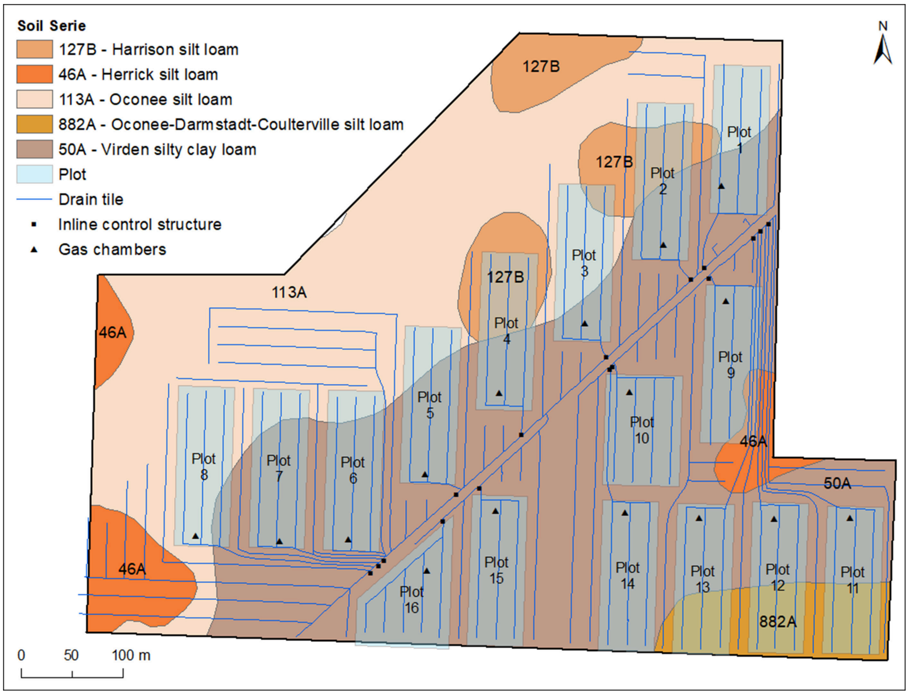

FIGURE 1 | Experiment and drainage design layout at the University of Illinois Dudley Smith Farm, Illinois, U.S.

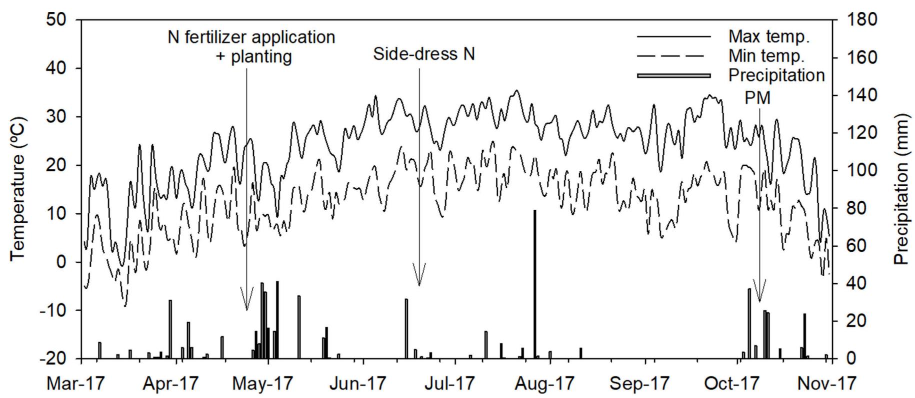

FIGURE 2 | Daily maximum and minimum air temperatures and precipitation during the corn growing season in 2017 at Dudley Smith Farm, Illinois, U.S. (N, nitrogen; PM, physiological maturity).

Soil samples for NO_3-N and NH_4-N determination were taken following procedures described by Graham et al. (2018). Briefly, composite samples were obtained from five equally spaced soil cores across the inter-row area along a transect running perpendicular to the crop row. Samples were collected to 20 cm depth near gas chambers in each plot using a 2 cm diameter probe. Soil inorganic N was extracted within 24 h using 2M KCl and NO_3-N and NH_4-N concentrations were determined using a Smartchem 170 discrete wet chemistry auto-analyzer (Unity Scientific, Milford, MD, U.S.).

Corn Management and Aerial Imagery Collection

Corn was grown with uniform management across all 16 plots in 2017. Following pre-plant tillage to prepare the seed bed (S-tine field cultivator 2210 John Deere, Moline, IL, U.S.), corn was planted on April 26 2017 at 80,000 seeds ha^{-1} and 76 cm row spacing. Nitrogen fertilizer management consisted of a pre-plant application (April 25 2017; 168 kg N ha^{-1}) and a side-dress application (June 14 2017; 135 kg N ha^{-1}), both as liquid urea ammonium nitrate (UAN) (28-0-0, N-P_2O_5-K_2O) using a coulter applicator (BLU-JET AT6020, Thurston Manufacturing

Company, NE, U.S.) that injected the liquid fertilizer between crop rows at a depth of 3.5 cm below the soil surface.

Aerial imagery was collected using a UAV (3DR® Drone Site Scan, Berkeley, CA, U.S.) equipped with a multi-spectral sensor (Parrot Sequoia®, Paris, France) on June 14 2017 and July 12 2017 (corn approximately at growth stages V6 and R1, respectively). The images were taken at an altitude of 100 m, with spatial resolution of 10 cm. The Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge Index (NDRE) were calculated from the reflectance measurements in the Red, Red Edge, and Near Infrared (NIR) portion of the spectrum, according to the following equations (Gitelson, 2011):

$$\mathbf{NDVI} = \frac{NIR - Red}{NIR + Red}$$

$$\mathbf{NDRE} = \frac{NIR - Red\ Edge}{NIR + Red\ Edge}$$

A total of 20 locations over the site were randomly selected to collect plant biomass samples after the drone flight on June 14 2017. The sample areas (0.76 m^2) were georeferenced using a Global Position System (GPS) (Geo 7X handheld GeoCollector™, Trimble®, Wesminster, CO, U.S.). The plants were clipped at ground level, dried at 60°C in a forced-air oven for 7 days, ground to pass through a 2 mm screen (Wiley Mill, Arthur H. Thomas Co., Philadelphia, PA, U.S.), and analyzed for N via combustion on an elemental analyzer (Brookside Labs, New Bremen, OH, U.S.).

After corn physiological maturity (growth stage R6), grain and biomass N concentration was determined following a standard research protocol in this region (Kitchen et al., 2017). A total of six whole plants were taken near the gas chambers within each plot and separated into ear and stover (stems + leaves) fractions. The dried stover was ground to pass through a 2 mm screen using the Wiley Mill. Corn grain was shelled from ears using an Almaco ECS (Nevada, IA, U.S.). Grain moisture and test weight were measured with a grain analyzer (Model GAC 2000, DICKEY-John Corp., Springfield, IL, U.S.). Grain yields were corrected to 155 g kg^{-1} moisture content. To calculate total aboveground N uptake, N concentration for both grain and stover samples were determined by Brookside Labs as described above.

Corn was harvested on October 17 2017 using a John Deere Combine equipped with a GREENSTAR™ Yield Monitor System and Yield Mapping System (John Deere, Moline, IL, U.S.). Grain yield was recorded every 3 s along with GPS location. Grain yield data consisted of 21,647 points (observations) for the entire field (41.5 ha). For each point, N content in grain was estimated using the average N concentration from the hand-harvested samples (1.4%). Nitrogen balance was estimated as an indicator of environmental loss, and was calculated by the difference between N input (fertilizer) and N output (N removed in grain) (McLellan et al., 2018).

Data Processing and Analysis

After each drone flight, aerial images were processed and analyzed using Pix4D Software (Pix 4D S.A., Switzerland). A raster image file with a spatial resolution of 10 cm was created for both NDVI and NDRE of corn at both growth stages. All maps were created using ArcGIS (version 10.5, ESRI®, Redlands, CA, U.S.) Geospatial Analyst tool.

The pixel values from the raster files were extracted and averaged based on the measurement scale at which the different observational data were collected. For instance, the NDVI and NDRE values were extracted and averaged within each plant biomass sampling area (0.76 m^2) to make inferences regarding the relationship between remote sensing indices and in-season plant N status and biomass production. Following the same logic both NDVI and NDRE values were extracted and averaged across the sampling area comprising the gas chamber (1.5 m^2) in order to evaluate the relationship between N_2O emissions and remote sensing indices. Average NDVI and NDRE values were also obtained for each plot (~0.85 ha) to evaluate the relationship between NO_3-N loads and remote sensing indices.

Before yield map analysis, grain yield data was filtered to remove the extreme outliers [i.e., values outside of the mean ± 3 standard deviation (Schwalbert et al., 2018)] due to common inherent errors when the combine changed speed and direction (Simbahan et al., 2004). The final data set was normally distributed and comprised 97% of the original data (mean 13.2 Mg ha^{-1}, standard deviation 2.15 Mg ha^{-1}). A grain yield map was created in raster format by spatial interpolation of point measurements using the Inverse Distance Weighted method. A grid-cell size of 12.2 × 12.2 m was selected to reflect the width of the combine's head used for harvesting.

Correlation analyses were conducted using PROC CORR of the SAS® Software (version 9.4, SAS Institute, Cary, NC, U.S.) to evaluate the degree of association among remote sensing vegetation indices, crop, air, and water quality data. Correlations were considered significant at $p < 0.1$.

RESULTS

Weather Conditions

Compared to the 30 years average for the region, monthly precipitation in 2017 was high early in the growing season (April and May) and low throughout the remainder of the season (except July) (data not shown). Precipitation amounts in April and May were 47.7 and 18.2 mm greater than the 30 years average. Total precipitation in August and September was 9.3 and 2 compared to 71 and 82 mm for the 30 year average, respectively. In addition, a period of high daily precipitation was observed from late April to early May, with daily precipitation totals ranging from 4.5 to 41 mm (**Figure 2**).

Soil N_2O Emissions, Tile Drainage NO_3-N Concentrations, and Soil Inorganic N Concentrations

The overall pattern of daily N_2O fluxes (dN_2O) during the growing season was similar among plots, despite differences in magnitude (**Figure 3A**). There were clear signals of increased N_2O fluxes on May 23, June 19, and July 25. For example, 5 days after UAN side-dress application (June 19), dN_2O increased from

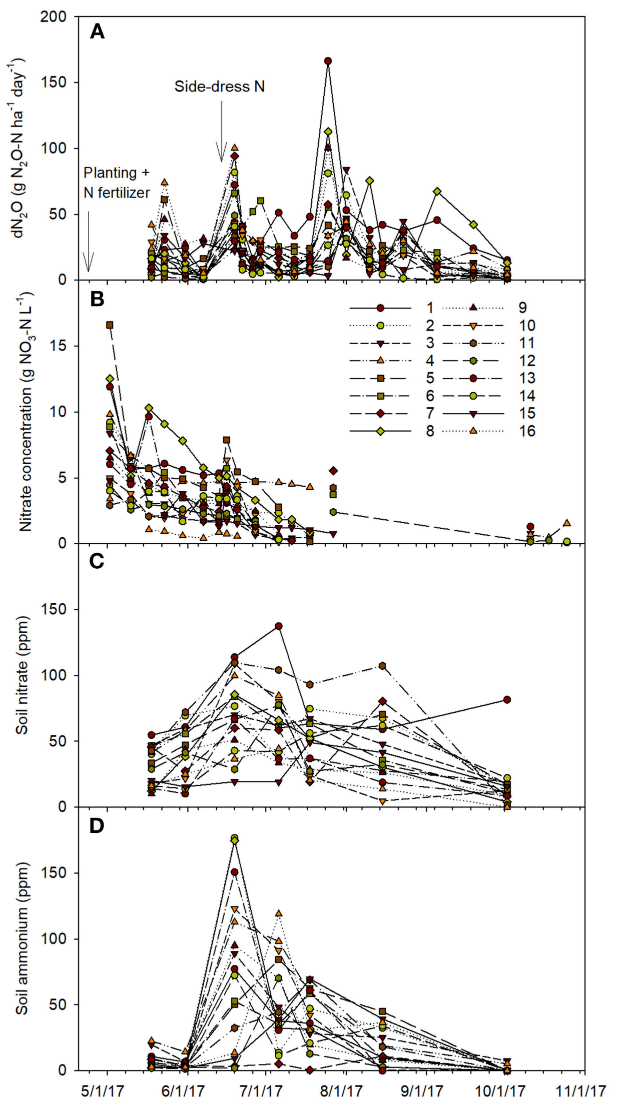

FIGURE 3 | Daily nitrous oxide fluxes (dN_2O) **(A)**, tile drainage nitrate concentration **(B)**, soil nitrate (NO_3-N) **(C)**, and ammonium (NH_4-N) concentration **(D)** during the 2017 corn growing season.

4.9 and 4.3 to 72.3 and 81.7 g N_2O-N ha^{-1} day^{-1} on plots 1 and 2, respectively. Similarly, dN_2O were above 90 g N_2O-N ha^{-1} day^{-1} for both plots 7 and 16 on that date. Spikes in dN_2O were also seen later in the growing season (July 25), particularly on plots 1, 2, 8, and 9.

Whereas, trends in N_2O emissions were relatively consistent across plots, tile drainage NO_3-N concentrations showed much greater variability (**Figure 3B**). While there was a similar decreasing seasonal trend in NO_3-N concentrations over the growing season, the coefficient of variation (CV) of daily NO_3-N concentration was above 40%, despite the similar soil types, weather patterns, and consistent drainage design for this experimental site. For instance, on the first sampling date (May 2), NO_3-N concentration ranged from 2.9 (plot 11) to 16.6 mg NO_3-N L^{-1} (plot 5), highlighting the within-field temporal and spatial variation. Elevated NO_3-N concentration also were observed during the last 2 weeks of May (May 17–30) on plots 8 and 13. Tile drainage flow stopped from July 27 to October 11, due to zero precipitation during this period (**Figure 2**), resulting in no samples being collected.

The temporal behavior of soil NO_3-N and NH_4-N concentrations were somewhat different from each other. Throughout the growing season, temporal variability was lower in soil NO_3-N (CV ranged from 42 to 60%) compared to NH_4-N concentration (CV ranged from 52 to 94%) (**Figures 3C,D**). Before UAN side-dress, soil NO_3-N concentration was greater (<70 ppm) in all plots compared to NH_4-N (<20 ppm). Yet, NH_4-N concentration rapidly increased in most of the plots after the second N fertilization event, with several spikes (>20 ppm increase) in NO_3-N concentration also being observed. For instance, NH_4-N concentration increased from approximately 5 to more than 150 ppm on plots 2, 8, and 13. In addition, NH_4-N concentration was above 50 ppm in all plots (except 7, 12, 15, and 16). Except for plot 1, soil NO_3-N and NH_4-N concentrations were lower toward the end of the growing season.

In-season Corn NDVI and NDRE

In general, higher spatial variability of both NDVI and NDRE were seen at V6 compared to when corn was at growth stage R1 (**Figure 4**). Across the entire field, the CV of NDVI and NDRE were 29 and 23% at V6 compared to 8 and 11% at R1, respectively. When averaged within plots, the CV ranged from 10 (plot 13) to 28% (plot 12) for NDVI at V6 compared to the range of 1 (plot 9) to 7% (plot 4) at R1. Similarly, higher CV was found on NDRE at V6 (ranging from 13 to 22%) than at R1 (ranging from 4 to 8%).

The linear regression models relating plant biomass and N content with both NDVI and NDRE showed a highly significant relationship ($p < 0.001$) (**Figure 5**). At growth stage V6, the variation in plant biomass was more strongly correlated with NDVI ($R^2 = 0.67$) compared to NDRE ($R^2 = 0.40$). Similar trends were seen when plant N content was plotted against NDVI and NDRE, with NDVI accounting for a larger proportion of variation in plant N content.

Corn Yield and N Balance

Corn grain yield was found to be highly variable both within-field and within-plots (**Figure 6A**). Across the entire field, mean grain yield was 13.2 Mg ha^{-1} and the CV was 16%. When averaged within-plots, grain yield ranged from 12.8 (plot 4) to 15 Mg ha^{-1} (plot 8), and the CV ranged from 5 (plot 7) to 17% (plot 14).

As the end-of-season N balance was estimated from grain yield and grain N concentration, the spatial variability of N balance followed a similar but inverse trend to yield. That is, areas in the field with low and high values of N balance corresponded to areas with high and low grain yields, respectively (**Figure 6B**). The average N balance across the whole field was 145 kg ha^{-1} with a CV 14%. Despite high grain yields in portions of the field, there were no negative values for N balance, which ranged from 75 to 242 kg ha^{-1}.

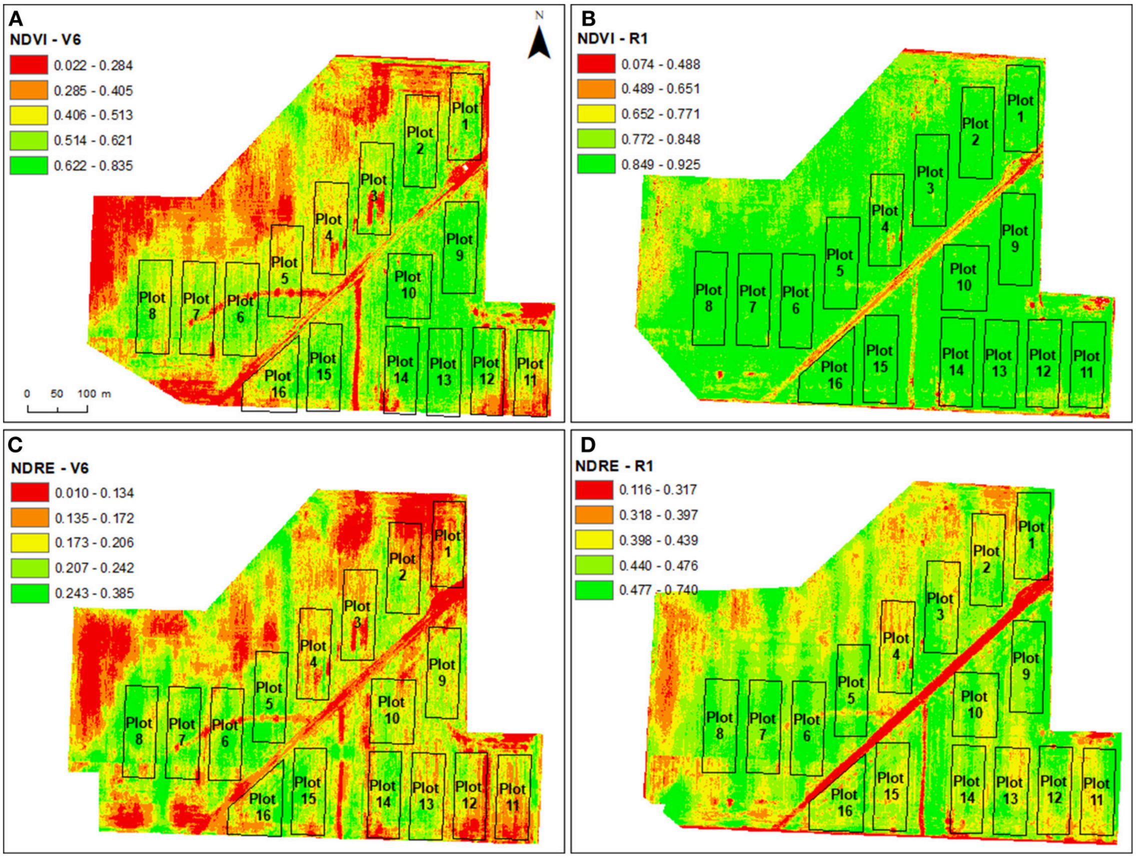

FIGURE 4 | Normalized Difference Vegetation Index (NDVI) **(A,B)** and Normalized Difference Red Edge (NDRE) **(C,D)** of corn at growth stage V6 and R1 during the 2017 corn growing season.

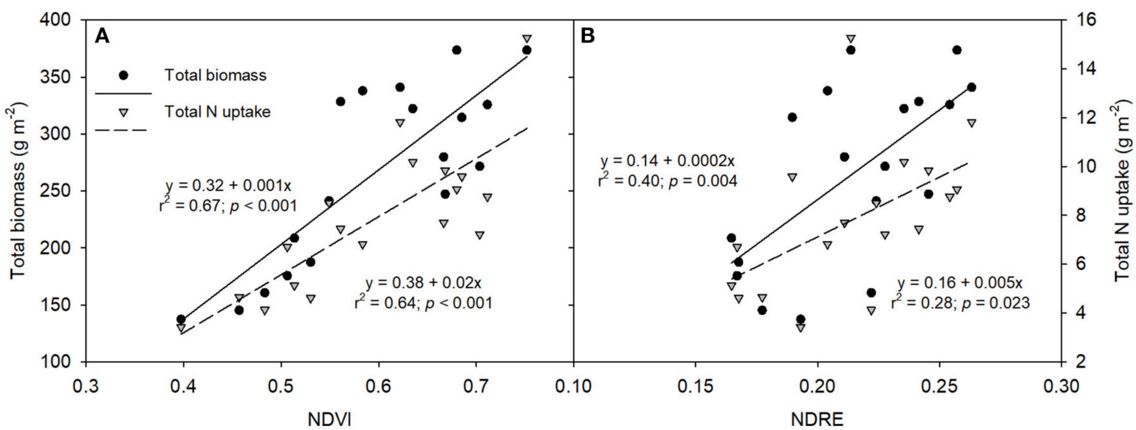

FIGURE 5 | Relationships of plant biomass **(A)** and nitrogen (N) uptake **(B)** with both Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE) at growth stage V6.

Relationship Between Remote Sensing Vegetation Indices, Crop, Air, and Water Quality Data

Overall, few significant relationships were observed between vegetation indices and crop, air, and water quality data. However, NDVI at growth stage V6 was negatively correlated with N_2O losses ($p < 0.1$) (**Table 1**). Also, the correlation coefficient (R) between NDVI and N_2O losses increased as the season progressed ($R = -0.44$, -0.56, and -0.66 for cN_2O at growth stage V6, R1, and seasonal cN_2O, respectively). Early- and

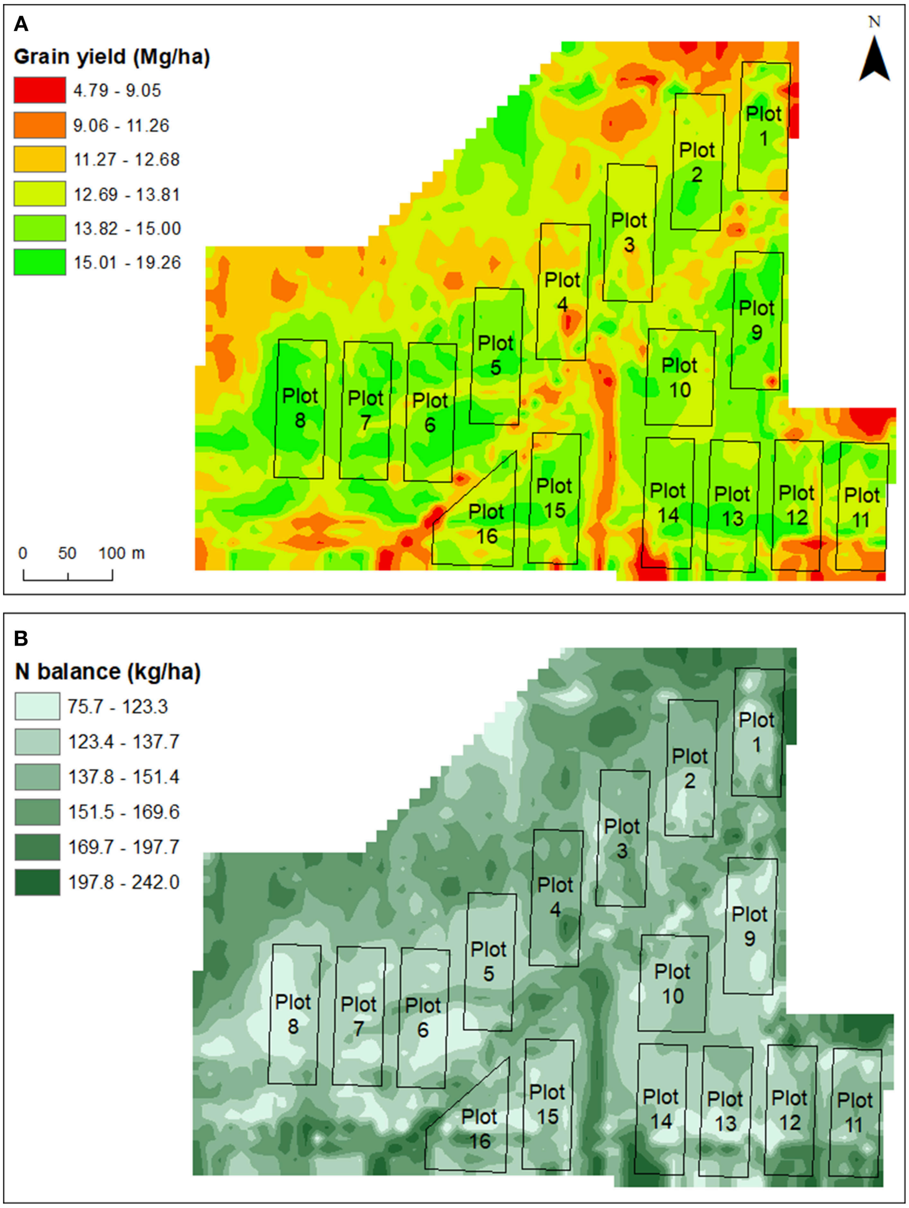

FIGURE 6 | Corn grain yield **(A)** and nitrogen (N) balance **(B)** at the end of the 2017 growing season.

mid-season remote sensing vegetation indices were significantly correlated with corn grain yield and end-of-season N balance. Corn grain yield and N balance was positively and negatively correlated with both NDVI and NDRE at both growth stage V6 and R1.

DISCUSSION

The lack of studies evaluating multiple pathways of N loss limits our overall understanding of, and ability to optimize, N management to achieve both crop production and environmental goals, particularly in highly productive tile-drained landscapes. In this study, we used recent developments in technologies to evaluate the variability and potential correlations between N cycling processes within 16 separate experimental units in a field. As noted above, 2017 corresponds to the baseline year of a long-term field experiment and no treatments were imposed. We also acknowledge that definitive relationships cannot be determined based on 1 year of data, and thus, preliminary results are interpreted with the goal of highlighting the type of knowledge gained using this unique approach and the benefits and limitations for developing strategies to mitigate N losses and enhance crop production sustainability.

TABLE 1 | Pearson's correlation coefficient of correlations analysis between remote sensing vegetation indices, crop, air, and water quality data.

	cN_2O V6	cN_2O R1	cN_2O R6	YSNE	NO_3-N load	$YSNO_3$	NDVI V6	NDVI R1	NDRE V6	NDRE R1	Grain yield	*N* balance
cN_2O V6	–											
cN_2O R1	0.89***	–										
cN_2O R6	0.44*	0.60**	–									
YSNE	0.45*	0.58**	0.98***	–								
NO_3-N load	−0.25	−0.28	0.55	0.65	–							
$YSNO_3$	−0.26	−0.33	0.45	0.63	0.99***	–						
NDVI V6	−0.44*	−0.56**	−0.66**	−0.61**	−0.37	−0.43	–					
NDVI R1	−0.56	−0.19	−0.16	−0.08	−0.04	−0.12	0.49*	–				
NDRE V6	0.21	0.09	−0.14	−0.17	−0.67	−0.66	0.22	0.44*	–			
NDRE R1	0.07	0.07	−0.30	−0.22	0.11	0.06	0.12	0.76***	0.47**	–		
Grain yield	0.05	0.15	0.17	0.00	−0.50	−0.54	0.45*	0.73***	0.79***	0.74***	–	
N balance	0.20	0.13	0.01	0.07	0.53	0.57	−0.46*	−0.67**	0.85***	−0.63***	−0.97***	–

cN_2O, cumulative N_2O emissions at corn growth stage V6, R1, and R6; YSNE, yield-scaled N_2O emissions; $YSNO_3$, yield-scaled nitrate load; NDVI, normalized difference vegetation index; NDRE, normalized difference red edge.
**$p < 0.1$, **$p < 0.05$, ***$p < 0.001$.*

Relationship Between Crop Productivity and N Losses

One common theory for minimizing the risk of N losses is to increase crop productivity per unit of applied N (Snyder et al., 2009; van Groenigen et al., 2010; McLellan et al., 2018). Yet, surprisingly few studies have evaluated within-field relationships between crop yield and both N_2O emissions and N leaching losses, perhaps because these parameters are not often collected or reported for the same experiment (Omonode et al., 2017). In this study, growing season N_2O emissions and NO_3-N loads were not significantly correlated with grain yield (**Table 1**). While this finding is not consistent with the theory that higher yields correspond with lower environmental N losses, it nonetheless illustrates the benefits of this experimental approach for simultaneously evaluating of agronomic and environmental performance in this region.

The need to identify potential tradeoffs between crop productivity and N losses is also important from a policy perspective. There is increasing emphasis on improving N use efficiency by reducing N balance, which is proposed as a robust index of potential N losses because it is a measure of anthropogenic N supply that exceeds crop N demand (McLellan et al., 2018). As the majority of crop N uptake is concentrated in grain at the end of the season, large N balances are generally associated with high N rates and/or low yields. In this study, relatively large N balances resulted from an N rate well above regional recommendations, suggesting that a greater portion of applied N fertilizer was susceptible to losses. However, similar to yield, correlations between N balance and N_2O and NO_3-N leaching losses were not significant (**Table 1**). This finding differs from McLellan et al. (2018) who found a significant relationship between N balance and yield-scaled N losses using data from published studies and modeling efforts in the U.S. Corn Belt. In another meta-analysis assessing N_2O emissions in North America's corn production systems, Omonode et al. (2017) found a strong and positive relationship between N_2O losses and N balance, suggesting that management systems achieving low N balance (<60 kg N ha^{-1}) would possibly increase N use efficiency and decrease cN_2O. Generating additional empirical evidence through field-scale experiments under commercial production conditions should help scientists further evaluate and strengthen these relationships, especially if N balance is to be used in developing policies or incentive programs.

Relationship Between N_2O Emissions and NO_3-N Leaching Losses

Evaluating patterns in N losses throughout the season may help elucidate potential relationships between N_2O emissions and NO_3-N leaching losses. In theory, N_2O and NO_3-N leaching losses should be related via soil N pools (Denk et al., 2017). Nitrogen fertilization is a major factor controlling N_2O production in agricultural soils because of its direct impact on soil mineral N availability (NH_4-N + NO_3-N) (Snyder et al., 2009), and N_2O emissions have been found to increase both linearly and non-linearly with N fertilizer rate (Kim et al., 2013; Decock, 2014; Shcherbak et al., 2014). In 2017, notable spikes in soil N_2O emissions occurred on several dates, with dN_2O increasing from 8 to 50 g N_2O-N ha^{-1} day^{-1} right after UAN side-dress application (**Figure 3A**). However, spikes did not always correspond with N application events, fluxes were also correlated with soil moisture ($R = 0.55$, $p < 0.001$, $n = 80$) and to a lesser extent soil temperature ($R = 0.25$, $p = 0.028$, $n = 80$). Following a similar logic as N_2O emissions, due to the high mobility of NO_3-N in the soil, tile drainage NO_3-N concentration is expected to increase after N fertilizer application, particularly if the N fertilizer source contains N in the form of NO_3-N and in years with high precipitation. However, in our study, only three plots showed an increase in tile drainage NO_3-N concentrations following the second N application event, whereas NO_3-N concentration remained relatively constant on the remaining plots (**Figure 3B**).

Soil N transformations following fertilizer N application events could help explain trends in N_2O and NO_3-N leaching losses. While there was a clear signal of increased soil NH_4-N after N side-dress application, this did not occur for NO_3-N concentrations (**Figures 3C,D**). In agricultural soils, NH_4-N concentration is generally low because it is rapidly converted to NO_3-N through the process of nitrification (Norton, 2008), as evidenced by the lower concentrations of NH_4-N compared to NO_3-N before UAN application events. Soil NO_3-N concentrations may not have increased because crop N uptake started to occur during the period of nitrification, which also corresponded with relatively few plots having increased NO_3-N concentrations in drainage following the second N application event. Several studies have emphasized the importance to synchronize soil N supply with crop N demand to improve N use efficiency and reduce N losses in croplands (Robertson and Vitousek, 2009; Snyder and Fixen, 2012). Often this corresponds to a split-application of N fertilizer: generally at planting (to ensure initial N supply) and right before the period of rapid crop growth and N uptake, which in corn is roughly between growth stages V8 and R1 (Sawyer et al., 2006). In the long-term, the unique approach in this experiment for monitoring N fluxes at the field-scale will provide a better understanding of how specific management practices (e.g., timing of N fertilizer application) may influence soil N availability, and in turn, the potential for either enhanced N_2O emissions or NO_3-N leaching losses depending on weather variability and crop growth patterns, among other factors.

Relationships between N loss pathways can also be compared across the growing season. Preliminary data from 2017 indicate that both daily ($R = 0.08$, $p = 0.327$, $n = 133$) and seasonal ($R = 0.55$, $p = 0.259$, $n = 6$) N_2O and NO_3-N leaching losses were not significantly correlated. While these results are only based on 1 year, they provide some important insights regarding temporal and spatial considerations when trying to link N_2O and NO_3-N leaching losses within a single study. First, there was an important temporal disconnect when N_2O vs. NO_3-N losses primarily occurred. On average, ∼96 and 86% of the seasonal NO_3-N leaching and N_2O losses occurred between April and May, and between May and August, respectively. This is consistent with other subsurface drainage work showing that the largest drainage volumes occur in the March-May timeframe (e.g., Jin and Sands, 2003), which is often a period of high precipitation coupled with N fertilizer application in corn-based cropping systems. Our results are also relatively consistent with the period of highest N_2O emissions in the Midwest, with approximately 50–80% of the seasonal cN_2O occurring within 30–40 days following N application early in the growing season (Omonode et al., 2017), when plant N uptake is relatively low and excess N becomes available for nitrification and denitrification. In our study, ∼42% of the seasonal cN_2O occurred within 40 days after UAN side-dress on June 14.

In this sense, the lack of a relationship between N_2O and NO_3-N leaching losses is not surprising due to the temporal difference of when these losses were occurring and the soil and climate conditions influencing those losses. However, in other years where warm, wet springs are followed by cool, dry summers, it would not be surprising if this resulted in high NO_3-N losses but low N_2O emissions. It is also important to highlight that the seasonal N losses measured here correspond to the corn growing season (April–October), and therefore do not reflect annual losses. To account for these limitations mentioned above, both N_2O and NO_3-N leaching losses will be monitored throughout the year in all 16 experimental units, which will also lead to better estimations of total N losses. Drainage events and N_2O fluxes during the winter by freeze/thaw cycles have been shown in separate studies to contribute significantly to the total N losses in certain locations and years (Christianson and Harmel, 2015b; Wagner-Riddle et al., 2017).

Beyond the temporal disconnect discussed above, there is an important spatial disconnect (i.e., measurement footprint) that may pose challenges in trying to develop quantitative relationships between N_2O and NO_3-N leaching losses. The different scale of measurements between N_2O and NO_3-N, and the within-plot variability that is likely observed for N_2O emissions in large-scale research, complicates any assessment of the relationship between these two variables. It has long been recognized that there is large spatial variability in soil N_2O emissions. Recent studies have shown that hotspots of N_2O emissions within field can account for as much as 30% of the cumulative emissions (Turner et al., 2016). While new measurement techniques are available to analyze emissions in large plots [e.g., see methods in Hensen et al. (2013)], they are considerably more expensive and may not support replicated treatment comparisons. Hence, new approaches may be needed to strengthen our ability to capture the spatial variability in soil N_2O emissions, specifically for plot sizes typical for assessing tile drainage nutrients concentrations. Recently there have been calls for not only additional field studies where multiple types of N loss pathways are simultaneously evaluated, but also for better data reporting to enhance future agro-ecosystem data syntheses and meta-analyses (Eagle et al., 2017a). A great deal of research activity is being directed toward addressing this knowledge gap, thus we encourage others to consider these temporal and spatial methodology points when evaluating both N_2O and NO_3-N leaching losses in the same study.

Remote Sensing Technologies for Monitoring Both Crop and Environmental Performance

Despite the rapid growth of UAVs in agriculture, little work has explored the potential for new technologies to directly link sustainability outcomes with improved agronomic efficiencies. The value in the present research is not only being able to assess these relationships after harvest, but also earlier in the growing season when adaptive N management decisions could still be made. To date, we are unaware of any effort to assess the degree to which in-season measurements of crop performance or N use efficiency may correspond with environmental N losses.

Our results from one growing season show that UAV images collected at corn growth stage V6 may be an indicator of N_2O losses, but not for NO_3-N leaching losses (**Table 1**). Vegetation indices such as NDVI have been extensively used to make inferences of in-season plant N status and biomass production, and generally, greater leaf area and greener plant biomass result in higher NDVI values (Rembold et al., 2013) (**Figure 5**). In theory, areas in the field with low early-season NDVI values correspond to areas with poor crop establishment and consequently low N uptake, and with more N accumulating in soil, it becomes susceptible for losses through denitrification. This rationale could help explain the strong and negative relationship between early-season NDVI and N_2O losses found in this study. In addition, the correlation coefficient between early-season NDVI and N_2O losses increased as the season progressed ($R = -0.44$, -0.56, and -0.66 for cN_2O at growth stage V6, R1, and seasonal cN_2O, respectively). On average, ~27 and 44% of the total N_2O losses had already occurred at growth stage V6 and R1, respectively. These results indicate that UAV platforms could represent an integrative tool for linking crop performance and air quality outcomes, but further research is necessary. Agricultural monitoring systems that provide timely and accurate information are of great interest to agricultural producers, allowing them to make in-season management decisions to enhance the efficiency of production. If relationships between N_2O emissions and NDVI were consistent under a wide range of conditions, such an approach could have the co-benefit of enhancing the sustainability of food production.

The correlation between remote sensing vegetation indices and NO_3-N leaching losses was not significant at any time throughout the growing season (**Table 1**). In fact, due to the temporal disconnect discussed above (i.e., 73% of the seasonal NO_3-N leaching losses occurred before crop emergence), this correlation was not expected to be significant. However, there might be cases where this relationship is observable, particularly if excess rainfall affects crop growth and losses during the period of crop growth contributing significantly to seasonal NO_3-N loads. In theory, it is possible that in years with significant flooding events, crop emergence/establishment would be poor (which is associated with NDVI/NDRE) and NO_3-N leaching losses would he high. Following similar logic as N_2O emissions discussed above, being able to link agronomic and environmental performance early in the growing season would provide enhanced and timely information for monitoring, measurement, and management to achieve both production and environmental goals. Nonetheless, because the majority of NO_3-N leaching on an annual basis occurs before UAVs are used to map early season crop N status, there are likely inherent limitations in using remote sensing technologies as an indicator of water quality outcomes.

CONCLUSION

Reducing the N footprint of high-yielding cropping systems in the U.S. Midwest has become of great interest to agricultural producers, policy-makers, and society. Understanding potential tradeoffs between crop productivity and environmental pollution is key to advancing the sustainability of N fertilizer use in this region. In this study, preliminary results from 2017 were used to (i) assess correlations between crop N dynamics and environmental losses and to (ii) discuss the benefits and limitations of using recent developments in technologies to monitor cropping systems N dynamics at the field-scale. There is a common consensus in the literature that enhancing crop yields and N use efficiency will result in lower environmental N losses. While growing season N_2O emissions and NO_3-N loads were not correlated with grain yield in this study, results illustrate how an integrated field-scale research approach can help further evaluate and strengthen current theories relating crop N dynamics to environmental losses. Despite the assumption that N_2O and NO_3-N leaching losses should be correlated with each other, our results showed that both daily and seasonal N_2O emissions and NO_3-N were not significant correlated, mainly due to a temporal disconnect when N_2O vs. NO_3-N losses primarily occurred. Hence, this is an important aspect that needs to be considered when trying to link N_2O and NO_3-N leaching losses in future research. With recent developments in UAV systems, remotely-sensed data at high temporal and spatial resolutions have become more affordable at the farm-level. While the results shown here are only based on 1 year, there are indications that remote sensing technologies could help early detection of poor cropping system performance, with lower NDVI values associated with higher N_2O emissions. However, the potential for UAVs to evaluate water quality appears much more limited because NO_3-N losses happened prior to early-season crop growth and image collection. Building on this work, we encourage future research to test the usefulness of remote sensing technologies for monitoring environmental quality, with the goal of providing timely and accurate information to enhance the efficiency and sustainability of food production.

AUTHOR CONTRIBUTIONS

CP, RB, and LC obtained the funding and designed the experiment. GPF and CP conceptualized the manuscript with ideas of relationships to be explored based on the journal research topic. GPF collected the data, conducted the statistical analysis, and wrote the first draft of the manuscript. RB helped with the geostatistical analysis. CP, RB, and LC helped guide the discussion as well as editing various drafts.

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REFERENCES

Atzberger, C. (2013). Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs. *Remote Sens.* 5, 949–981. doi: 10.3390/rs5020949

Bell, M. J., and Tzimiropoulos, G. (2018). Novel monitoring systems to obtain dairy cattle phenotypes associated with sustainable production. *Front. Sustain. Food Syst.* 2:31. doi: 10.3389/fsufs.2018.00031

Christianson, L. E., and Harmel, R. D. (2015a). 4R water quality impacts: an assessment and synthesis of forty years of drainage nitrogen losses. *J. Environ. Qual.* 44, 1852–1860. doi: 10.2134/jeq2015.03.0170

Christianson, L. E., and Harmel, R. D. (2015b). The MANAGE drain load database: review and compilation of more than fifty years of North American drainage nutrient studies. *Agric. Water Manag.* 159, 277–289. doi: 10.1016/j.agwat.2015.06.021

Christianson, L. E., Harmel, R. D., Smith, D., Williams, M. R., and King, K. (2016). Assessment and synthesis of 50 years of published drainage phosphorus losses. *J. Environ. Qual.* 45, 1467–1477. doi: 10.2134/jeq2015.12.0593

Chun, J. A., and Cooke, R. A. (2008). Calibrating agridrain water level control structures using generalized weir and orifice equations. *Appl. Eng. Agric.* 24, 595–602. doi: 10.13031/2013.25274

Coyne, M. S. (2008). "Biological denitrification," in *Nitrogen in Agricultural Systems*, eds J. S. Schepers and W. R. Raun (Madison, WI: ASA, CSSA, SSSA), 201–253.

David, M. B., Drinkwater, L. E., and McIsaac, G. F. (2010). Sources of nitrate yields in the Mississippi river basin. *J. Environ. Qual.* 39, 1657–1667. doi: 10.2134/jeq2010.0115

Decock, C. (2014). Mitigating nitrous oxide emissions from corn cropping systems in the midwestern U.S.: Potential and data gaps. *Environ. Sci. Technol.* 48, 4247–4256. doi: 10.1021/es4055324

Denk, T. R. A., Mohn, J., Decock, C., Lewicka-Szczebak, D., Harris, E., Butterbach-Bahl, K., et al. (2017). The nitrogen cycle: a review of isotope effects and isotope modeling approaches. *Soil Biol. Biochem.* 105, 121–137. doi: 10.1016/j.soilbio.2016.11.015

Eagle, A. J., Christianson, L. E., Cook, R. L., Harmel, R. D., Miguez, F. E., Qian, S. S., et al. (2017a). Meta-analysis constrained by data: recommendations to improve relevance of nutrient management research. *Agron. J.* 109, 2441–2449. doi: 10.2134/agronj2017.04.0215

Eagle, A. J., Olander, L. P., Locklier, K. L., Heffernan, J. B., and Bernhardt, E. S. (2017b). Fertilizer management and environmental factors drive N O and NO losses in corn: a meta-analysis. *Soil Sci. Soc. Am. J.* 81, 1191–1202. doi: 10.2136/sssaj,2016.09.0281

EU Nitrogen Expert Panel (2015). *Nitrogen Use Efficiency (NUE) - An Indicator for the Utilization of Nitrogen in Agriculture and Food Systems*. Wageningen. Available online at: https://www.unece.org/fileadmin/DAM/env/documents/2017/AIR/WGSR/10_The_EU_Nitrogen_Expert_Panel_and_its_indicator_forNitrogen_Use_Efficiency__Tiffanie_Stephanie.pdf

Gitelson, A. (2011). "Remote sensing estimation of crop biophysical characteristics at various scales," in *Hyperspectral Remote Sensing of Vegetation,* eds P. S. Thenkabail, J. G. Lyon, and A. Huete (Boca Raton, FL: CRC Press), 329–358.

Godfray, H. C. J. (2014). The challenge of feeding 9-10 billion people equitably and sustainably. *J. Agric. Sci.* 152, S2–S8. doi: 10.1017/S0021859613000774

Graham, R. F., Greer, K. D., Villamil, M. B., Nafziger, E. D., and Pittelkow, C. M. (2018). Enhanced efficiency fertilizer impacts on yield-scaled nitrous oxide emissions in maize. *Soil Sci. Soc. Am. J.* 82, 1–35. doi: 10.2136/sssaj2018.05.0196

Hensen, A., Skiba, U., and Famulari, D. (2013). Low cost and state of the art methods to measure nitrous oxide emissions. *Environ. Res. Lett.* 8:025022. doi: 10.1088/1748-9326/8/2/025022

Jin, C.-X., and Sands, G. R. (2003). The long-term field-scale hydrology of subsurface drainage systems in a cold climate. *Trans. ASAE* 46, 1011–1021. doi: 10.13031/2013.13963

Kim, D. G., Hernandez-Ramirez, G., and Giltrap, D. (2013). Linear and nonlinear dependency of direct nitrous oxide emissions on fertilizer nitrogen input: a meta-analysis. *Agric. Ecosyst. Environ.* 168, 53–65. doi: 10.1016/j.agee.2012.02.021

Kitchen, N. R., Shanahan, J. F., Ransom, C. J., Bandura, C. J., Bean, G. M., Camberato, J. J., et al. (2017). A public–industry partnership for enhancing corn nitrogen research and datasets: project description, methodology, and outcomes. *Agron. J.* 109, 2371–2388. doi: 10.2134/agronj2017.04.0207

Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., and Garnier, J. (2014). 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. *Environ. Res. Lett.* 9:105011. doi: 10.1088/1748-9326/9/10/105011

McLellan, E. L., Cassman, K. G., Eagle, A. J., Woodbury, P. B., Sela, S., Tonitto, C., et al. (2018). The nitrogen balancing act: tracking the environmental performance of food production. *Bioscience* 68, 194–203. doi: 10.1093/biosci/bix164

Mueller, N. D., Gerber, J. S., Johnston, M., Ray, D. K., Ramankutty, N., and Foley, J. A. (2012). Closing yield gaps through nutrient and water management. *Nature* 490, 254–257. doi: 10.1038/nature11420

Mulla, D. J., and Strock, J. S. (2008). "Nitrogen transport processes in soil," in *Nitrogen in Agricultural Systems*, eds J. S. Schepers and W. R. Raun (Madison, WI: ASA, CSSA, SSSA), 361–400.

Norton, J. M. (2008). "Nitrification in agricultural soils," in *Nitrogen in Agricultural Systems*, eds J. S. Schepers and W. R. Raun (Madison, WI: ASA, CSSA, SSSA), 173–199.

Omonode, R. A., Halvorson, A. D., Gagnon, B., and Vyn, T. J. (2017). Achieving lower nitrogen balance and higher nitrogen recovery efficiency reduces nitrous oxide emissions in North America's maize cropping systems. *Front. Plant Sci.* 8:1080. doi: 10.3389/fpls.2017.01080

Parkin, T. B., and Venterea, R. T. (2010). "USDA-ARS GRACEnet project protocols. Chapter 3. chamber-based trace gas flux measurements," in *Sampling Protocols*, ed R. F. Follett, 1–39. Available online at: www.ars.usda.gov/research/GRACEnet

Ravishankara, A. R., Daniel, J. S., and Portmann, R. W. (2009). Nitrous oxide (N2O): the dominant ozone-depleting substance emitted in the 21st century. *Science* 326, 123–125. doi: 10.1126/science.1176985

Rembold, F., Atzberger, C., Savin, I., and Rojas, O. (2013). Using low resolution satellite imagery for yield prediction and yield anomaly detection. *Remote Sens.* 5, 1704–1733. doi: 10.3390/rs5041704

Robertson, G. P., and Vitousek, P. M. (2009). Nitrogen in agriculture: balancing the cost of an essential resource. *Annu. Rev. Environ. Resour.* 34, 97–125. doi: 10.1146/annurev.environ.032108.105046

Sawyer, J., Nafziger, E., Randall, G., Bundy, L., Rehm, G., and Joern, B. (2006). *Concepts and Rationale for Regional Nitrogen Rate Guidelines for Corn Concepts and Rationale for Regional Nitrogen Rate Guidelines for Corn*. Ames, IA: Iowa State University Extension.

Scharf, P. C. (2015). *Managing Nitrogen in Crop Production, Understanding Nitrogen*. Madison, WI: ACCESS Publications, 1–24.

Scharf, P. C., Kitchen, N. R., Sudduth, K. A., Davis, J. G., Hubbard, V. C., and Lory, J. A. (2005). Field-scale variability in optimal nitrogen fertilizer rate for corn. *Agron. J.* 97, 452–461. doi: 10.2134/agronj2005.0452

Schmidt, J. P., Sripada, R. P., Beegle, D. B., Rotz, C. A., and Hong, N. (2011). Within-field variability in optimum nitrogen rate for corn linked to soil moisture availability. *Soil Sci. Soc. Am. J.* 75, 306–316. doi: 10.2136/sssaj2010.0184

Schwalbert, R. A., Amado, T. J. C., Nieto, L., Varela, S., Corassa, G. M., Horbe, T. A. N., et al. (2018). Forecasting maize yield at field scale based on high-resolution satellite imagery. *Biosyst. Eng.* 171, 179–192. doi: 10.1016/j.biosystemseng.2018.04.020

Shcherbak, I., Millar, N., and Robertson, G. P. (2014). Global metaanalysis of the nonlinear response of soil nitrous oxide (N2O) emissions to fertilizer nitrogen. *Proc. Natl. Acad. Sci. U.S.A.* 111, 9199–9204. doi: 10.1073/pnas.1322434111

Simbahan, G. C., Dobermann, A., and Ping, J. L. (2004). Screening yield monitor data improves grain yield maps. *Agron. J.* 96, 1091–1102. doi: 10.2134/agronj2004.1091

Snyder, C. S., Bruulsema, T. W., Jensen, T. L., and Fixen, P. E. (2009). Review of greenhouse gas emissions from crop production systems and fertilizer management effects. *Agric. Ecosyst. Environ.* 133, 247–266. doi: 10.1016/j.agee.2009.04.021

Snyder, C. S., and Fixen, P. E. (2012). Plant nutrient management and risks of nitrous oxide emission. *J. Soil Water Conserv.* 67, 137A—144A. doi: 10.2489/jswc.67.5.137A

Sobota, D. J., Compton, J. E., McCrackin, M. L., and Singh, S. (2015). Cost of reactive nitrogen release from human activities to the environment in the United States. *Environ. Res. Lett.* 10:025006. doi: 10.1088/1748-9326/10/2/025006

Turner, P. A., Griffis, T. J., Mulla, D. J., Baker, J. M., and Venterea, R. T. (2016). A geostatistical approach to identify and mitigate agricultural nitrous oxide emission hotspots. *Sci. Total Environ.* 572, 442–449. doi: 10.1016/j.scitotenv.2016.08.094

USDA-ERS (2018). *Outlook for U.S. Agricultural Trade.* Available online at: https://www.ers.usda.gov/ (Accessed October, 1, 2018).

USDA-NASS (2012). *2012 Census of Agriculture: Tile Drained Acres by State.* Available online at: http://www.nass.usda.gov/AgCensus/ (Accessed October, 23, 2018).

USDA-NASS (2018). *Agricultural Statistics 2017*. Washington, DC. Available online at: http://www.nass.usda.gov/ (Accessed August 1, 2018).

USEPA (2007). *Hypoxia in the Northen Gulf of Mexico: An Update by the EPA Science Advisory Board*. Washington, DC

USEPA (2018). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2016.*

van Groenigen, J. W., Velthof, G. L., Oenema, O., van Groenigen, K. J., and van Kessel, C. (2010). Towards an agronomic assessment of N2O emissions: a case study for arable crops. *Eur. J. Soil Sci.* 61, 903–913. doi: 10.1111/j.1365-2389.2009.01217.x

Venterea, R. T., Bijesh, M., and Dolan, M. S. (2011). Fertilizer source and tillage effects on yield-scaled nitrous oxide emissions in a corn cropping system. *J. Environ. Qual.* 40, 1521–1531. doi: 10.2134/jeq2011.0039

Wagner-Riddle, C., Congreves, K. A., Abalos, D., Berg, A. A., Brown, S. E., Ambadan, J. T., et al. (2017). Globally important nitrous oxide emissions from croplands induced by freeze-thaw cycles. *Nat. Geosci.* 10, 279–283. doi: 10.1038/ngeo2907

Web Soil Survey (2018) *Soil Survey Staff, Natural Resources Conservation Services, and United States Department of Agriculture Web Soil Survey*. Available online at: https://websoilsurvey.sc.egov.usda.gov/ (Accessed September 15, 2018).

Zhang, X., Davidson, E. A., Mauzerall, D. L., Searchinger, T. D., Dumas, P., and Shen, Y. (2015). Managing nitrogen for sustainable development. *Nature* 528, 51–59. doi: 10.1038/nature15743

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Using 3D Imaging and Machine Learning to Predict Liveweight and Carcass Characteristics of Live Finishing Beef Cattle

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Selection of finishing beef cattle for slaughter and evaluation of performance is currently achieved through visual assessment and/or by weighing through a crush. Consequently, large numbers of cattle are not meeting target specification at the abattoir. Video imaging analysis (VIA) is increasingly used in abattoirs to grade carcasses with high accuracy. There is potential for three-dimensional (3D) imaging to be used on farm to predict carcass characteristics of live animals and to optimise slaughter selections. The objectives of this study were to predict liveweight (LW) and carcass characteristics of live animals using 3D imaging technology and machine learning algorithms (artificial neural networks). Three dimensional images and LW's were passively collected from finishing steer and heifer beef cattle of a variety of breeds pre-slaughter (either on farm or after entry to the abattoir lairage) using an automated camera system. Sixty potential predictor variables were automatically extracted from the live animal 3D images using bespoke algorithms; these variables included lengths, heights, widths, areas, volumes, and ratios and were used to develop predictive models for liveweight and carcass characteristics. Cold carcass weights (CCW) for each animal were provided by the abattoir. Saleable meat yield (SMY) and EUROP fat and conformation grades were also determined for each individual by VIA of half of the carcass. Performance of prediction models was assessed using R^2 and RMSE parameters following regression of predicted and actual variables for LW ($R^2 = 0.7$, RMSE = 42), CCW ($R^2 = 0.88$, RMSE = 14) and SMY ($R^2 = 0.72$, RMSE = 14). The models predicted EUROP fat and conformation grades with 54 and 55% accuracy (R^2), respectively. This study demonstrated that 3D imaging coupled with machine learning analytics can be used to predict LW, SMY and traditional carcass characteristics of live animals. This system presents an opportunity to reduce a considerable inefficiency in beef production enterprises through autonomous monitoring of finishing cattle on the farm and marketing of animals at the optimal time.

Keywords: finishing beef cattle, 3D imaging, carcass characteristics, machine learning, precision livestock farming

INTRODUCTION

In 2017, 51% of prime beef carcasses in the UK did not meet target fat and conformation grades: 40% had poor conformation and 15% were too fat (AHDB, 2018a). The cost to UK producers of sending over-finished cattle to slaughter has been estimated at £8.8 million per year (AHDB, 2018b). For example Roehe et al. (2013) estimated that for an increase in EUROP grade from R4L to R4H for an intensively fed steer of a medium sized breed, a loss of £11.37 would be made in feeding costs alone. Furthermore, processors set weight limits on carcasses and penalise producers for sending overweight cattle, despite them being otherwise to specification. Sending cattle to slaughter too lean equally results in a loss due to the lower price paid for the carcass. Identifying the optimum slaughter point to meet market specifications for beef cattle has economic benefits (Roehe et al., 2013), and reduces the environmental impact of cattle production (de Vries and de Boer, 2010). Therefore, to improve sustainability in the beef production sector it is important for farmers to be able to predict carcass value in the live animal.

Some equations exist for the prediction of carcass characteristics in live animals (Realini et al., 2001; Greiner et al., 2003; Afolayan et al., 2006; Lambe et al., 2008; Minchin et al., 2009; Pogorzelska-Przybylek et al., 2014) but they generally rely on obtaining manual measurements of body dimensions, body condition or tissue depth using ultrasound scanners. Obtaining these measurements is time consuming, may require a level of training and skill, and they can be stressful and potentially dangerous for both animals and handlers.

As imaging technologies become more advanced and affordable it is now economically feasible to implement them on commercial farms. Ozkaya et al. (2016) demonstrated that body measurements of cattle (body length, wither height, chest depth. and hip height) can be accurately determined from 2-dimensional (2D) digital image analysis (90–98% accuracy). Applications for 2D imaging have included estimating liveweight (LW) of broiler chickens (Mollah et al., 2010), pigs (Kashiha et al., 2014; Wongsriworaphon et al., 2015; Shi et al., 2016) and beef cattle (Ozkaya et al., 2016), and LW (Tasdemir et al., 2011), body condition score (Bewley et al., 2008), and lameness (Viazzi et al., 2014) in dairy cows.

Using both Limousin or Aberdeen Angus crossbred steers managed under typical UK conditions Hyslop et al. (2008, 2009) used 2D digital imaging to estimate LW and carcass characteristics. Successful prediction of slaughter parameters included LW ($R^2 = 0.81$, RMSE = 15.7); cold carcass weight (CCW) ($R^2 = 0.81$, RMSE = 10.4); killing out proportion ($R^2 = 0.91$, RMSE = 5.3), sirloin weight ($R^2 = 0.58$, RMSE = 2.1) and proportions ($R^2 = 0.61$, RMSE = 5.1) along with fat ($R^2 = 0.81$) and conformation ($R^2 = 0.81$) gradings.

Advances in imaging technology have allowed for the use of three-dimensional (3D) imaging in the livestock sector with applications in estimating LW (Mortensen et al., 2016) and lying behaviour (Aydin, 2017) in broiler chickens and body condition scoring (Weber et al., 2014; Fischer et al., 2015; Kuzuhara et al., 2015), LW (Kuzuhara et al., 2015), milking traits (Kuzuhara et al., 2015), and lameness (Van Hartem et al., 2014; Viazzi et al., 2014) in dairy cows. 3D imaging is also successfully used in estimating LW in pigs (Wang et al., 2008). There are no known reports where 3D imaging has been applied in estimating both LW and carcass characteristics of beef cattle.

Whilst multiple 2D cameras have been investigated (Hyslop et al., 2009), it was concluded that a "top down" camera view rather than the addition of side and rear view 2D cameras was sufficient for accurate prediction. Application of a 3D camera suspended above the animal would extend the range of potential "top down" predictor variables and refine prediction models further, with the continued advantage of equipment being kept away from animals and potential damage as well as being accessible for both installation and maintenance.

Increasingly, video image analysis (VIA) is being used to grade carcasses in the abattoir, improving the consistency of grading by removing subjective differences in visual assessment by trained graders (Craigie et al., 2012). However, many producers still subjectively select animals for slaughter by visual assessment of fat and condition score and by weighing manually through a crush. This is a clear inefficiency in the beef market. 3D imaging technology has the potential to provide predictions of carcass characteristics from live animals on farm, allowing farmers to send cattle to slaughter as soon as they are within the parameters specified by the abattoir. Having more animals slaughtered within specification increases the profit to the producer, improves the uniformity of the products produced for down-stream customers and reduces the environmental impact per kg of product produced (i.e., lower greenhouse gas emissions and reduced water use).

The objectives of this study were to use live animal body measurements automatically extracted from 3D images to build machine learning algorithms to predict LW and carcass characteristics of finishing beef cattle.

METHODS

Ethics Statement

The animal trials described below were approved by the Animal Experiment Committee of SRUC and were conducted in accordance with the requirements of the UK Animals (Scientific Procedures) Act 1986.

Measurements—Live Animals

The 3D cameras used were Basler Time-of-Flight near infrared cameras (Basler Inc., Exton, PA). The camera specifications are as follows: 640 × 480 pixels, 20 frames *per second*, 57° horizontal × 43° vertical angular field of view, accuracy of +/− 1 cm. Eighteen measurements (5 widths, 6 lengths, 5 heights, and 2 diagonals, **Figure 1**) were extracted from each 3D image and 20 ratios, 11 areas, and 11 volumes were calculated, giving a total of 60 potential predictor variables available for evaluation. Measurements were extracted in real time from 3D images using algorithms developed by Innovent Technology Ltd. using Halcon software (MVTec Software GmbH, München, Germany).

Live animal data was gathered from a range of sources: including both commercial and research farms and from an abattoir lairage.

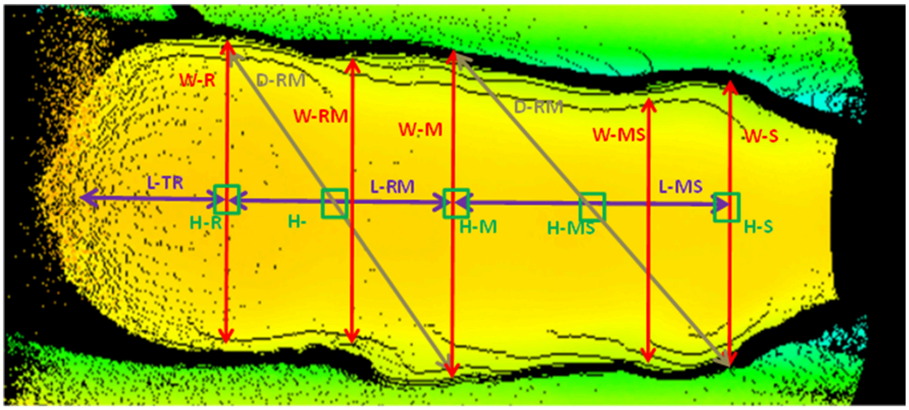

FIGURE 1 | Measurements acquired from 3D images. W, width; L, length; D, diagonal; H, height; S, shoulder; M, middle; R, rump, T, tail.

Farm Trials

Five automatic Beef Monitor weigh crates (Ritchie Ltd, Turriff, UK) fitted with Tru-test weigh heads and electronic ID (EID) readers (Tru-Test Corporation Ltd., Auckland, New Zealand) were installed on four commercial finishing units throughout Scotland and two were installed at SRUC's Beef Research Centre near Edinburgh. The crates were the sole water source for up to 50 steers or heifers in group pens. All animals behind the system were allocated low frequency EID ear tags to allow individual identification and automated weight recording. Three dimensional cameras were suspended from custom made frames 3 m above each crate. Liveweight and 3D images were recorded at every visit to the water trough. Variables were automatically linked to the EID and LW recorded by the Beef Monitor crate and immediately uploaded to a database. Data extracted from images which had poor animal outlines (determined visually) or where the automatically calculated variables were 0 (i.e., a height, width etc. cannot be 0) were removed from the analysis. Poor outlines were generally caused by strong direct sunlight below the camera, a second animal's head against the rear of the animal being measured or the animal leaning against the side of the crate or race. Across the five farms, 17127 LWs were collected from 674 animals (see **Table 1** for a breakdown of sexes and breeds).

Abattoir Trial

A ten day data collection trial was undertaken in a commercial abattoir in Scotland. This allowed a large number of individual animal data points from a variety of breeds, sexes, and animal types with a range of conformation and fat grades to be obtained rapidly. A weigh platform was placed between two sliding gates in the race leading up to the stun box and a 3D camera was secured 3 m above the platform. This allowed individual animals to be held for a short time immediately pre-slaughter to record UKID and LW and to capture a 3D image. Liveweights and clear images were recorded for 1,484 beef animals. A summary of animal numbers by breed and sex are shown in **Table 1**.

TABLE 1 | Summary of cattle used in the development of liveweight prediction algorithms.

	AA (x)	LIM (x)	SIM (x)	CH (x)	Other	Total
Total	909	556	300	225	168	2158
FARM TRIALS						
Total	88	253	139	118	76	674
Steers	5	203	99	91	34	432
Heifers	83	50	40	27	42	242
ABATTOIR TRIAL						
Total	821	303	161	107	92	1484
Steers	436	190	93	52	59	830
Heifers	385	113	68	55	33	654

AA, Aberdeen Angus; LIM, Limousin, SIM, Simmental; CH, Charolais.

Measurements—Slaughter Data

Cattle were stunned by captive bolt, exsanguinated and their hides were removed. Carcasses were split down the midline and dressed as per normal abattoir practice. Conformation class and fatness class were visually assessed for each carcass by trained abattoir staff (according to the abbreviated EUROP grid commonly used in UK abattoirs). VIA technology (VBS 2000, E+V GmbH, Germany) was operated on-line to predict fat and conformation grades on both the 15 point scale and the EUROP grid (7 fat and 8 conformation grades). Cold carcass weight, saleable meat yield (SMY) estimated by VIA along with visually assessed EUROP fat and conformation grades were provided by the abattoir. Carcass characteristics data for a total of 1649 carcases from both the abattoir and on-farm trial datasets were matched to clear pre-slaughter 3D images, see **Table 2** for a breakdown of breeds and sexes.

Statistical Analysis and Development of Predictive Models

Data from all abattoir and on-farm sources were combined into one dataset. For the LW predictions the abattoir data consisted of a single LW per animal taken immediately pre-slaughter. The commercial and SRUC on-farm trial data consisted of multiple

TABLE 2 | Summary of cattle used in the development of carcass characteristics prediction algorithms.

	AA(x)	LIM(x)	SIM(x)	CH(x)	Other	Total
Total	842	395	175	131	106	1649
Farm Trials	22	92	15	24	14	167
Steers	0	77	3	11	2	93
Heifers	22	15	12	13	12	74
FAT GRADE						
1	28	31	13	12	10	94
2	373	194	103	69	38	777
3	339	112	43	35	38	567
4L	85	50	15	15	14	179
4H	17	8	1	0	6	32
5L	0	0	0	0	0	0
CONFORMATION GRADE						
–P	0	0	0	0	1	1
P+	24	2	1	0	6	33
–O	286	41	25	7	46	405
O+	395	118	95	51	38	697
R	127	146	47	59	14	393
–U	10	83	7	14	1	115
U+	0	5	0	0	0	5
E	0	0	0	0	0	0

*See **Table 1** for breakdown of animal breeds and sexes from the abattoir trial. Fat and conformation grades as predicted by VIA. AA, Aberdeen Angus; LIM, Limousin; SIM, Simmental; CH, Charolais.*

weights per animal across the finishing period. For the fat grade, conformation grade, CCW and SMY predictions, only the final LW recorded in the beef monitor crates on farms was used alongside the LWs collected in the abattoir trial. No 5L or 5H fat grades and no E and insufficient U+ conformation grades ($n = 5$) were recorded and so these grades could not be included in the prediction model. A summary of the breeds, sexes, fat grades and conformation grades are shown in **Table 2**.

Sex was included as a factor in the model. Cattle were categorised as either native type (smaller, quick finishing breeds such as Aberdeen Angus) or continental type (larger breeds such as Charolais) (see **Supplementary Table 1** for categorisation of breeds), and this was also included as a factor in the model. From the commercial farm trials, the final measured LW from the weigh crate was included as a predictor variable for carcass characteristics.

Artificial neural networks (ANNs) were selected for this study as they can be used for both regression and classification problems and are capable of handling complex non-linear relationships between large numbers of variables. ANNs comprise a framework of "neurons" which are connected by weighted links (Agatonovic-Kustrin and Beresford, 2000). ANNs can be used for regression and classification problems and have many applications in financial forecasting, machine vision, game theory, medicine and ecology to name only a few. ANNs were developed using the caret package in R (version 3.4.1, R Core Team, 2017). To optimise neural network training, continuous input variables were standardised using a Gaussian transformation (subtracting the mean and dividing by one standard deviation) and min-max scaling between −0.9 and 0.9. The data was then randomly split into training (70%) and validation (30%) subsets.

In this study ANNs were developed through supervised training by backward propagation. The model was presented with the training set and known target values. Weights and biases were automatically randomly initialised to non-zero values (between 1 and −1) by the ANN software and during the training phase the model adjusted the weighted connections by feeding back the error and optimising the weights to decrease the difference between target and output values. Repeated training iterations (three repeats of 10-fold repeated cross validation) further reduced the model error. Models were regularised to prevent overfitting to the training data subset by applying a penalty (a weight decay value) to weights which became relatively much larger than others in the model. Parameter estimation (model size and weight decay values) were optimised after testing 100 potential models (10 possible values per parameter). Several topographies (number of hidden layers and nodes in each layer) were tested for each ANN. The topography which produced the best performance results without overfitting to the training data sub-sets was selected for each ANN. All of the ANNs had one hidden layer with five nodes, except the fat grade classification ANN which only had one node in the hidden layer. The model was then tested on the validation data subset. Model performance was assessed by R^2 and RMSE for regression (LW, CCW, and SMY). Classification accuracy for fat and conformation grades were assessed by way of confusion matrices. A confusion matrix is a table summarising the number of validation sub-set data points in each class and the predicted classes, and the sensitivity (Equation 1) and specificity (Equation 2) for each class.

$$\text{sensitivity} = \text{true positive}/\text{true positive} + \text{false negative} \quad (1)$$

$$\text{specificity} = \text{true negative}/\text{true negative} + \text{false positive} \quad (2)$$

Where for any class (x), a true positive is a data point that is correctly predicted to be within class x, a false negative is a data point incorrectly predicted to not be in class x, a true negative is a data point which is correctly predicted to not be in class x and a false positive is a data point which is incorrectly predicted to be in class x.

Stepwise linear regression models were also created for the continuous variables (LW, CCW, and SMY) using the same training and validation data subsets as were used to create the ANNs and were cross validated using the same method. Summary results (R^2 and RMSE) are reported alongside the ANN results.

Finally, the importance of each predictor variable to the overall ANN was assessed using the VarImp function in R. This function calculates the influence each input variable has on the output by using the connection weight between the input and each hidden neuron and apportioning the connection weights between each hidden neuron and the output between each input variable (based on the method described in Gevrey et al., 2003). Connection weights are analogous to coefficients in a linear model (although the number of connection weights in an ANN is excessive compared to coefficients in a linear model) and so dictate the influence any variable has on the hidden nodes and ultimately on the output e.g., variables with low weights are suppressed and so have little importance and those with large weights are influential and have high importance. Variable importance was scaled from 100 to 0 with 100 being the predictor variable with the highest calculated influence and 0 being redundant. The following calculations below are quoted from Gevrey et al. (2003).

1. For each hidden neuron, divide the absolute value of the input-hidden layer connection weight by the sum of the absolute value of the input-hidden layer connection weight of all input neurons, i.e.,

For h = 1 to *n*h, and for i = 1 to *n*i

$$Q_{ih} = \frac{|W_{ih}|}{\sum_{i=1}^{ni} |W_{ih}|}$$

2) For each input neuron i, divide the sum of the Q_{ih} for each hidden neuron by the sum for each hidden neuron of the sum for each input neuron of Q_{ih}, multiply by 100. The relative importance of all output weights attributable to the given input variable is then obtained.

For i = 1 to *n*i

$$RI\,(\%) = \frac{\sum_{h=i}^{nh} Q_{ih}}{\sum_{h=i}^{nh} \sum_{i=1}^{ni} Q_{ih}}\, x\, 100$$

Where Q is the proportional influence an input neuron has on a hidden neuron, h is a hidden neuron, i is an input neuron, W is a weight and RI is the relative influence of an input neuron (%).

RESULTS AND DISCUSSION

3D Image Collection

A total of 18,134 3D images were collected during this trial. Of the 16,100 3D images collected on commercial and research farms 1,292 (8%) of images were removed due to a poor outline being obtained. From the abattoir trial 550 of 2,034 3D images (27%) were removed from the analysis. The more stressful environment in the abattoir lairage led to a higher proportion of 3D images being removed from the analysis. Animals were more likely to be agitated and so a good quality 3D image was difficult to obtain. Removal of images from the on-farm data sets is not deemed to be a concern for commercial implementation as multiple images are collected per animal per day; therefore not all images of each individual animal are required to provide a prediction to the end user.

Prediction of Liveweight, Cold Carcass Weight, and Saleable Meat Yield

Pre-slaughter LW's ranged from 341 to 774 kg and the mean weight at slaughter was 608 ± 57 kg. The mean CCW was 339 ± 39 kg and mean SMY was 223 ± 32 kg.

In this study LW was predicted for a wide variety of breeds, both steers and heifers, with an R^2 of 0.70 (RMSE = 42, *n* = 4443, **Figure 2**). The performance of the stepwise linear regression for LW was much poorer than the ANN ($R^2 = 0.54$, RMSE = 51). Ozkaya et al. (2016) used multiple linear regression of measurements extracted from lateral 2D digital images of Limousin cattle to predict LW with an R^2 of 0.89. Although sex and breed type had low importance (3 and 0, respectively, **Table 3**), to investigate the performance of sex and breed specific models the ANN was trained only using the Aberdeen Angus steers data subset (*n* = 441, **Table 1**). The model performance increased to $R^2 = 0.77$ (RMSE = 37), suggesting that the further development of this system may benefit from breed and sex specific models. As LW had the highest importance (100) for the prediction of CCW, SMY and fat grade, and the importance of sex (CCW: 51, SMY: 29, conformation grade: 1, fat grade: 11) and breed type (CCW: 32, SMY: 15, conformation grade: 18, fat grade: 32) are generally of higher importance for prediction of carcass characteristics (**Table 3**), breed and sex specific LW models should also improve prediction of these carcass characteristics.

Carcasses which are over a defined weight face a penalty at the abattoir. Being able to predict CCW in the live animal would allow producers to ensure that animals are sent to slaughter before they grow beyond the weight limit. The ANN predicted CCW with R^2 = 0.88 (RMSE = 14, *n* = 449, **Figure 3**) and SMY with R^2 = 72 (RMSE = 14, *n* = 448, **Figure 4**). The stepwise linear regression models predicted CCW with R^2 = 0.83 (RMSE = 16) and SMY with R^2 of 0.63 (RMSE = 16). LW was of most importance in the ANNs for CCW and SMY in this study (**Table 3**). LW has previously been shown to have a strong linear relationship with CCW (Minchin et al., 2009), hot carcass weight (Pogorzelska-Przybylek et al., 2014), and SMY (Realini et al., 2001; Greiner et al., 2003). However, predictor variables extracted from the 3D images still had significant influence over the ANN model outputs (**Table 3**), and the ANNs had improved performance over the stepwise linear regression

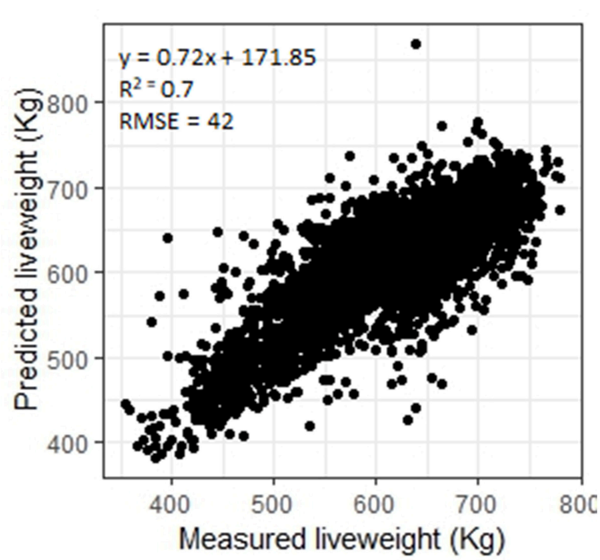

FIGURE 2 | Measured liveweights plotted against liveweights predicted using an artificial neural network.

TABLE 3 | Relative importance (scaled from 100 to 0 where 100 is most influential in the model and 0 is redundant) of the 5 predictor variables with highest influence [and liveweight (LW), sex and breed type if not already included], for each ANN.

ANN	Predictor variable	Scaled relative importance
LW		
	Height (S)	100
	Height (R)	80
	Diagonal (RM)	79
	Length ratio (RM/MS)	75
	Width ratio (R/RM)	71
	Sex	3
	Breed "type"	0
CCW		
	LW	100
	Sex	51
	Breed "type"	32
	Volume (MS)	24
	Height (M)	18
SMY		
	LW	100
	Diagonal (MS)	30
	Sex	29
	Width (RM)	27
	Length ratio (RM/MS)	26
	Breed "type"	15
CONFORMATION GRADE		
	Height (M)	100
	Width (M-S)	79
	Width Ratio (R/M)	78
	Diagonal (MS)	78
	Length (TM)	78
	LW	30
	Breed "type"	18
	Sex	1
FAT GRADE		
	LW	100
	Height (M)	68
	RateA_TR_RM	49
	Height (R)	36
	VolumeTR	35
	Breed "type"	32
	Sex	11

*See **Figure 1** for definition of predictor variables.*

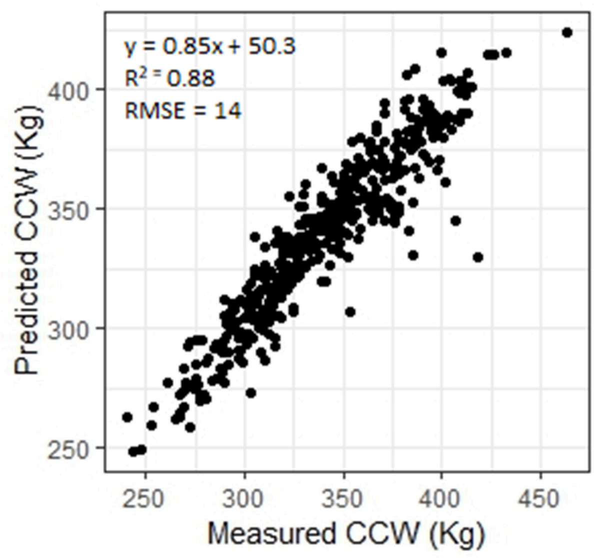

FIGURE 3 | Measured cold carcass weight (CCW) plotted against CCW predicted using an artificial neural network.

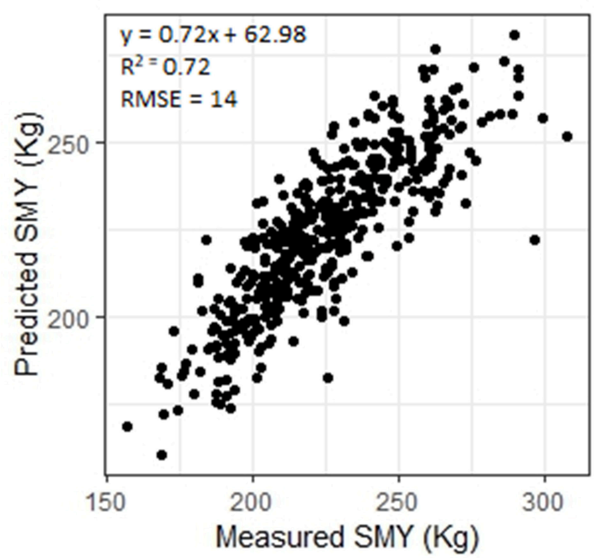

FIGURE 4 | Measured saleable meat yield (SMY) plotted against SMY predicted using an artificial neural network.

models. Greiner et al. (2003) found that when LW was used as a single predictor for SMY their regression model had an R^2 of 0.66 for a more limited range of animals (534 cross-bred steers) than used in the present study, demonstrating the potential of 3D imaging to provide more accurate predictions of carcass characteristics.

Prediction of Fat and Conformation Grades

Farmers in the UK are currently paid for their animals on both carcass weight and fat and conformation grades. ANNs were developed for fat and conformation grade using the abbreviated EUROP scale in operation at the abattoir. The accuracy of the classification ANNs for the validation data subset were 54.2% for fat grade and 55.1% for conformation grade. The confusion matrices are shown for the fat (**Table 4**) and conformation grades (**Table 5**), along with the sensitivity (ability of the model to correctly classify a data point to that particular grade) and specificity (ability of the model to correctly identify a data

TABLE 4 | Confusion matrix for the fat grade classification artificial neural network and the sensitivity and specificity of the model to each grade.

	VIA predicted fat class				
ANN predicted fat class	**1**	**2**	**3**	**4L**	**4H**
1	0	0	0	0	0
2	24	191	98	16	1
3	3	40	62	25	1
4L	0	0	9	12	7
4H	0	0	0	0	0
Sensitivity	0	0.83	0.37	0.23	0
Specificity	1	0.46	0.78	0.96	1
Observations in validation dataset	27	231	169	53	9

TABLE 5 | Confusion matrix for the conformation grade classification artificial neural network and the sensitivity and specificity of the model to each grade.

	VIA predicted conformation class					
ANN predicted conformation class	**P+**	**–O**	**O+**	**R**	**–U**	**U+**
P+	0	0	0	0	0	0
–O	5	58	37	2	0	0
O+	4	61	146	50	10	0
R	0	2	23	55	13	0
–U	0	0	1	11	11	1
U+	0	0	0	0	0	0
Sensitivity	0.00	0.48	0.71	0.47	0.32	0.00
Specificity	1.00	0.88	0.56	0.90	0.97	1.00
Observations in validation dataset	9	121	207	118	34	1

point as not belonging to that particular grade) of the model to each grade.

The majority of carcasses were classed as fat grade 2 (47%) or 3 (34%) (**Table 2**). The fat grade model had a sensitivity of 0.83 for grade 2, but a specificity of 0.46 (**Table 4**). This low specificity was due to the tendency of the algorithm to classify the grade 3 carcasses as grade 2. The model classified all of the grade 1 carcasses in the validation subset as grade 2 and most of the 4H carcasses as 4L. It did not correctly classify to either grade 1 or 4H (sensitivity equal to 0, **Table 4**), this was likely due to there being insufficient data points in the training set for these two grades. The specificity of the conformation grade classification ANN model to both P+ and U+ was 1 (**Table 5**). There were also only a small number of data points collected for carcases of these grades. There was a tendency for the model to classify the O- and R carcases as O+ (O+ had a specificity of 0.56), likely due to the relatively large number of data points in the training data set which were grade O+. It is anticipated that increasing the number of data points in the less desirable grades would improve the predictive performance of these models.

Lambe et al. (2010) used ultrasound measurements of tissue depth in live finishing beef steers and heifers to predict conformation and fat grades using linear regression. The predictions in their study were slightly more accurate (R^2 = 0.60) for fat grade and similar (R^2 = 0.56) for conformation class than in the present study, however their models performed poorly on validation data sets (fat class: R^2 = 0.39–0.46, conformation class: R^2 = 0.07–0.24). SMY has also been successfully (R^2 = 0.80) predicted using similar ultrasound measurements (Realini et al., 2001). No literature could be found where a classification model had been used to predict fat and conformation grade of beef carcases. The advantage of a 3D imaging system over manual measurements such as ultrasound are the reduction in stress caused by handling of animals and the automated system can passively provide multiple estimates per animal per day at minimal cost.

In this study LW was found to be the most important predictor of fat grade (weighted importance of 100, **Table 3**), and was less important, but not redundant (weighted importance of 30) for conformation grade. Minchin et al. (2009) found that LW was not a significant predictor of fat or conformation grade for cull cows from either dairy or beef sired lines. This is likely due to the generally lower body condition and fat cover of cull cows compared to finished beef heifers and steers.

CONCLUSIONS

This study has shown that there is potential to use 3D imaging technology to automate the process of selecting cattle for slaughter at the correct specification, so improving the efficiency and profitability of beef enterprises through marketing of animals at the optimal time. Further work to improve the prediction of fat and conformation grades in the live animal is required. Particularly more data needs to be collected from animals with carcass grades out with the desirable target grades. Addressing this imbalance of carcass grades in the dataset will allow the model to better distinguish between grades. Further development of this technology also requires the development of breed and sex specific algorithms for LW and carcass characteristics.

ETHICS STATEMENT

The animal trials described below were approved by the Animal Experiment Committee of SRUC and were conducted in accordance with the requirements of the UK Animals (Scientific Procedures) Act 1986.

AUTHOR CONTRIBUTIONS

C-AD, JJH, WT, DB, and AE conceived and designed the project. GAM, DB, WT, and AE collected the data. GAM and JJH processed the data. GAM analysed the data. GAM and C-AD prepared the manuscript which was reviewed by all authors.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2019.00030/full#supplementary-material

REFERENCES

Afolayan, R. A., Adeyinka, I. A., and Lakpini, C. A. M. (2006). The estimation of live weight from body measurements in Yankasa sheep. *Czech J. Anim. Sci.* 8, 343–348. doi: 10.17221/3948-CJAS

Agatonovic-Kustrin, S., and Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modelling and its application in pharmaceutical research. *J. Pharmac. Biomed. Anal.* 22, 717–727. doi: 10.1016/S0731-7085(99)00272-1

AHDB (2018a). *UK Yearbook 2018, Cattle*. Kenilworth: Agriculture and Horticulture Development Board.

AHDB (2018b). *Marketing Prime Beef Cattle for Better Returns. Booklet*. Kenilworth: AHDB Beef and Lamb.

Aydin, A. (2017). Using 3D vision camera system to automatically assess the level of inactivity in broiler chickens. *Comput. Electr. Agri.* 135, 4–10. doi: 10.1016/j.compag.2017.01.024

Bewley, J. M., Peacok, A. M., Lewis, O., Boyce, R. E., Roberts, D. J., Coffey, M. P., et al. (2008). Potential for estimation of body condition scores in dairy cattle from digital images. *J. Dairy Sci.* 91, 3439–3453. doi: 10.3168/jds.2007-0836

Craigie, C. R., Navajas, E. A., Purchas, R. W., Maltin, C. A., Bünger, L., Hoskin, S. O., et al. (2012). A review of the development and use of video image analysis (VIA) for beef carcass evaluation as an alternative to the current EUROP system and other subjective systems. *Meat Sci.* 92, 307–318. doi: 10.1016/j.meatsci.2012.05.028

de Vries, M., and de Boer, I. J. M. (2010). Comparing environmental impacts for livestock products: a review of life cycle assessments. *Livestock Sci.* 128, 1–11. doi: 10.1016/j.livsci.2009.11.007

Fischer, A., Luginbühl, T., Delattre, L., Delouard, J. M., and Faverdin, P. (2015). Rear shape in 3 dimensions summarized by principal component analysis is a good predictor of body condition score in Holstein dairy cows. *J. Dairy Sci.* 98, 4465–4476. doi: 10.3168/jds.2014-8969

Gevrey, M., Dimopoulos, I., and Lek, S. (2003). Review and comparison of methods to study the contribution of variables in artificial neural network models. *Ecol. Model.* 160, 249–264. doi: 10.1016/S0304-3800(02)00257-0

Greiner, S. P., Rouse, G. H., Wilson, D. E., Cundiff, L. V., and Wheeler, T. L. (2003). Prediction of retail product weight and percentage using ultrasound and carcass measurements in beef cattle. *J. Anim. Sci.* 81, 1736–1742. doi: 10.2527/2003.8171736x

Hyslop, J. J., Ross, D. W., Schofield, C. P., Navajas, E., Roehe, R., and Simm, G. (2008). "An assessment of the potential for live animal digital image analysis to predict the slaughter liveweights of finished beef cattle," in *Proceedings of the British Society of Animal Science, 2008, Abstract 050*.

Hyslop, J. J., Ross, D. W., Schofield, C. P., Navajas, E., Roehe, R., and Simm, G. (2009). "Predicting the slaughter characteristics of finished beef cattle using a live animal digital image analysis system under typical on-farm management conditions," in *Proceedings of the British Society of Animal Science, 2009, Abstact 139*.

Kashiha, M., Bahr, C., Ott, S., Moons, C. P. H., Niewold, T. A., Ödberg, F.O., et al. (2014). Automatic weight estimation of individual pigs using image analysis. *Comput. Electr. Agric.* 107, 38–44. doi: 10.1016/j.compag.2014.06.003

Kuzuhara, Y., Kawamura, K., Yoshitoshi, R., Tamaski, T., Sugai, S., Ikegami, M., et al. (2015). A preliminary study for predicting body weight and milk properties in lactating Holstein cows using a three-dimensional camera system. *Comput. Electr. Agric.* 111, 186–193. doi: 10.1016/j.compag.2014.12.020

Lambe, N. R., Navajas, E. A., Schofield, C. P., Fisher, A. V., Simm, G., Roehe, R., et al. (2008). The use of various live animal measurements to predict carcass and meat quality in two divergent lamb breeds. *Meat Sci.* 80, 1138–1149. doi: 10.1016/j.meatsci.2008.05.026

Lambe, N. R., Ross, D. W., Navajas, E. A., Hyslop, J. J., Prieto, N., Craigie, C., et al. (2010). The prediction of carcass composition and tissue distribution in beef cattle using ultrasound scanning at the start and/or end of the finishing period. *Livestock Sci.* 131, 193–202. doi: 10.1016/j.livsci.2010.03.019

Minchin, W., Buckley, F., Kenny, D. A., Keane, M. G., Shalloo, L., and O'Donovan, M. (2009). Prediction of cull cow carcass characteristics from live weight and body condition score measured pre slaughter. *J. Agric. Food Res.* 48, 75–86.

Mollah, B. R., Hassan, A., Salam, A., and Ali, A. (2010). Digital image analysis to estimate the live weight of broiler. *Comput. Electr. Agric.* 72, 48–52. doi: 10.1016/j.compag.2010.02.002

Mortensen, A. K., Lisouski, P., and Ahrendt, P. (2016). Weight prediction of broiler chickens using 3D computer vision. *Comput. Electr. Agric.* 123, 319–326. doi: 10.1016/j.compag.2016.03.011

Ozkaya, S., Neja, W., Krezel-Czopek, S., and Oler, A. (2016). Estimation of bodyweight from body measurements and determination of body measurements on Limousin cattle using digital image analysis. *Anim. Product. Sci.* 56, 2060–2063. doi: 10.1071/AN14943

Pogorzelska-Przybylek, P., Nogalski, Z., Wielgosz-Groth, Z., Winarski, R., Sobezuk-Szul, M., Łapińska, P., et al. (2014). Prediction of the carcass value of young Holstein-Friesian bulls based on live body measurements. *Ann. Anim. Sci.* 14, 429–439. doi: 10.2478/aoas-2014-0004

R Core Team (2017). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Realini, C. E., Williams, R. E., Pringle, T. D., and Bertrand, J. K. (2001). Gluteus medius and rump fat depths as additional live animal ultrasound measures for predicting retail product and trimmable fat in beef carcasses. *J. Anim. Sci.* 79, 1378–1385. doi: 10.2527/2001.7961378x

Roehe, R., Morgan, C., and Clarkson, A. (2013). *Understanding the Inefficiency of Too Much Fat*. Kenilworth: AHDB Beef and Lamb.

Shi, C., Teng, G., and Li, Z. (2016). An approach of pig weight estimation using binocular stereo system based on LabVIEW. *Comput. Electr. Agric.* 129, 37–43. doi: 10.1016/j.compag.2016.08.012

Tasdemir, S., Urkmez, A., and Inal, S. (2011). Determination of body measurements on the Holstein cows using digital image analysis and estimation of live weight with regression analysis. *Comput. Electr. Agric.* 76, 189–197. doi: 10.1016/j.compag.2011.02.001

Van Hartem, T., Viazzi, S., Steensels, M., Maltz, E., Antler, A., Alchanatis, V., et al. (2014). Automatic lameness detection based on consecutive 3D-video recordings. *Biosyst. Eng.* 119, 108–116. doi: 10.1016/j.biosystemseng.2014.01.009

Viazzi, S., Bahr, C., Van Hartem, T., Schlageter-Tello, A., Romanini, C. E. B., Halachmi, I., et al. (2014). Comparison of a three-dimensional and two-dimensional camera system for automated measurement of back posture in dairy cows. *Comput. Electr. Agric.* 100, 139–147. doi: 10.1016/j.compag.2013.11.005

Wang, Y., Yang, W., Winter, P., and Walker, L. (2008). Walk-through weighing of pigs using machine vision and an artificial neural network. *Biosyst. Eng.* 100, 117–125. doi: 10.1016/j.biosystemseng.2007.08.008

Weber, A., Salau, J., Haas, J. H., Junge, W., Bauer, U., Harms, J., et al. (2014). Estimation of backfat thickness using extracted traits from an automatic 3D optical system in lactating Holstein-Fresian cows. *Livestock Sci.* 165, 129–137. doi: 10.1016/j.livsci.2014.03.022

Wongsriworaphon, A., Arnonkijpanich, B., and Pathumnakul, S. (2015). An approach based on digital image analysis to estimate the live weights of pigs in farm environments. *Comput. Electr. Agric.* 115, 26–33. doi: 10.1016/j.compag.2015.05.004

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A Generic Approach for Live Prediction of the Risk of Agricultural Field Runoff and Delivery to Watercourses: Linking Parsimonious Soil-Water-Connectivity Models With Live Weather Data Apis in Decision Tools

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This paper describes the development and application of a novel and generic framework for parsimonious soil-water interaction models to predict the risk of agro-chemical runoff. The underpinning models represent two scales to predict runoff risk in fields and the delivery of mobilized pesticides to river channel networks. Parsimonious field and landscape scale runoff risk models were constructed using a number of pre-computed parameters in combination with live rainfall data. The precomputed parameters included spatially-distributed historical rainfall data to determine long term average soil water content and the sensitivity of land use and soil type combinations to runoff. These were combined with real-time live rainfall data, freely available through open data portals and APIs, to determine runoff risk using SCS Curve Numbers. The rainfall data was stored to provide antecedent, current and future rainfall inputs. For the landscape scale model, the delivery risk of mobilized pesticides to the river network included intrinsic landscape factors. The application of the framework is illustrated for two case studies at field and catchment scales, covering acid herbicide at field scale and metaldehyde at landscape scale. Web tools were developed and the outputs provide spatially and temporally explicit predictions of runoff and pesticide delivery risk at 1 km^2 resolution. The model parsimony reflects the driving nature of rainfall and soil saturation for runoff risk and the critical influence of both surface and drain flow connectivity for the risk of mobilized pesticide being delivered to watercourses. The novelty of this research lies in the coupling of live spatially-distributed weather data with precomputed runoff and delivery risk parameters for crop and soil types and historical rainfall trends. The generic nature of the framework supports the ability to model the runoff and field-to-channel delivery risk associated with *any* in-field agricultural application assuming application rate data are available.

Keywords: big data & analytics, spatial data integration, pesticides, metaldehyde, web-based model, R, API (application program interface), United Kingdom

INTRODUCTION

Rainfall-induced surface and subsurface runoff mobilizes and transports the chemicals used for in-field agricultural applications (fertilizers, herbicides, and pesticides) from land to receiving freshwaters. Agriculture is therefore a significant source of water pollution, affecting drinking water quality and treatment costs. In England, for example, water companies spent £92 million in 2008–09 removing pollutants from water supplies to meet drinking water standards (National Audit Office, 2010). However, for some pollutants, such as metaldehyde, there are currently no cost-effective methods of removal, although the UK's first treatment plant has recently been constructed at significant cost to the water company in question[1] Concentrations of such agrochemicals above safe limits in surface and groundwaters creates not only environmental risk, but also a risk to human health.

Agricultural applications can enter surface water via a number of pathways. Spills, spray-drift and illegal disposal are generally managed by best practice guidance and prosecution. Surface and subsurface runoff can transport agrochemicals in dissolved and particulate form, from the field to watercourses. The proportion that is removed in solution relative to that attached to mobilized soil particles depends on the intrinsic soil properties, topography/slope and the characteristics of the agrochemicals such as pesticides, including their sorption and solubility properties (Guo et al., 2000; Louchart, 2001; Newell-Price et al., 2011).

The biggest driver of surface and subsurface runoff is precipitation and the timing and characteristics of the first rainfall event after application are very important. Antecedent weather determines the wetness of the soil and therefore the degree to which the chemical is "held" by the soil. Applications made to wet soil (at field capacity or wetter), or just before heavy rainfall, are more likely to be lost in surface runoff or by-pass flow to field drains, with negative environmental and water quality impacts as they are transferred to surface or groundwater (Mitchell et al., 2005; Gao et al., 2008; Lapworth et al., 2012), although the propensity for mobilized pollution to reach watercourses also depends on additional factors affecting delivery (e.g., the status and maintenance of field drains, the topology of the landscape, distance to watercourses). Thus, water pollution risk is enhanced by poor timing of applications in relation to weather events which can result in pollutant concentrations in surface waters that exceed drinking water standards (Pretty et al., 2003).

In addition to the environmental benefits, the efficacy of any agricultural application is severely reduced if runoff washes it from the crop or the field. For the farmer, the reduced efficacy leads to risks of reduced yields (income) and/or increased costs (and thereby lower gross margins) if the treatment has to be re-applied to protect the crop. The annual cost to farmers of agricultural runoff has been estimated at £238 m (Jacobs UK Ltd, 2008) a significant part of which can be attributed to the impact of runoff losses associated with compromised pesticide and herbicide effectiveness. There are additional environmental (damage) costs and, in future, there may be financial penalties for pesticides and herbicides being washed into watercourses. Preventing agro-chemicals reaching surface and groundwaters by imparting source control measures is more cost-effective than water treatment and some initial research has identified a benefit-to-cost ratio of 65:1 for prevention over treatment (Defra, 2013).

Direct detection of the source of pesticides and herbicides carried by runoff is difficult due to the diffuse nature and temporal variability of the sources and the high cost of instrumentation (Meyer et al., 2019) and with some pollutants, the length of time taken to analyse water samples makes real-time risk mapping impractical. Consequently, modeling water pollution risk is the only practical option in most cases.

This paper describes the development of two decision tools operating over different scales of decision making. The tools provide interfaces to two parsimonious soil-water runoff models; one supporting on-farm decisions at the field scale and another supporting landscape scale management. Both include inputs and outputs at a1 km^2 spatial scale, but their aims are very different and their outputs should be interpreted in very different ways. The field scale tool provides the end-user with point-based information of runoff risk derived from a model operating over each 1 km^2 independently. It uses a meta-model to forecast surface runoff risk for a given land use on a given soil from recent recorded and forecast rainfall alone. It aims to support farmers and land managers to better manage pesticide applications. The catchment scale model also uses a 1 km^2 scale (in part because most of the data available to support such analyses and models are at best at 1 km^2 resolution). However, the inputs and outputs do not describe processes that operate independently over each 1 km^2. Rather, the inputs describe landscape processes that are topologically connected such as field drain and surface flows as well as landscape connectivity between fields and watercourses. In this case, the outputs provide Tier 1 screening to identify hotspots requiring further investigation, with the aim

[1] https://wwtonline.co.uk/features/project-focus-hall-claims-uk-first-in-water-treatment.

of supporting informed on-the-ground catchment management by environmental agencies and water companies.

BACKGROUND

This research is informed by two limitations arising from previous work: the difficulties of determining antecedent soil water status (and thereby the potential for soil to hold water) and the temporally static nature of many landscape scale decision support tools in this domain.

Modeling Runoff

The SCS Curve Number (CN) method (USDA SCS, 1972) is commonly used to model surface runoff depth from rainfall amount, soil surface characteristics and antecedent wetness. It is also used to predict runoff and infiltration (USDA, 2004). It is applicable to small catchments ($\leq$ 6,500 ha) (NRCS, 2002) and has been implemented in models to estimate agrochemical transport to water (e.g., SWAT—Arnold et al., 1998; PRZM—Carsel et al., 2003; APEX—Williams et al., 2006; CREAMS—Knisel, 1980) and has been shown to be robust for a range of climates, soil types and land uses (e.g., Gassman et al., 2007). It has been found to perform better than an infiltration model in modeling runoff in an agricultural catchment in England (Kannan et al., 2007). Many CN models predict runoff depths for individual weather events using an empirical relationship between direct runoff depth, rainfall amount, soil surface characteristics and antecedent wetness (USDA, 2004). The rainfall amount at which runoff starts depends on the maximum potential retention, which in turn, depends on land use and soil type. The CN approach provides a widely used and effective method for estimating direct runoff due to rainfall. Despite its simplicity, and the availability of CNs for various land use and soil type combinations (Chow et al., 1988; Pilgrim and Cordery, 1993; USDA, 2004), operationally it can be difficult to estimate the antecedent soil moisture conditions. Although the antecedent soil water status has been estimated from 5-day antecedent rainfall (e.g., Mishra et al., 2005), this has been shown to be poorly correlated with maximum potential retention (USDA, 2004).

Decision Support Tools

User-facing decision tools started to emerge with the advent of easily programmable GISs with graphical user interfaces. These were developed to support farming compliance under newly legislated environmental directives, such as the Water Framework Directive (WFD Water Framework Directive, 2000) in Europe, and sought to minimize the externalities of agricultural activity on waterbodies. Decision tools, for use by both farmers and policy makers, were developed over a range of spatial scales: nationally, at typical scales of 1, 5, and 10 km^2 and Europe-wide at scales of 10, 20 and 50 km^2. Examples of UK models include those of Webb and Misselbrook (2004), Chadwick et al. (2005), Chambers et al. (1999), Davison et al. (2008), Lord and Anthony (2000) and Lord (1992) many of which are summarized in Anthony et al. (2008). At the European scale, similar models include PyCatch (Schmitz et al., 2017) and the FOOTPRINT (Functional Tools for Pesticide Risk Assessment and Management) framework which integrates pesticide use information with a physically based field scale soil water model (Jarvis et al., 2000) for drainage and leaching pathways and PRZM (Suarez, 2005) for runoff and erosion pathways. Hydrological modeling frameworks have also been used to simulate agrochemical runoff (Kannan et al., 2006; Ficklin et al., 2013; Bannwarth et al., 2014; Zhang et al., 2018). A key and unavoidable characteristic of existing landscape process-based models is that their outputs and the scales they report over are spatially and temporally incompatible with the expectations and needs of land managers. Here, a key limitation is the fact they are underpinned by highly static, spatially and temporally aggregated data by way of model inputs such as underlying soil types, drainage, land use, climate, terrain characteristics and farming practice.

Research Aims

The critical gap, common to SCN models and decision support tools, regardless of scale, is that they do not incorporate live and dynamically updated data on soil condition or rainfall. Very detailed and precise prediction models for soil water balances and associated runoff, leaching and pollution risks (e.g., Pullan et al., 2016; Morselli et al., 2018) require specific, local information that cannot be obtained from generalized GIS layers, often requiring *in situ* parameterisation and measurement. This is because data may not be freely available (e.g., soils data), are dis-aggregates of coarser scale data (e.g., agricultural land use) or are themselves modeled outputs (e.g., landscape connectivity data). A further key issue across scales and model types is that they commonly suffer from poor performance when evaluated using monitoring data despite being very heavily parameterized (Bieger et al., 2014; Gassmann et al., 2014; Zeiger and Hubbart, 2016). For this reason, recent research has explored the use of parsimonious tools for pesticide risk (e.g., Gaßmann et al., 2013; Steffens et al., 2015; Pullan et al., 2016).

It is against this background, that this paper describes the development of two decision tools providing real-time, spatially-explicit and temporally-dynamic field runoff and field-to-channel pesticide delivery risk information for supporting decisions regarding pesticide application (field scale) or management of surface water withdrawal for public water supply (catchment scale). These are demonstrated for two example agro-chemical applications in two differing environmental settings in the UK. The tools incorporate parsimonious field runoff and field-to-channel delivery models that combine real-time data of antecedent, current and predicted rainfall obtained from a national meteorological institute API. Both tools generate real-time predictions of current and future agro-chemical field runoff or field-to-channel delivery risk over a 5-day window. A key distinction is that the field scale tool has a focus on quantifying runoff risk, whereas the catchment scale tool focuses on quantifying the risk of delivery to the channel network—i.e., pesticide delivery risk rather than runoff risk.

METHODS AND NEW MODELS

Two case-study catchments were selected. The Wissey catchment in eastern England is dominated by arable cropping and has a potential risk of metaldehyde in waterbodies. Metaldehyde is used to treat slugs on oil seed rape, potatoes and horticultural crops and was responsible for 23% of failures to meet drinking water standards in the 4th quarter of 2016 in England and Wales (Defra, 2017a). Metaldehyde also topped the list of pesticides which breached the 0.1 μg/l drinking water safety limit between 2013 and 2015 (Defra, 2017b). In contrast, the Teifi catchment in mid-Wales, is dominated by grassland used for livestock. Here, acid herbicide applications for managing weeds in pastures represents a risk for drinking water quality. Field and landscape (catchment) scale models were developed for both case studies using the methods described below. For illustration in this paper, the results present the application of the field model and tool for runoff risk in the Teifi catchment in Wales, and the landscape scale model and tool for metaldehyde delivery risk in the Wissey catchment in England.

Field Scale Model

Overview

The aim of the field scale model was to provide location specific information of current and predicted future (5 day) runoff risks, at a 1 km^2 grid cell scale representing the field. It sought to support on-farm decisions about agro-chemical applications and to provide forecasts of whether any surface runoff is expected at the field scale. Although a soil water balance model could be used to antecedent soil water conditions and the CN method (USDA, 2004) to assess potential field runoff in real-time, data and computational requirements are an important limitation. In addition, fully parameterized soil water balance models require a known starting condition and are prone to cumulative errors, particularly during periods of low rainfall. From an operation point of view, using a soil water balance model to estimate antecedent soil water conditions also requires the user (farmer) to collect and process rainfall data even during periods when runoff risk forecasts are not required. To overcome this, a meta-modeling approach was used to estimate antecedent soil conditions from soil type, long-term average soil water content for the day of year, recent recorded rainfall and short-term forecast rainfall. An overview of the field scale model is shown in **Figure 1**.

Data and Model

The soil water balance model, WaSim (Hess and Counsell, 2000), was used to estimate daily soil water condition (θ) using the approach described by Hess et al. (2010) and Holman et al. (2011). It used a long time-series (1961 to 2015) of daily rainfall and reference evapotranspiration data at 1 km^2 resolution from the CEH CHESS dataset (Robinson et al., 2016, 2017) for each of the 28 hydrology of soil type (HOST) (Boorman et al., 1995) classes found in England and Wales, and three land cover classes.

WaSim is a daily soil water balance model that simulates changes in root zone soil water content and water table position in response to weather and water management. It estimates changes in soil water content by combining data on rainfall, crop specific evapotranspiration, soil characteristics and field drainage. It estimates daily surface runoff using a CN approach based on the soil water content using the approach of Hawkins et al. (1985) and Garen (1996).

The water content of the upper (0–0.15 m) layer (θ_0) is estimated from daily effective rainfall, evapotranspiration and drainage to a lower layer. The proportion of the soil water stored above field capacity (θ_{FC}) that is released from a saturated soil increases from zero at θ_{FC} to a maximum at saturation (θ_{SAT}) following an exponential function (Raes and van Aelst, 1985) dependent on the texture of the upper soil layer. Validation of predicted field-scale runoff is difficult due to the paucity of field-scale runoff data for a sufficient range of soil, crop and climate conditions for national application. However, Holman et al. (2011) evaluated partitioning of hydrologically effective rainfall between slow and quick flow-paths in the WaSim model by upscaling to the catchment scale across all of England and Wales. For 27 out of the 29 HOST soil classes (Boorman et al., 1995) (peat soils excepted). The WaSim estimates of baseflow index (BFI) were within the 95% confidence intervals of the national-average BFI , suggesting that the model is adequately capturing the effect of soil type and wetness on runoff generation.

Using linear regression on a subset of the data (1961–2000), the daily soil water condition was modeled from the 10 previous days' accumulated rainfall (P_{10}), the number of days since the last day with rainfall >2 mm (P_2) and long-term average modeled daily soil water condition (θ_i) for each the day of the year, i. The resulting linear regression models were shown to fit well to the soil water conditions modeled by the soil water balance model for an independent timeseries (2001-2015), summarized in Section Model Validation and as described in Comber et al. (2018). The parameterized regression model was then used with recent and short-term forecast rainfall data to forecast runoff, R, using the CN method of Hawkins *et al.* (1985) and Garen (1996) as follows: for rainfall, P (mm d^{-1}), greater than a threshold value, I (mm), direct runoff, R (mm d^{-1}), is estimated from:

$$R = \frac{(P - \lambda S)^2}{(P + (1 - \lambda)\, S)} \text{ for } P > \lambda S \quad (1)$$

$$R = 0 \text{ for } P \leq \lambda S \quad (2)$$

where S is the maximum retention, mm and the threshold I is defined as

$$I = \lambda S \quad (3)$$

Note that λ (dimensionless) is an empirical value that represents the proportion of rainfall on a soil at average antecedent conditions that can fall without generating runoff, and is typically set to 0.2.

On a particular day, S was estimated from the retention at dry antecedent conditions, S_1 (mm), the relative saturation of the top

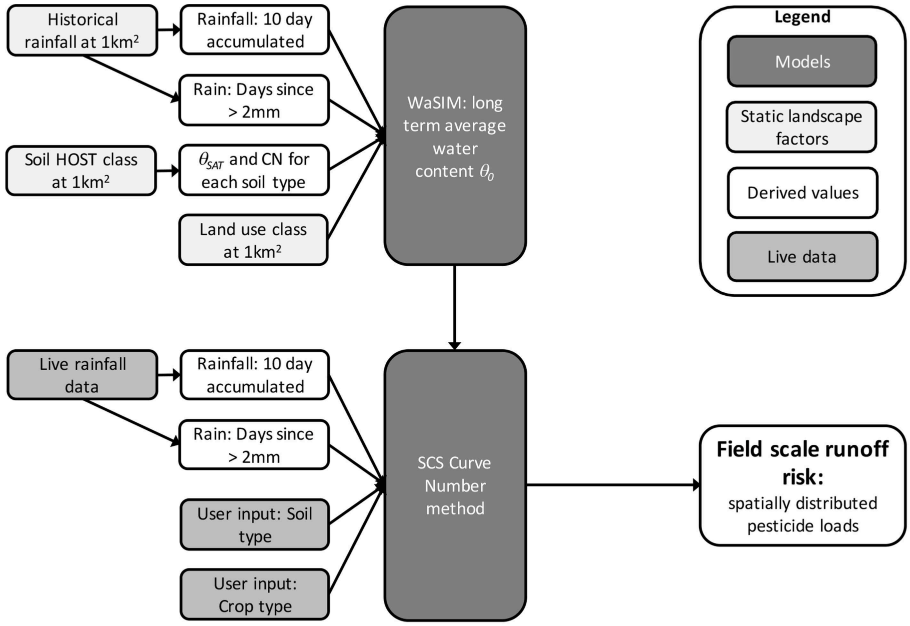

FIGURE 1 | The field scale runoff risk model.

0.15 m of the soil, f_s (dimensionless) and two weighting factors, W_1 and W_2 for retention (Hawkins et al., 1985):

$$S = S_1 \left[1 - \frac{f_s}{f_s + exp\left(W_1 - W_2 f_s\right)} \right] \tag{4}$$

$$f_s = \frac{\theta_i}{\theta_s} \tag{5}$$

$$W_1 = ln\left[\frac{1}{1 - \frac{S_3}{S_1}} - 1 \right] + W_2 \tag{6}$$

$$W_2 = 2\left[ln\left(\frac{0.5}{1 - \frac{S_2}{S_1}} - 0.5 \right) - ln\left(\frac{1}{1 - \frac{S_3}{S_1}} - 1 \right) \right] \tag{7}$$

The retention, S_n (mm), at dry ($n = 1$), average ($n = 2$) and wet (n=3) antecedent conditions, is estimated from the curve number, N_2 (dimensionless) at average antecedent conditions (Garen, 1996).

$$S_n = 250\left(\frac{100}{N_n} - 1 \right) \tag{8}$$

$$N_1 = \frac{N_2}{2.281 - 0.01281 N_2} \tag{9}$$

$$N_3 = \frac{N_2}{0.427 + 0.00573 N_2} \tag{10}$$

Model Validation

Hess et al. (2010) used a continuous water balance model, WaSim (Hess and Counsell, 2000) to model daily soil water content and estimate daily surface runoff using a CN approach. WaSim is a one-dimensional, field-scale layered soil-water balance model that operates on a daily timestep. The water content of the upper (0–0.15 m) layer, θ_0 (dimensionless), is estimated from daily effective rainfall (P - R), evapotranspiration, E (mm d^{-1}) and drainage to a lower layer, D (mm d^{-1}). D increases with θ_0 from zero at field capacity, θ_{FC}, to a maximum at saturation, θ_{SAT}, following an exponential function (Raes and van Aelst, 1985):

$$D = \tau \left(\theta_0 - \theta_{FC}\right) \frac{e^{(\theta_0 - \theta_{FC})} - 1}{e^{(\theta_{SAT} - \theta_{FC})} - 1} 150 \tag{11}$$

Where τ (d^{-1}) is the proportion of the soil water stored above field capacity that is released from a saturated soil in 1 day and is dependent on the soil texture, and 150 (mm) is the thickness of the upper soil layer.

Three linear regression models, M1 to M3, were calibrated against θ_0 for each soil and climate combination in each of the two study areas:

- M1 is a simple linear regression of θ_0 against the 5-day accumulated antecedent rainfall, P_5 under the expectation that for a given location and soil type, θ_0 will be correlated with the antecedent rainfall;
- M2 considered the 10-day accumulated antecedent rainfall, P_{10}, and the number of days since the last rainfall >2 mm, $J_{P>2}$;
- M3 considered the 10-day accumulated antecedent rainfall, P_{10}, the number of days since the last rainfall >2 mm, $J_{P>2}$ and also considers the long-term average value of θ_0 for the day of the year, (θ_i). This assumed that the effect of antecedent rainfall on θ_0 may vary with seasonal

variation in θ_0. For example, a small P_{10} on at a time of year when the soil is generally wet would result in wetter antecedent conditions than at a time when the soil is generally drier.

Each model is summarized in **Table 1** and was calibrated against the WaSim continuous model and then used to estimate θ_0.

Table 2 shows the coefficient estimates of the three locally calibrated linear models to estimate antecedent soil moisture conditions, adjusted for each site and soil type. It also includes the root mean squared error (RMSE), mm d^{-1}, between upper layer soil water content from a continuous model and the three meta-models for the calibration (1961-2000) and validation (2001-2015) periods. For the two models relying only on antecedent rainfall (M1 and M2) the intercept is the most important coefficient of the model, taking values close to the volume water fraction at field capacity. The M3 coefficients demonstrate the importance of including average soil moisture conditions and the major difference between parameters is driven by weather conditions rather than by soil type. Similarly the validation results show that M3 achieves the best results for both soil types and both climates. Moreover, the results suggest that introducing the daily average soil moisture content has an important impact on the quality of the model.

Landscape Scale Model

Overview

The landscape scale model provides spatially distributed information on pesticide delivery risk. The overarching aim was to identify field-to-channel delivery risk hotspots to support and inform catchment management and on-the-ground follow up by environmental agencies and water companies. It therefore identifies locations of high risk that may require further investigation. The landscape scale tool generates a spatially-distributed field-to-channel delivery risk surface to inform drinking water abstraction decisions. The output predicts the spatial pattern of mobilized pesticide loadings delivered to receiving watercourses. The parsimonious approach combines layers of intrinsic landscape scale factors, runoff and pollutant transfer, national historical daily rainfall data from the CEH Gridded Estimates of Areal Rainfall dataset (Keller et al., 2015), as well as live data of current and antecedent rainfall, as summarized in **Figure 2**.

A source-mobilization-delivery-impact model of the water pollutant transfer continuum (Lemunyon and Gilbert, 1993; Haygarth et al., 2005; Zhang et al., 2017b) was adopted. In this framework, runoff following rainfall is the key mobilization force and the proportion of pesticide load available for mobilization into the runoff moving down the soil profile to field drains or downslope across the land surface is assumed to be the same as the ratio of runoff amount to event rainfall total. Pesticides are therefore partly absorbed by the soil and non-binding pesticides are mobilized in runoff. This multiplicative correction approach is similar to that used by Verro et al. (2002). The landscape model recognizes that rainfall can reach watercourses via different delivery pathways (e.g., surface runoff, drain flow) and measures of hydrological connectivity between agricultural fields and the river channel network influence the propensity for mobilized pollution (e.g., pesticides) to reach the watercourses. In the case of the latter, surface runoff connectivity is calculated using distance to river channel and the downslope average slope gradient using a high resolution digital elevation model (DEM) and channel network data layer (Prosser and Rustomji, 2000; Walling and Zhang, 2004), whereas drain flow connectivity uses farm-type specific estimates based on recent surveys of drain maintenance associated with the upkeep of the permeable backfill or drain freeboard, as well as the frequency of supportive mole plowing (Zhang et al., 2016).

Data and Model

Data at 1 km^2 resolution were assembled for each case study area. The proportions of different land use including crop types in each grid cell (Comber et al., 2008) were matched with freely available data on pesticide application rates to determine pesticide loadings to farmed land. The land use data described in Comber et al. (2008) uses advanced spatial disaggregation methods to robustly allocate agricultural census data from the June Survey of Agriculture and Horticulture (JAS). JAS data are reported at coarse spatial units (such as Parish level) and the disaggregation is to finer spatial units such as 1 km^2. This data underpins many tools supporting national level policy support. Garthwaite et al. (2013, 2014, 2015) describe pesticide usage on different agricultural land uses and spatially distributed pesticide loadings to agricultural land were estimated by linking the land use proportions of each 1 km^2 to the reported pesticide usage for that land use.

The loadings from all applications to agricultural land are then modified to estimate the loading susceptible to runoff mobilization and delivery from field-to-channel by the soil sorption capacity for the pesticide in question, which is modeled as a function of known pesticide behavior and soil organic carbon content (% OC). Accordingly, the proportion of chemical loading susceptible to mobilization and runoff loss with rainfall, K is calculated as follows:

$$K = \frac{1}{1 + Koc \times OC/100} \tag{12}$$

where Koc is a measure of the tendency of a chemical to bind to soils (an adsorption coefficient) set at 67 in the Wissey and 20 in the Teifi study catchments.

Runoff was estimated using the Mishra-Singh model (Mishra et al., 2005), a modified CN method, that accounts for event rainfall and antecedent soil moisture conditions. To estimate runoff (R, mm), event rainfall (P, mm) and the antecedent 5-day rainfall (P_5, mm) are required, as well as an estimate of storage depth (S, mm), initial abstraction (Ia) and an intermediary term, M:

TABLE 1 | A summary of the different models that were evaluated.

Model Coefficients	Model 1 (M1)	Model 2 (M2)	Model 3 (M3)
X_1	Accumulated 5-day antecedent rainfall, P_5	Accumulated 10-day antecedent rainfall, P_{10}	Accumulated 10-day antecedent rainfall, P_{10}
X_2		Number of days since the last rainfall >2 mm, $J_{P>2}$	Number of days since the last rainfall >2 mm, $J_{P>2}$
X_3			Long-term average value of θ_0 for the day of the year, $(\overline{\theta_i})$

TABLE 2 | Coefficients of the three linear models and the root mean squared error (RMSE), mm d^{-1}, for the calibration (1961–2000) and validation (2001–2015) periods.

Case study	Soil type	Model	Coefficients				RMSE	
			Intercept	X_1	X_2	X_3	Calibration	Validation
Teifi	Clay Loam	M1	0.376	0.002			0.030	0.031
		M2	0.393	0.001	−0.004		0.027	0.029
		M3	0.126	0.001	−0.004	0.675	0.024	0.025
	Sandy Loam	M1	0.266	0.002			0.033	0.033
		M2	0.284	0.001	−0.004		0.030	0.031
		M3	0.090	0.001	−0.004	0.664	0.026	0.026
Wissey	Clay Loam	M1	0.351	0.003			0.035	0.032
		M2	0.361	0.002	−0.002		0.031	0.028
		M3	0.029	0.002	−0.002	0.875	0.023	0.020
	Sandy Loam	M1	0.241	0.004			0.033	0.033
		M2	0.252	0.002	−0.003		0.030	0.031
		M3	0.027	0.002	−0.002	0.833	0.026	0.026

$$S = \frac{25400}{CN} - 254 \tag{13}$$

$$Ia = \lambda S \tag{14}$$

$$M = -\left(\frac{(1+\lambda)}{2}\right) S + \sqrt{(1-\lambda)^2 S^2 4 P_5 S} \tag{15}$$

$$R = \left(\frac{(P - Ia)\,(P - Ia + M}{P - Ia + M + S}\right) \tag{16}$$

where λ is an empirical value which typically set to 0.2. The CN values for different soil types, land use and surface conditions are based on Hess et al. (2010) using the UK Hydrology of Soil Type (HOST) classification (Boorman et al., 1995). These were mapped into four hydrological soil groups (A, B, C, D) to reflect the minimum rate of rainfall infiltration for bare soil after prolonged wetting and the transmission rate within the soil profile, under five land use types; grass, row crops, small grains, semi-naturals and woodlands (**Table 3**).

The JAS classes were linked to pesticide survey usage categories and, in turn, the CN categories in Hess et al. (2010). Hess et al. (2010) proposed appropriate CNs for each unique combination of grouped soil type and land cover, dependent upon the surface condition which is classified as either "good" or "poor". A CN of 0 represents maximum storage, whilst a score of 100 suggests zero storage (i.e., a totally impermeable soil). The hydrological soil groups reflect the minimum rate of rainfall infiltration for bare soil after prolonged wetting and the transmission rate within the soil profile. Group A soils are characterized by low runoff potential and high infiltration rate even when wetted, with a transmission rate of >7.6 mm/hr. Group B soils have a moderate infiltration rate and are typified by moderate to well drained soils with transmission rates of 3.8–7.6 mm/hr. Group C soils have low infiltration rates and are typified by moderately fine to fine texture and a layer impeding downward water movement, yielding transmission rates of 1.3–3.8 mm/hr. Finally, group D soils have high runoff potential and very low infiltration rates, typifying clay soils with very low transmission rates of 0–1.3 mm/hr. CN values recommended by Hess et al. (2010) are presented in **Table 4**.

Finally, hydrology outputs from a process-based model developed for national policy support, namely PSYCHIC (Collins et al., 2007, 2009; Collins and Anthony, 2008; Davison et al., 2008; Stromqvist et al., 2008; Comber et al., 2013; Collins and Zhang, 2016; Phosphorus and Sediment Yield CHaracterisation In Catchments), were used to derive monthly soil runoff partitioning between surface and drain flow pathways for each 1 km^2. The PSYCHIC model runs use a combination of baseline climate conditions (1961 to 1990) and 2010 JAS.

Model Validation

The validation of a landscape scale model predicting 1 km^2 risk surfaces, i.e., providing information to support Tier 1 screening of risk, is inherently difficult. The model reported here provides information on landscape scale risk and empirical pesticide data, collected at an appropriate resolution, simply does not exist at appropriate scales for validating the modeled patterns of spatial risk. However, previous research (e.g., Collins and Anthony,

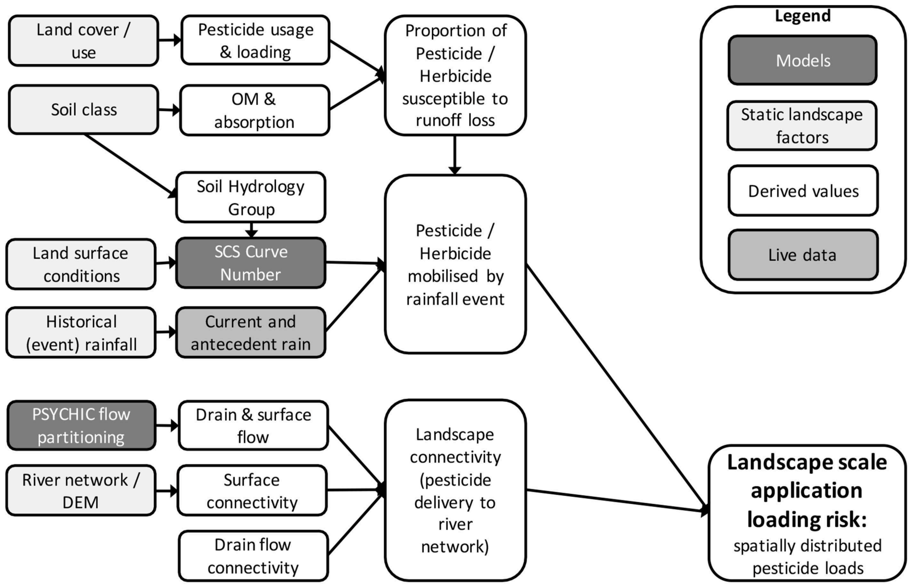

FIGURE 2 | The parsimonious landscape scale model. OM, organic matter.

2008; Stromqvist et al., 2008; Collins and Zhang, 2016; Collins et al., 2016; Zhang et al., 2017a,b) has evaluated the catchment and broader scale spatial patterns predicted for aggregated diffuse pollution (nutrients and sediment, not pesticides) delivery to watercourses using the underlying algorithms from PSYCHIC that are incorporated in the landscape model, using available local (i.e., original PSYCHIC model research project) or strategic monitoring data in the form of 1991-2010 PARCOM (Neal and Davies, 2003) reporting and the Harmonized Monitoring Scheme (https://data.gov.uk/dataset/b17a2efa-bdd6-4740-8030-fb87f7f2bcff/historic-uk-water-quality-sampling-harmonized-monitoring-scheme-detailed-data) at 33 stations for the period 1980-2010. Paris Commission (PARCOM) monitoring is undertaken as part of the 1992 OSPAR (Oslo–Paris) Convention which combined the 1972 Oslo Convention on dumping waste at sea and the 1974 Paris Convention on land-based sources of marine pollution. PARCOM monitoring is undertaken to report the delivery of terrestrial pollutants to the maritime area in accordance with the OSPAR Convention. The Harmonized Monitoring Scheme is a long-term water quality scheme in the UK that was initiated by the Department of the Environment in 1974.

RESULTS

The field and catchment scale models were coded in R and interactive web tools with an Open Street Map front end were created in RMarkdown using the *leaflet*, *flexdashboard*, *shiny*, *sp*, *dygraphs* and *reshape2* R packages. Recent and short-term forecast rainfall was recognized as a critical input for each scale in order to determine field runoff and field-to-channel delivery risk. For each study catchment, live weather data and precipitation forecasts from the Meteorological Office (the UK's national weather service) *DataPoint* API (The Met Office, 2018) were downloaded for each day, interpolated into a 1 km^2 grid and stored in raster stack. These were used to serve the online models with antecedent, current and predicted rainfall data for each 1 km^2. The online web tools are dynamic, calculating field runoff or field-to-channel delivery risk at each location from the live precipitation data and the user inputs. A zoomable OpenStreetMap layer provided the background mapping.

Field Scale Tool

The intention of the field scale tool was that it would be used by farmers and farm managers to inform their day-to-day decision making around agricultural chemical applications. The web interface asks users to enter a postcode, and then to click on an individual 1 km^2 grid cell. For the purposes of the models demonstrated here, the interface in Wales assumes an Acid herbicide application decision and in the East of England a Metaldehyde application (only the Wales tool is illustrated). The runoff risk for the selected grid cell for the next 5 days is shown in text format below the map and there are a number of tabs containing additional information. A screen grab of the catchment scale tool is shown in **Figure 3**. Here rainfall and runoff risk are not quantified, they are simply stated if predicted to be present at the selected location for the selected time period +5 days, as described above.

Catchment Scale Tool

The catchment scale tool was aimed at land and environmental managers with catchment / sub-catchment and watershed remits, including local water companies. Runoff and pesticide field-to-channel delivery risk is mapped and indicates locations with

TABLE 3 | Pesticide usage and Curve Number (CN) groups for different land use categories.

June agricultural census description[1]	Pesticide usage group[2]	CN group[3]
Wheat	Cereals	Row crops
Early potatoes	Potatoes	Row crops
Late potatoes	Potatoes	Row crops
Sugar beet	Beet crops	Row crops
Leguminous forage crops	Other fodder crops	Row crops
All Other crops for stockfeeding	Other fodder crops	Row crops
Root crops, brassicas & fodder beet	Vegetable brassicas	Row crops
Winter barley	Cereals	Row crops
Borage	Other arable crops	Row crops
Field beans	Peas & beans	Row crops
Peas for harvesting dry	Peas & beans	Row crops
Maize	Maize & sweetcorn	Row crops
Maize—grain	Maize & sweetcorn	Row crops
Maize—fodder	Maize & sweetcorn	Row crops
Winter oilseed rape	Oilseeds	Row crops
Spring oilseed rape	Oilseeds	Row crops
Linseed	Other arable crops	Row crops
Spring barley	Cereals	Row crops
All Other crops	Other arable crops	Small grains
Bare fallow	Set aside	Semi-natural
Short rotation coppice	Other arable crops	Row crops
Miscanthus	Other arable crops	Row crops
Crops for aromatic or medicinal use	Other arable crops	Row crops
Oats	Cereals	Row crops
Mixed corn	Other arable crops	Small grains
Rye	Other arable crops	Small grains
Triticale	Other arable crops	Small grains
Other peas and beans	Other outdoor vegetables	Row crops
Culinary plants for human consumption (e.g., herbs)	Lettuce & other leafy salads	Row crops
All other veg and salad including carrots and onions	Lettuce & other leafy salads	Row crops
Vining peas for processing	Other outdoor vegetables	Row crops
Orchards commercial	Top fruit & hops	Row crops
Wine grapes	Other soft fruit	Small grains
All other small fruit	Other soft fruit	Small grains
Orchards non-commercial	Top fruit & hops	Row crops
Orchards	Top fruit & hops	Row crops
Strawberries	Strawberries	Small grains
Raspberries	Other soft fruit	Small grains
Blackcurrants	Other soft fruit	Small grains
Temporary Grass	Grassland	Grass
Woodland	Woodland	Woodland
Land used for outdoor pigs	Set aside	Semi-natural
Other non-agricultural land	Set aside	Semi-natural
Permanent Grass	Set aside	Grass
Rough Grazing	Set aside	Semi-natural

(Continued)

TABLE 3 | Continued

[1]*The June Survey of Agriculture and Horticulture (JAS) is an annual survey which collects detailed information on arable and horticultural cropping activities, land usage, livestock populations and farming labor force figures—https://data.gov.uk/dataset/june_survey_of_agriculture_and_horticulture_uk.*
[2]*The pesticide usage group reflects the key groups used in surveys reporting publicly available data on pesticide applications (e.g., Garthwaite et al., 2013, 2014, 2015.)*
[3]*Taken from Hess et al. (2010).*

varying risk, given current and antecedent rainfall conditions, with the aim of supporting drinking water abstraction operations. The on-line tool asks users to indicate the agro-chemical they are interested in, the status of the soil and the date for which they require field-to-channel delivery risk estimates. For this proof of concept tool, the choices for agro-chemicals are limited to "Metaldehyde" and "Acid Herbicide," and the choices for soil status to "Good" or "Poor." The runoff risk is R (mm) from Equation 15 was categorized into 4 classes of risk: *None* when $R = 0$, *Low* when $0 < R <= 0.02$, *Moderate* when $0.02 < R <= 0.05$ and *High* when $R > 0.05$. In contrast to the field scale tool, the aim here was to provide users with landscape and catchment scale policy responsibilities with some information about the degree of pesticide delivery risk across the 1 km^2 grid cells comprising the study area. The user can pick any date between current date and October 2017 with the aim of allowing users to explore known runoff events and the degree to which the tool predicted any locally observed runoff and this is supported by an interactive (dy)graph of the mean rainfall in this period for this area. When the user selects a date, the current and previous 5-day rainfall for each 1 km^2 are extracted and the model is run generating a surface of predicted pesticide delivery risk. The boxplots show the rainfall for the previous 5 days and the date being queried. A screen grab of the catchment scale model application to the Wissey catchment is shown in **Figure 4**.

CONCLUDING REMARKS

The effective use of agrochemicals in modern agriculture contributes to sustained crop yields and quality. However, agrochemicals are less effective when they "run off" into surface and groundwaters soon after they are applied. The risk of this happening increases when agrochemicals are applied to wet (saturated) soils and when rainfall occurs soon after application. Runoff and associated pollutant delivery from field-to-channel also has negative impacts on environmental and drinking

TABLE 4 | Curve Numbers (CN) for surface runoff generation based on Hess et al. (2010).

Hydrological soil group	Vegetation type	Surface condition	
		Good[1]	Poor[2]
A	Grass	39	68
A	Row crops	65	72
A	Small grains	61	65
A	Semi-natural	39	68
A	Woodland	30	45
B	Grass	39	79
B	Row crops	65	81
B	Small grains	61	76
B	Semi-natural	39	79
B	Woodland	30	66
C	Grass	74	86
C	Row crops	82	88
C	Small grains	81	84
C	Semi-natural	74	86
C	Woodland	70	77
D	Grass	80	89
D	Row crops	86	91
D	Small grains	85	88
D	Semi-natural	80	89
D	Woodland	77	83

[1] *Good soil structure, limited management activities (e.g. contour plowing) to reduce runoff transmission from the field.*
[2] *Degraded soil structure resulting in enhanced runoff generation, plus evidence of management activities increasing runoff transmission (e.g. downslope tramlines, compaction due to livestock trampling or use of heavy farm machinery, fine seed beds).*

water quality when agrochemicals are transferred to surface or groundwater.

This paper describes a novel, generic and parsimonious modeling framework that integrates dual-scale soil water interaction models with real-time weather data. It addresses a number of impediments to the use of existing runoff risk models to inform on-farm management decisions and catchment management.

i) Most soil-water interaction models have high data and input parameter requirements to generate daily time-step simulations of processes related plant and crop growth.

ii) Consequently they require in-depth knowledge about input process parameters.

iii) They frequently require data which may not be available, for example to non-academic or non-research organizations, or to farmers and commercial companies.

iv) Many of these models perform poorly when compared with observed monitoring data (e.g., Zeiger and Hubbart, 2016).

v) Finally, because of these issues, existing models are not easily integrated into tools able to quantify the real-time field runoff and field-to-channel delivery risks which are required to support more reactive and effective agrochemical management decisions on the ground.

The dynamic, real-time decision tools developed in this research do not address all of these issues (there remain difficulties in validating the detailed spatial patterns predicted by any catchment scale model, for example). However, the provision of spatially- and temporally- explicit runoff and pesticide delivery risk information using parsimonious models is novel. We have demonstrated their applicability for two spatial scales of decision making: on-farm and catchment. The individual components of the parsimonious tools are not new: field and catchment scale models of pesticide and herbicide runoff have existed for a long time. But, critically, existing tools fail to provide *timely* and thereby *useful* information to managers. There are many live and location specific weather forecasting websites, smartphone apps and tools. As yet, however, real-time forecasting and soil water models have not been linked in an accessible and user-friendly way. In most decision tools, the model data inputs are relatively static (e.g., cropping systems, soil conditions, measures of catchment scale field drainage, etc) and do not support location- and time-specific queries. The result is that the modeled soil-water interactions and pesticide persistence represent some kind of generalized overall runoff trend rather than a specific local runoff measure.

There are a number of areas of potential future work emerging from this research for the further development of this modeling framework. The field and catchment scale models are very much proofs of concept and demonstrate how parsimonious but sensitive runoff risk models could be included in such frameworks. The utility of the tools and the interfaces from the end user perspective could be enhanced and the scope of the tools could be expanded in a number of ways. In our generic approach for both field and catchment scales, the critical variables driving field runoff and field-to-channel delivery risk are those related to antecedent, current and forecast rainfall in combination with fundamental intrinsic controls. In previous models, these have been assumed under a suite of potential scenarios that the user has to choose from. However, the ability to link to spatially- and temporally- explicit data for the rainfall variables through APIs offers a new avenue for enhancing the wider application and utility of soil-water-connectivity models. The future ability to serve many different types of geo-spatial data in this way via distributed data portals will only increase, reducing the dependency on locally held data. The landscape scale tool could be expanded to include nested watershed, catchment and sub-catchment scales and any corresponding aggregation associated with instream transfer processes. A further area for development would be to account for "noise" in runoff from agricultural applications, not least of which are point pollution due to poor on farm practice (incidental spillages, etc), runoff from domestic and managed green space applications as well as pesticide spray drift. A final and critical area of further work in the context of the approaches described is the inclusion of high accuracy rainfall data. This project used publicly available rainfall data served through the UK Met Office's API and interpolated over a 1 km^2 grid. Higher quality data is not provided for free. As the models inherently depend on rainfall (to parameterise the soil wetness factors through antecedent rainfall, to model current risk and determine future risk projections), the greatest influence on the quality of the model outputs is driven by this data.

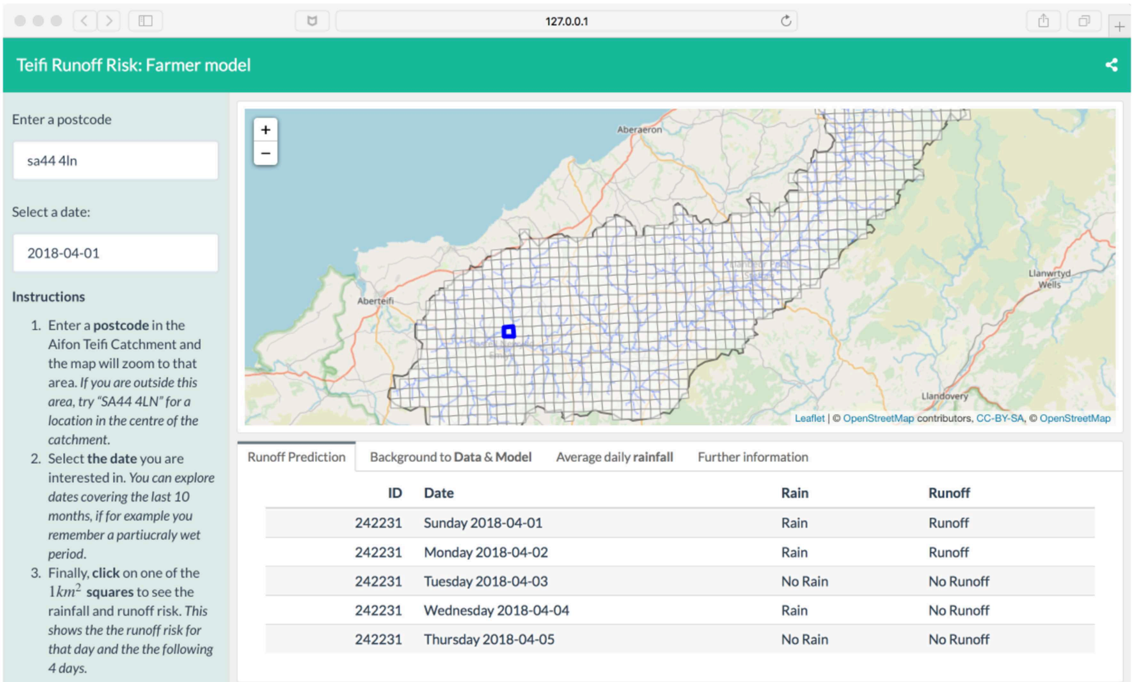

FIGURE 3 | A screenshot of output from the Teifi catchment field scale runoff risk model at https://github.com/lexcomber/saric.

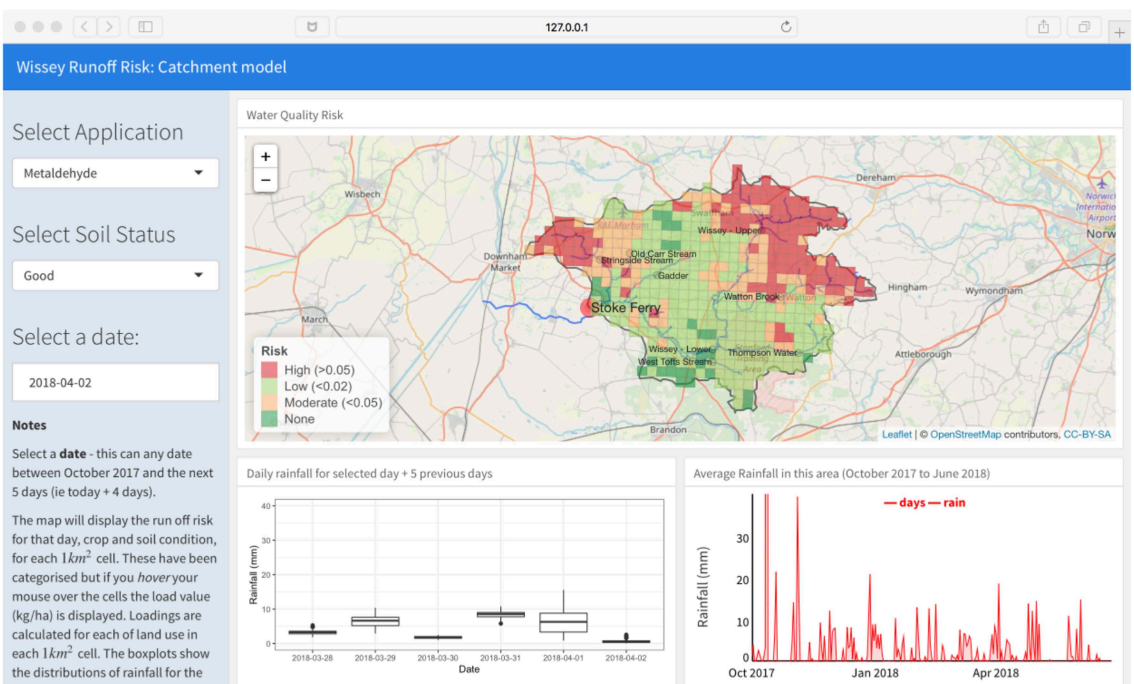

FIGURE 4 | A screenshot of output from the Wissey catchment scale field-to-channel delivery risk model at https://github.com/lexcomber/saric.

In summary, the tools developed in this research provide user interfaces to stripped down, parsimonious soil-water-connectivity models that take advantage of the availability of live rainfall data. Their components reflect the importance of knowledge of past and current rainfall as drivers of field runoff and field-to-channel delivery. To this end, each model pre-computed long-term water content for different soil types and crops, was linked to a live rainfall data feed and requested a very small amount of information from users (date, soil status, crop type) from which field runoff and field-to-channel delivery risk was computed using antecedent and current rainfall. The wider applicability of this research is underpinned by the generic nature of the parsimonious modeling framework. Assuming the availability of relevant mechanistic understanding and information on application doses, the models could easily be extended to predict risks to water quality and the wider environment for ***any*** agricultural application at the farm decision scale or at the landscape management scale. Future work will develop a more strategic and commercial framework for a wider suite of parsimonious models.

AUTHOR CONTRIBUTIONS

AC, ALC, TH, and AS conceived the ideas behind the study and guided other contributors. DH-M and YZ developed the models. AT developed the underpinning data collection. AC developed the web-based models. AC, ALC, and TH led the writing.

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REFERENCES

Anthony, S., Duethman, D., Gooday, R., Harris, D., Newell-Price, P., Chadwick, D., et al. (2008). *Quantitative Assessment of Scenarios for Managing Trade-Off Between Economics, Environment and Media*. Report No. Defra WQ0106 (Module 6). Defra, ADAS, North Wyke Research.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., and Williams, J. R. (1998). Large area hydrologic modeling and assessment part I: model development 1. *J. Am. Water Resour. Assoc.* 34, 73–89. doi: 10.1111/j.1752-1688.1998.tb05961.x

Bannwarth, M. A., Sangchan, W., Hugenschmidt, C., Lamers, M., Ingwersen, J., Ziegler, A. D., et al. (2014). Pesticide transport simulation in a tropical catchment by SWAT. *Environ. Pollut.* 191, 70–79. doi: 10.1016/j.envpol.2014.04.011

Bieger, K., Hörmann, G., and Fohrer, N. (2014). Simulation of streamflow and sediment with the soil and water assessment tool in a data scarce catchment in the three Gorges region, China. *J. Environ. Wual.* 43, 37–45. doi: 10.2134/jeq2011.0383

Boorman, D. B., Hollis, J. M., and Lilly, A. (1995). *Hydrology of Soil Types: a Hydrologically Based Classification of the Soils of the United Kingdom*. Wallingford, UK: Institute of Hydrology.

Carsel, R. F., Imhoff, J. C., Hummel, P. R., Cheplick, J. M., and Donigian, A. S. Jr. (2003). *PRZM-3, A Model for Predicting Pesticide and Nitrogen Fate in the Crop Root and Unsaturated Soil Zones: Users Manual for Release 3.12*. Athens, GA: Center for Exposure Assessment Modeling (CEAM). 535 U.S. Environmental Protection Agency (USEPA).

Chadwick, D., Misselbrook, T., Gilhespy, S., Williams, J., Bhogal, A., Sagoo, L., et al. (2005). *Ammonia Emissions and Crop N Use Efficiency to Grassland and Tillage Land; Factors Affecting Ammonia Emissions From Urea Based Fertilisers; Ammonia Emissions Model*. Report No. Defra NT2605 WP1b. Defra, IGER, ADAS.

Chambers, B. J., Lord, E. I., Nicholson, F. A., and Smith, K. A. (1999). Predicting nitrogen availability and losses following application of organic manures to arable land: MANNER. *Soil Use Manag.* 15, 137–143. doi: 10.1111/j.1475-2743.1999.tb00079.x

Chow, V. T., Maidment, D. R., and Mays, L. W. (1988). *Applied hydrology. New York,NY: McGraw-Hill*

Collins, A. L., and Anthony, S. G. (2008). Assessing the likelihood of catchments across England and Wales meeting 'good ecological status' due to sediment contributions from agricultural sources. *Environ. Sci. Policy* 11, 163–170. doi: 10.1016/j.envsci.2007.07.008

Collins, A. L., Anthony, S. G., Hawley, J., and Turner, T. (2009). The potential impact of projected change in farming by 2015 on the importance of the agricultural sector as a sediment source in England and Wales. *Catena* 79, 243–250. doi: 10.1016/j.catena.2009.05.007

Collins, A. L., Stromqvist, J., Davison, P. S., and Lord, E. I. (2007). Appraisal of phosphorus and sediment transfer in three pilot areas identified for the catchment sensitive farming initiative in England: application of the prototype PSYCHIC model. *Soil Use Manag.* 23, 117–132. doi: 10.1111/j.1475-2743.2007.00119.x

Collins, A. L., and Zhang, Y. (2016). Exceedance of modern 'background' fine-grained sediment delivery to rivers due to current agricultural land use and uptake of water pollution mitigation options across England and Wales. *Environ. Sci. Pol.* 61, 61–73. doi: 10.1016/j.envsci.2016.03.017

Collins, A. L., Zhang, Y. S., Winter, M., Inman, A., Jones, J. I., Johnes, P. J., et al. (2016). Tackling agricultural diffuse pollution: what might uptake of farmer-preferred measures deliver for emissions to water and air. *Sci. Total Environ.* 547, 269–281. doi: 10.1016/j.scitotenv.2015.12.130

Comber, A., Collins, A., Haro, D., Hess, T., Smith, A., Turner, A., et al. (2018). "Real-time predictions of pesticide runoff risk: linking multi-scale runoff models and weather data APIs to improve water quality," in *Geospatial Technologies for All 21st AGILE Conference Proceedings* (Lund). Available online at: https://agile-online.org/conference_paper/cds/agile_2018/shortpapers/93%20Agile_paper_sub.pdf

Comber, A. J., Proctor, C., and Anthony, S. (2008). The creation of a national agricultural land use dataset: combining pycnophylactic interpolation with dasymetric mapping techniques Transactions in *GIS* 12, 775–791. doi: 10.1111/j.1467-9671.2008.01130.x

Comber, S. D., Smith, S., Daldorph, P., Gardner, M. J., Constantino, C., and Ellor, B. (2013). Development of a chemical source apportionment decision support framework for catchment management. *Environ. Sci. Technol.* 47, 9824–9832. doi: 10.1021/es401793e

Davison, P. S., Withers, P. J., Lord, E. I., Betson, M. J., and Stromqvist, J. (2008). PSYCHIC – a process-based model of phosphorus and sediment mobilisation and delivery within agricultural catchments. Part 1: model description and parameterisation. *J. Hydrol.* 350, 290–302. doi: 10.1016/j.jhydrol.2007.10.036

Defra (2013). *Developing the potential for Payments for Ecosystem Services: an Action Plan*. Available online at: https://www.gov.uk/government/publications/payments-for-ecosystem-services-pes-action-plan (accessed May 20, 2019)

Defra, Drinking Water 2016 Q3 (2017a). *A Report by the Chief Inspector of Drinking Water for England and Wales*.

Defra, Drinking Water 2016 Q4 (2017b). *A Report by the Chief Inspector of Drinking Water for England and Wales*.

Ficklin, D. L., Luo, Y., and Zhang, M. (2013). Watershed modelling of hydrology and water quality in the Sacramento River watershed, California. *Hydrol. Proc.* 27, 236–250. doi: 10.1002/hyp.9222

Gao, J., Liu, L., Liu, X., Lu, J., Zhou, H., Huang, S., et al (2008) Occurrence and distribution of organochlorine pesticides – lindane, p,p'- DDT, and heptachlor epoxide – in surface water of China. *Environ. Int.* 34, 1097–1103. doi: 10.1016/j.envint.2008.03.011

Garen, D. (1996). *Technical Description for Logical Module: Curve_Number_Parameters and Technical Descripton for Logical Module:*

Runoff. Portland, OR: Natural Resources Conservation Service, National Water and Climate Center

Garthwaite, D., Barker, I., Laybourn, R., Huntly, A., Parrish, G. P., Hudson, S., et al. (2014). *Pesticide Usage Survey Report 263*. Arable crops in the United *Kingdom*.

Garthwaite, D., Barker, I., Mace, A., Parrish, G. P., Frost, S., Hallam, C., et al. (2015). *Pesticide Usage Survey Report 270*. Outdoor vegetable crops in the United Kingdom.

Garthwaite, D., Hudson, S., Barker, I., Parrish, G. P., Smith, L., and Pietravalle, S. (2013). *Pesticide Usage Survey Report 255*. Grassland & fodder crops in the United Kingdom.

Gassman, P. W., Reyes, M. R., Green, C. H., and Arnold, J. G. (2007). The soil and water assessment tool: historical development, applications, and future research directions. *Trans. ASABE* 50, 1211–1250. doi: 10.13031/2013.23637

Gassmann, M., Khodorkovsky, M., Friedler, E., Dubowski, Y., and Olsson, O. (2014). Uncertainty in the river export modelling of pesticides and transformation products. *Environ. Modell. Softw*. 51, 35–44. doi: 10.1016/j.envsoft.2013.09.021

Gaßmann, M., Stamm, C., Olsson, O., Lange, J., Kümmerer, K., and Weiler, M. (2013). Model-based estimation of pesticides and transformation products and their export pathways in a headwater catchment. *Hydrol. Earth Syst. Sci.* 17, 5213–5228. doi: 10.5194/hess-17-5213-2013

Guo, L., Jury, W. A., Wagenet, R. J., and Flury, M. (2000). Dependence of pesticide degradation on sorption: nonequilibrium model and application to soil reactors. *J. Contam. Hydrol.* 43, 45–62. doi: 10.1016/S0169-7722(99)00097-2

Hawkins, R. H., Hjelmfelt A. T. Jr., and Zevenbergen, A. W. (1985). Runoff probability, storm depth, and curve numbers. *J. Irrigat. Drainage Eng.* 111, 330–340. doi: 10.1061/(ASCE)0733-9437(1985)111:4(330)

Haygarth, P. M., Condron, L. M., Heathwaite, A. L., Turner, B. L., and Harris, G. P. (2005). The phosphorus transfer continuum: linking source to impact with an interdisciplinary and multi-scaled approach. *Sci. Total Environ.* 344, 5–14. doi: 10.1016/j.scitotenv.2005.02.001

Hess, T. M., and Counsell, C. (2000). *A Water Balance Simulation Model for Teaching and Learning-WaSim. ICID British Section Irrigation and drainage Research Day* 29, 1204–1213.

Hess, T. M., Holman, I. P., Rose, S. C., Rosolova, Z., and Parrott, A. (2010). Estimating the impact of rural land management changes on catchment runoff generation in England and Wales. *Hydrol. Proc.* 24, 1357–1368. doi: 10.1002/hyp.7598

Holman, I. P., Hess, T. M., and Rose, S. C. (2011). A broad-scale assessment of the effect of improved soil management on catchment Baseflow Index. *Hydrol. Proce.* 25, 2563–2572. doi: 10.1002/hyp.8131

Jacobs UK Ltd (2008). *Environmental Accounts for Agriculture: Report to Defra, Welsh Assembly Government, Scottish Government*. London: Department of Agriculture and Rural Development (N. Ireland), Jacobs UK Ltd.

Jarvis, S., Brown, C. D., and Granitz, E. (2000). Sources of error in model predictions of pesticide leaching: a case study using the MACRO model. *Agricul. Water Manag.* 44, 247–262. doi: 10.1016/S0378-3774(99)00094-3

Kannan, N., White, S. M., Worrall, F., and Whelan, M. J. (2006). Pesticide modelling for a small catchment using SWAT-2000. *J. Environ. Sci. Health, Part B* 41, 1049–1070. doi: 10.1080/03601230600850804

Kannan, N., White, S. M., Worrall, F., and Whelan, M. J. (2007). Sensitivity analysis and identification of the best evapotranspiration and runoff options for hydrological modelling in SWAT-2000. *J. Hydrol.* 332, 456–466. doi: 10.1016/j.jhydrol.2006.08.001

Keller, V. D. J., Tanguy, M., Prosdocimi, I., Terry, J. A., Hitt, O., Cole, S. J., et al. (2015). CEH-GEAR: 1 km resolution daily and monthly areal rainfall estimates for the UK for hydrological and other applications. *Earth Syst. Sci. Data* 7, 143–155. doi: 10.5194/essd-7-143-2015

Knisel, W. G. (1980). *CREAMS: a Field Scale Model for Chemicals*, *Runoff, and Erosion from Agricultural Management Systems.* Conservation research report (USA). Washington, DC: Department of Agriculture.

Lapworth, D. J., Baran, N., Stuart, M. E., and Ward, R. S. (2012) Emerging organic contaminants in groundwater: a review of sources, fate and occurrence. *Environ. Pollut.* 163, 287–303. doi: 10.1016/j.envpol.2011.12.034

Lemunyon, J. L., and Gilbert, R. G. (1993). The concept and need for a phosphorus assessment tool. *J. Product. Agricul.* 6, 483–486. doi: 10.2134/jpa1993.0483

Lord, E. I. (1992). Modelling of nitrate leaching: nitrate sensitive areas. *Aspects Appl. Biol.* 30, 19–28.

Lord, E. I., and Anthony, S. G. (2000). MAGPIE: a modelling framework for evaluating nitrate losses at national and catchment scales. *Soil Use Manag.* 16, 167–174. doi: 10.1111/j.1475-2743.2000.tb00222.x

Louchart, X. (2001). *Bassin Versant Roujan: Etude des Processus de Contamination Des Eaux Par Les Pesticides in Compte-rendu de l'atelier Dispositifs Pour l'étude du Comportement Des Pesticides Dans L'environnement. Montpellier*: INRA, Coordinateur E. *Bariuso*.

Meyer, A. M., Klein, C., Fünfrocken, E., Kautenburger, R., and Beck, H. P. (2019) Real-time monitoring of water quality to identify pollution pathways in small and middle scale rivers. *Sci. Total Environ.* 651, 2323–2333. doi: 10.1016/j.scitotenv.2018.10.069

Mishra, S. K., Jain, M. K., Bhunya, P. K., and Singh, V. P. (2005) Field applicability of the SCS-CN-based Mishra–Singh general model and its variants. *Water Res. Manage*. 19, 37–62. doi: 10.1007/s11269-005-1076-3

Mitchell, C., Brodie, J., and White, I. (2005) Sediments, nutrients and pesticide residues in event flow conditions of the Mackay Whitsunday Region, Australia. *Mar. Pollut. Bull.* 51, 23–26 doi: 10.1016/j.marpolbul.2004.10.036

Morselli, M., Vitale, C. M., Ippolito, A., Villa, S., Giacchini, R., Vighi, M., et al. (2018) Predicting pesticide fate in small cultivated mountain watersheds using the DynAPlus model: toward improved assessment of peak exposure. *Sci. Total Environ.* 615, 307–318. doi: 10.1016/j.scitotenv.2017.09.287

National Audit Office (2010). *Tackling Diffuse Water Pollution in England. Report by the Comptroller and Auditor General.* London: National Audit Office.

Neal, C., and Davies, H. (2003). Water quality fluxes for eastern UK rivers entering the North sea: a summary of information from the Land Ocean Interaction Study (LOIS). *Sci. Total Environ. 314–316,* 821–882. doi: 10.1016/S0048-9697(03)00086-X

Newell-Price, J. P., Harris, D., Chadwick, D. R., Misselbrook, T. H., Taylor, M., Williams, J. R., et al. (2011). *Mitigation Methods—User Guide. An Inventory of Mitigation Methods and Guide to Their Effects on Diffuse Water Pollution, Greenhouse Gas Emissions and Ammonia Emissions From Agriculture*. Prepared as part of Defra project *WQ*0106. 158. Available online at: https://www.feedadviserregister.org.uk/latest-documents/mitigation-methods--user-guide/mitigationmethods-userguidedecember2011final.pdf

NRCS (2002). *Urban Hydrology for Small Watersheds, Technical Release 55 (TR-55)*. Washington D.C: Natural Resources Conservation Service

Pilgrim, D. H., and Cordery, I. (1993). "Chapter 9: Flood runoff," in *Handbook of hydrology*, eds D. R. Maidment (NewYork, NY: McGraw-Hill), 9.1–9.42.

Pretty, J. N., Mason, C. F., Nedwell, D. B., Hine, R. E., Leaf, S., and Dils, R. (2003). Environmental costs of freshwater eutrophication in England and Wales. *Environ. Sci. Technol.* 37, 201–208. doi: 10.1021/es020793k

Prosser, I. P., Rustomji, P. (2000). Sediment transport capacity relations for overland flow. *Progr Physical Geogr*. 24, 179–193. doi: 10.1177/030913330002400202

Pullan, S. P., Whelan, M. J., Rettino, J., Filby, K., Eyre, S., Holman, I. P. (2016) Development and application of a catchment scale pesticide fate and transport model for use in drinking water risk assessment. *Sci. Total Environ.* 563–564, 434–447. doi: 10.1016/j.scitotenv.2016.04.135

Raes, D. D., and van Aelst, P. (1985). *The Field Parameters of the BUDGET Model*. Internal note, Lab. of Soil and Water Engineering. Leuven: University of Leuven.

Robinson, E. L., Blyth, E., Clark, D. B., Comyn-Platt, E., Finch, J., Rudd, A. C. (2016). *Climate Hydrology and Ecology Research Support System Potential Evapotranspiration Dataset for Great Britain (1961-2015) [CHESS-PE]*. NERC Environmental Information Data Centre.

Robinson, E. L., Blyth, E., Clark, D. B., Comyn-Platt, E., Finch, J., Rudd, A. C. (2017). *Climate Hydrology and Ecology Research Support System Meteorology Dataset for Great Britain (1961-2015) [CHESS-met] v1.2*. NERC Environmental Information Data Centre.

Schmitz, O., van der Perk, M., Karssenberg, D., Häring, T., and Jene, B. (2017). Spatially distributed modelling of pesticide leaching at European scale with the PyCatch modelling framework. *Geophys. Res. Abstract.* 19, EGU2017-14737.

Steffens, K., Jarvis, N., Lewan, E., Lindström, B., Kreuger, J., Kjellström, E., et al. (2015). Direct and indirect effects of climate change on herbicide leaching—A regional scale assessment in Sweden. *Sci. Total Environ.* 514, 239–249. doi: 10.1016/j.scitotenv.2014.12.049

Stromqvist, J., Collins, A. L., Davison, P. S., and Lord, E. I. (2008). PSYCHIC – a process-based model of phosphorus and sediment transfers within agricultural catchments. Part 2. A preliminary evaluation. *J. Hydrol.* 350, 303–316. doi: 10.1016/j.jhydrol.2007.10.044

Suarez, L. A. (2005). *PRZM-3, A Model for Predicting Pesticide and Nitrogen Fate in the Crop Root and Unsaturated Soil Zones: Users Manual for Release 3.12.2*. Athens: National Exposure Research Laboratory, US Environmental Protection Agency.

The Met Office (2018). *Met Office DataPoint*. Available online at: https://www.metoffice.gov.uk/datapoint (accessed 30th *October*, 2018)

USDA (2004). "Chapter 10: Estimation of direct runoff from storm rainfall," in *National Engineering Handbook. Part 630 Hydrology* (Washington, DC: United States Department of Agriculture; Natural Resources Conservation Service). Available online at: https://www.defra.gov.uk/Document.aspx/Document/MitigationMethods-UserGuideDecember2011FINAL.pdf

USDA SCS (1972). *National Engineering Handbook, Part 630 Hydrology, Section 4, Chapter 10*. Washington, DC: Natural Resources Conservation Service, U.S. Department of Agriculture.

Verro, R., Calliera, M., Maffioli, G., Auteri, D., Sala, S., Finizio, A., et al. (2002). GIS-based system for surface water risk assessment of agricultural chemicals. 1. Methodological approach. *Environ. Sci. Technol.* 36, 1532–1538. doi: 10.1021/es010089o

Walling, D. E., Zhang, Y. (2004). "Predicting slope-channel connectivity: a national-scale approach," in *Sediment Transfer through the Fluvial System* (Wallingford: IAHS Press), 107–114.

Webb, J., Misselbrook, T. H. (2004). A mass-flow model of ammonia emissions from UK livestock production. *Atmosphere. Environ.* 38, 2163–2176. doi: 10.1016/j.atmosenv.2004.01.023

WFD Water Framework Directive (2000). *Directive 2000/60*. EC of the European Parliament and of the Council of, 23.

Williams, J. R., Izaurralde, R. C., Singh, V. P., and Frevert, D. K. (2006). The APEX model. *Watershed Models*, 437–482. doi: 10.1201/9781420037432.ch18

Zeiger, S. J., and Hubbart, J. A. (2016). A SWAT model validation of nested-scale contemporaneous stream flow, suspended sediment and nutrients from a multiple-land-use watershed of the central USA. *Sci. Total Environ.* 572, 232–243. doi: 10.1016/j.scitotenv.2016.07.178

Zhang, X., Luo, Y., Goh, K. S. (2018). Modelling spray drift and runoff-related inputs of pesticides to receiving water. *Environ. Pollut.* 234, 48–58. doi: 10.1016/j.envpol.2017.11.032

Zhang, Y., Collins, A. L., and Hodgkinson, R. A. (2016). Use of farm survey returns from the Demonstration Test Catchments to update modelled predictions of sediment and total phosphorus loadings from subsurface drains across England and Wales. *Soil Use Manag.* 32, 127–137. doi: 10.1111/sum.12249

Zhang, Y., Collins, A. L., Johnes, P. J., and Jones, J. I. (2017a). Projected impacts of increased uptake of source control mitigation measures on agricultural diffuse pollution emission to water and air. *Land Use Policy* 62, 185–201. doi: 10.1016/j.landusepol.2016.12.017

Zhang, Y., Collins, A. L., Jones, J. I., Johnes, P. J., Inman, A., and Freer, J. E. (2017b). The potential benefits of on-farm mitigation scenarios for reducing multiple pollutant loadings in prioritised agri-environment areas across England. *Environ. Sci. Policy* 73, 100–114. doi: 10.1016/j.envsci.2017.04.004

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frontiers in Sustainable Food Systems

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Using a Crop Modeling Framework for Precision Cost-Benefit Analysis of Variable Seeding and Nitrogen Application Rates

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A key goal of precision agriculture is to achieve the maximum crop yield while minimizing inputs and loses from cropping systems. The challenge for precision agriculture is that these factors interact with one another on a subfield scale. Seeding density and nitrogen (N) fertilizer application rates are two of the most important inputs influencing agronomic, economic and environmental outcomes in cropping systems including yield, return on investment (ROI), and nitrate (NO_3^-) leaching. Here a cropping system model framework is used to predict site-specific subfield optimum seeding density and (N) fertilizer application rates based on publicly available data sources. The framework is used estimate differences in yield, ROI, NO_3^- leaching, and N_2O emissions corresponding with economic optimum (maximum ROI) and agronomic optimum (maximum yield) inputs. The framework couples the process-based APSIM cropping system model with the SSURGO soils database, Daymet weather data service, land grant university estimates of crop production costs and commodity price estimates, and the R statistics software. Framework performance was evaluated using multiple years of precision yield monitor data obtained from a conventionally managed continuous maize (*Zea mays* L.) cropping system field located in north central Iowa on which varying N-fertilizer rates were applied. Subfield model estimates of crop yield were sensitive to initial conditions related to historical management of the field and had an $r^2 = 0.65$ and a root mean square error of 1645.0 kg ha^{-1}. A site-specific application of the framework comparing economic optimum seeding density and N-fertilizer rates with agronomic optimum values estimated an average ROI benefit of 7.2% as well as an average NO_3^- leaching and N_2O emissions reductions of 2.5 and 7.6 kg ha^{-1}, respectively. However, in a minority of cases NO_3^- leaching was greater at the economic optimum, indicating that managing to maximize ROI rather than yield may not always reduce environmental impacts. Our results suggest that managing cropping systems for the economic optimum is plausible using publicly available data with our framework and will likely lead to improved environmental outcomes.

Keywords: economic optimum nitrogen, economic optimum seeding, nitrate leaching, APSIM, model framework

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INTRODUCTION

Optimizing the use of input resources in agricultural land management is critical to maintaining sustainable and profitable cropping systems. However, farm fields are characterized by subfield variability linked to soil properties, topography, competition with pests and weeds, as well as other factors that directly or indirectly influence plant health. This spatial variability leads to over- and under-fertilization in different parts of the field when using uniform seeding densities and nitrogen (N) fertilizer rates. Areas where N-fertilizer is applied in excess of crop demand are often correlated with higher susceptibility to nitrate (NO_3^-) leaching, nitrous oxide (N_2O) emissions, and other environmental losses, while under-fertilized areas may result in limited crop productivity, lost opportunity for profit, and decreased economic return (Link et al., 2006; Basso et al., 2016). Variable rate technology (VRT) provides a mechanism for varying the allocation of input resources. In maize (*Zea mays* L.) cropping systems seed density and N-fertilizer are two of the most important decision criteria influencing yield, profitability, and nutrient losses to the environment (Licht et al., 2017; Morris et al., 2018). Yet, making informed subfield seeding and N-fertilizer decisions that maximize return on investment (ROI) and minimize environmental impacts is often difficult without an abundance of site-specific data spanning multiple years and weather conditions (Morris et al., 2018). Consequently, modest increases in ROI are reported from the use of VRT and adoption has remained relatively limited (28% of US maize hectares) compared to other precision agriculture technologies such as yield monitors and GPS guidance systems (70 and 54% of US maize hectares, respectively, Schimmelpfennig, 2016).

A number of approaches have been used to predict economically optimal N-fertilizer application rates (EONR) including yield goal assessments, pre-plant and pre-sidedress soil NO_3^- tests, crop canopy sensing, and maximum return to N calculators based on regionally specific empirical N-fertilizer rate trials (Sawyer and Nafziger, 2005; Puntel et al., 2016, 2019; for a review see Morris et al., 2018). Additionally, studies have also attempted to quantify optimum site-specific seed densities (Licht et al., 2017), which may represent a more economically impactful management change in many cropping systems compared to changes in nutrient applications. Variable rate zones defining different application rates have been generated using precision agriculture data sources including yield monitor maps (Adamchuk et al., 2004; Basso et al., 2016; Maestrini and Basso, 2018), remotely sensed data (Hong et al., 2006; Basso et al., 2016; Gao et al., 2018; Jin et al., 2019), gridded soil sampling (Fleming et al., 2000), digital soil maps (Bobryk et al., 2016), topography (Long et al., 2015; Walters et al., 2017), and real-time optical sensors (Raun et al., 2002; Tremblay et al., 2009; Kitchen et al., 2010; Stefanini et al., 2018).

However, large uncertainty and financial risk exists with the prediction of EONR and economic optimum seed rate (EOSR) across multiple years, particularly at field-to-subfield spatial scales (Licht et al., 2017; Puntel et al., 2018). Uncontrollable factors impacting N-cycle dynamics and crop uptake, including temperature and precipitation event timing and intensity, make accurate EONR and EOSR difficult. Additionally, crop yields are not linearly related to seeding densities due to inter-plant interactions and competition which has been demonstrated to decrease yields beyond certain plant population (i.e., plants m^{-2}) rates (Woli et al., 2014). This warrants a systems-based approach for determining economically optimum seeding densities and N-fertilizer rates that are capable of predicting crop yields, N-dynamics, and environmental losses based on the complex interaction between crops, weather conditions, soil properties, and land management practices (Banger et al., 2017).

Simulation models have previously been used to predict spatially-explicit nutrient losses (Paz et al., 1999; Holland and Schepers, 2010; Solie et al., 2012) as well as EONR and EOSR. Commercial tools offering prescription management recommendations and in-season N-fertilizer recommendations such as Adapt-N (http://www.adapt-n.com), Encirca (https://www.pioneer.com/home/site/us/encirca/), and Climate FieldView (https://climate.com) incorporate real-time data as well as local soil and crop management factors. However, these models and tools are typically conceived for in-season N-management decisions during crop growth based on historical and predicted weather data. Such tools have been demonstrated to improve resource use-efficiency and yield (Sela et al., 2016), but rely on non-publicly available data and algorithms.

The goal of this study was to develop an automated predictive framework for estimating site-specific, subfield-scale economic optimum combinations of seeding densities and N-fertilizer rates using publicly available, spatially-explicit data and models. The Agricultural Production Systems sIMulator (APSIM; Holzworth et al., 2014) crop model was coupled with the SSURGO soils database, Daymet weather data service, and public financial data to create a spatially explicit modeling framework for estimating yield and ROI responses based on varying combinations of seeding densities and N-fertilizer rates for a given cropping system field. Outputs of the APSIM analyses for all seeding and N-fertilizer combinations are then aggregated and processed using the R statistical package to identify the agronomic and economic optimum input combinations as well as corresponding differences in environmental outcomes such as NO_3^- leaching and soil N_2O emissions. Therefore, the framework may be used in making more informed subfield seeding and N-management decisions by weighting corresponding economic outcomes with potential environmental risks. The specific objectives of this study were to: (1) Evaluate the accuracy of the model simulations at a subfield spatial scale; (2) Evaluate modeled subfield ROI responses to variable management conditions based on experimental observations; and (3) Quantify differences in ROI, NO_3^- leaching, and soil N_2O emissions between agronomic and economic optimum inputs.

METHODS

Integrated Modeling Approach

The model framework couples APSIM (Holzworth et al., 2014) with the SSURGO soils database and Daymet weather data service to simulate subfield soil-specific, cropping system processes for a user defined field (**Figure 1**; **Table 1**). Historical

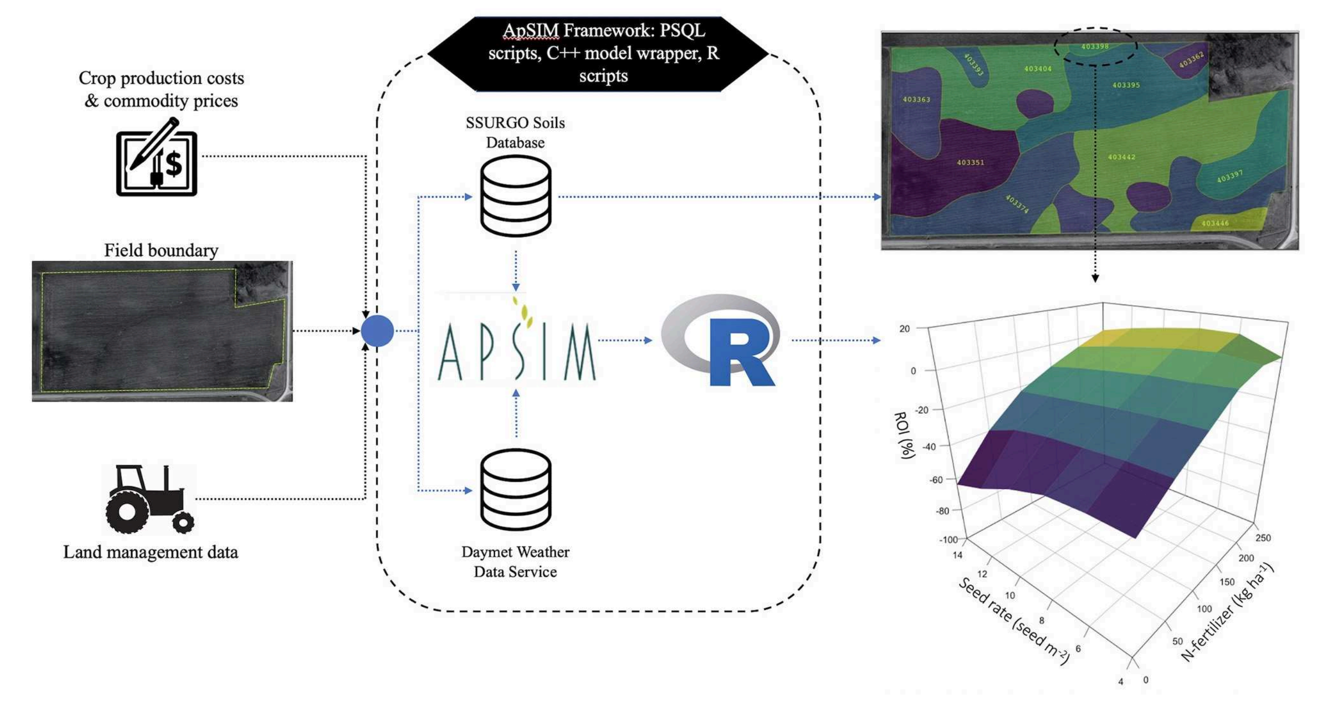

FIGURE 1 | Data flow through the model framework, which automates the parameterization of the APSIM model for all SSURGO soils within a specified cropping system field boundary and estimates economic and environmental responses to varying management combinations for each soil.

crop production cost estimates and commodity prices obtained from Iowa State University Extension and Outreach Ag Decision Maker Historical Costs of Crop Production (Johanns and Plastina, 2019) were added to the framework for converting predicted yields to profit and ROI. Based on a geospatial field boundary, the framework identifies all subfield SSURGO soils within the field, retrieves daily historical weather data, and executes APSIM to simulate multiple seeding density and N-fertilizer rate combinations. Output from APSIM is then aggregated to a centralized database and processed using an R script to identify both the economic and agronomic optimum (defined as the maximum ROI and yield, respectively) combinations of input resources for all subfield soil types.

TABLE 1 | Framework components and data sources.

Component	Description	References
APSIM	Cropping system model	http://www.apsim.info/
Soil Survey Geographic Database (SSURGO)	Soil database	https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm
Daymet Weather Data	Weather database	https://daymet.ornl.gov/
Ag decision maker	Extension database	https://www.extension.iastate.edu/agdm/
R	Statistics software package	https://www.r-project.org

APSIM Cropping Systems Model

The APSIM model is composed of several modules that enable the simulation of agricultural systems based on plant, animal, soil, climate, and management interactions. In this case, the framework incorporated APSIM version 7.7 modules for maize growth, soil water dynamics, soil and surface organic matter dynamics, and crop management rules (Holzworth et al., 2014). The maize crop growth module simulates maize growth and development of different cultivars on a daily time-step based on temperature, precipitation, solar radiation, water and nitrogen availability, soil properties, and land management practices. The model separates crop phenology into several phases, the duration of each dependent on daily temperature, water availability, N stress, and carbon (C) availability. Daily biomass increases are calculated as the minimum of two model estimates representing light-limited and water-limited productivity conditions, respectively. Daily biomass gain predicted by the model is partitioned into root, stem, leaf, and grain components depending on the plant stage of growth. In addition to the impact of N-fertilizer application rates on plant N availability within the soil profile, seeding density, and depth influence simulated leaf area index and subsequent biomass production and grain yield. APSIM has previously been used and validated in several studies similar to our cropping system to estimate crop productivity responses to varying levels of N-fertilizer rates (Puntel et al., 2016, 2018; Martinez-Feria et al., 2018).

Model Inputs and Data Sources

The SSURGO soils database contains geospatially explicit soil types and corresponding physical soil properties across U.S. territories. To identify soils within a specific field, the field boundary is intersected with the SSURGO map unit polygon data layer stored in a PostgreSQL (www.postgresql.org) database with Post-GIS (www.postgis.net) extension. Vertical horizons data corresponding with the dominant component of each identified SSURGO soil map unit is used to define the initial soil condition within the APSIM model. The process requires several parameters to be derived from the available SSURGO soil properties (**Table 2**).

Daily maximum and minimum temperature, precipitation, and solar radiation estimates are obtained from the Daymet weather data service (Thornton et al., 2018) based on the geospatial coordinates of the field centroid and the specific years of the analysis (**Figure S1**). Weather attribute values from the incoming data stream from Daymet are converted to the appropriate units and used to generate the daily weather input file (.met), native to APSIM. To analyze cropping system fields where financial data is unavailable, modeled and measured yield values are converted to a profit and ROI basis using annual crop production cost estimates and commodity prices generated by Iowa State University Extension and Outreach (Plastina, 2018; Johanns, 2019). These costs represent typical input costs and grain prices specific to Iowa (**Table 3**). Similarly, alternative financial data from other land grant universities could be added to the framework to increase the scope of the tool beyond Iowa.

Subfield Analysis of Continuous Maize System

To evaluate the ability of the framework to differentiate subfield differences in crop productivity and corresponding ROI, it was applied to model a continuous maize field located in Butler County, Iowa, U.S. (**Table S1**). Subfield simulations were created by executing APSIM for each of the identified SSURGO soil types such that field scale management was repeated for each polygon. The simulation spanned the 2012–2017 growing seasons during which manure was the primary source of N, excluding commercial N-fertilizer applied during an N-treatment study in 2015 and 2016. From 2012 to 2014, land management operations included a fall manure application with a total target N-application rate of approximately 224.5 kg ha^{-1}, and an early spring urea ammonium nitrate (UAN) fertilizer application equivalent to 28.1 kg ha^{-1} of N. Prior to planting, a cultivator tillage pass was typically used to condition the seed bed for planting. Additionally, a tillage pass with a chisel plow was used to incorporate a portion of the surface residue remaining in the field following maize harvests. During the 2015 and 2016 seasons N-management practices were altered and commercial N-fertilizer was applied. Following the 2014 harvest, a fall anhydrous ammonia application equivalent to 252.6 kg ha^{-1} of N was applied using a 12-row knife applicator. Similar to the previous years, a uniform spring UAN application of 28.1 kg ha^{-1} was then applied in the spring of 2015. After the 2015 harvest, a uniform fall manure application (168.4 kg ha^{-1} of N) was applied followed by a spring 2016 UAN application of 112.3 kg ha^{-1} of N. Crop production cost estimates for each year of the analysis were adjusted to represent the annual seeding density, manure, and N-fertilizer application rates. Manure amendments were modeled using manure storage pit analysis values obtained from Sawyer and Mallarino (2008) for C to N ratio and C to Phosphorus (P) ratio values required by the APSIM model. Use of the maximum grain price documented for each modeled year was based on the assumption that the grain would be stored on site and sold at an economically advantageous time. For years in which manure was applied, associated manure application costs were obtained from organic maize production budgets, and N-fertilizer costs were adjusted accordingly. Modeled yield estimates corresponding with each subfield soil type were compared with multiple years (2012–2017) of precision yield monitor data averaged to each unique soil boundary.

Evaluating Simulated Subfield Yield Response to Variable Inputs

The framework was used to model multiple combinations of input resources against the various soil types identified within the continuous maize system field. In addition to uniform field rates, varying seeding densities and N-fertilizer rates were simulated in an effort to find the agronomic and economic optimum combination of input resources. Seeding density varied from 1 to 15 seeds m^{-2} and N-fertilizer rates were varied based on a percentage of the field-scale application rate during 2015 and 2016. N-application rates ranging from 0 to 150% of the field-scale N-fertilizer rates were modeled for the Fall 2014 and Spring 2016 applications. In addition to estimating the economic benefit, model outputs were used to estimate and soil N_2O emissions and NO_3^- leaching (below 2 m; which exceeds the expected maize rooting depth; Ordóñez et al., 2018) associated with the economically optimum management rates compared to the agronomically optimum rates. Simulated 2015 and 2016 yields and ROI were compared with observations obtained from six subfield zones (97.5 m × 36.6 m) within the field (**Figure 2**). Each zone was divided into eight strips on which randomized N-fertilizer treatments were applied during the fall of 2014 and spring of 2016 including 0, 50, 100, and 125% of field-scale application rates (224.5 and 112.3 kg ha^{-1}, respectively). Zones were identified using mean yield monitor data from 2013 and 2014. Data from 2012 was excluded from the zone classification process due to drought conditions that resulted in abnormally low crop productivity.

Each of the zones were divided into eight equal (12.2 m × 36.6 m) strips on which one of four N-fertilizer treatments were applied (one replication per treatment). To prevent disrupting normal field operations, plot positions were constrained to be in line with one another. This allowed the N-treatments to be applied during normal field operational passes using a two-rate applicator system, in which one rate was set to the field-scale baseline and the other to the specific plot treatment rate. The secondary application rate was switched on and off by the operator at the boundaries of each N-treatment strip.

TABLE 2 | Derivation of APSIM soil properties from available SSURGO soil attribute data.

APSIM parameter	SSURGO parameter	SSURGO units	Conversion factor	APSIM units
Bulk density of the soil for each layer (BD)	dbThirdBar_r	g cm^{-3}	1	g cm^{-3}
Volumetric water content for air dry soil in each layer (AirDry)	wFifteenBar_r	%	0.5 * wFifteenBar_r at depth <= 15 cm wFifteenBar_r at depth > 15 cm	mm^3 mm^{-3}
Volumetric water content for each layer corresponding to a soil potential of 15 bar (LL15)	wFifteenBar_r	%	0.01 * wFifteenBar_r	mm^3 mm^{-3}
Volumetric water content at drained upper limit for each soil layer (DUL)	wThirdBar_r	%	0.01 * wThirdBar_r	mm^3 mm^{-3}
Volumetric water content at saturation for each soil layer (SAT)	wThirdBar_r	%	1 – (wThirdBar_r/2.65)	mm^3 mm^{-3}
Drainage rate from soil layer when the soil water is above saturation (KS)	ksat_r		0.001 * 3600 * 24 * ksat	mm day^{-1}
Soil organic carbon content of soil layer (OC)	om_r		om_r/1.724	%

TABLE 3 | Annual crop production cost estimates and maize grain price.

Year	Seed price ($ 1,000 $seed^{-1}$)	*N* price[1] ($ kg^{-1})	Land rent ($ ha^{-1})	Max. grain price ($ bu^{-1})	Min. grain price ($ bu^{-1})	Mean grain price ($ bu^{-1})	Total budget w/o N and seed ($ ha^{-1})
2012	3.40	1.39	705.6	7.89	5.99	6.67	1573.85
2013	3.64	1.28	756	7.13	4.32	6.23	1610.06
2014	3.78	0.97	787.2	4.76	3.51	4.13	1636.49
2015	3.86	1.03	748.8	3.86	3.53	3.67	1595.09
2016	3.70	0.88	710.4	3.75	3.08	3.40	1492.10
2017	3.43	0.68	648	3.43	3.14	3.30	1355.78

Reflects costs of commercial N-fertilizer per unit applied. For our case study the N-fertilizer cost was $0 in 2012, 2013, 2014, and 2017 because N was applied only in the form of manure.

Yield monitor data from 2015 and 2016 was geospatially intersected with the zone and sub-zone plot boundaries to estimate the mean observed yield and ROI associated with each N-treatment. The model results for each plot were derived by using the area-weighted average results corresponding with the different soil types intersecting each plot.

RESULTS

Objective 1: Evaluation of Subfield Model Results Against Observations

Linearly regressing simulated yield predictions against spatially-averaged yield monitor observations corresponding with all soil types resulted in an $r^2 = 0.48$ and a root mean square error of 2171.8 kg ha^{-1}, or 27.1% ROI (**Figure 3**; **Table 4**; **Table S2**). The largest modeling errors were associated with overestimates that occurred for limited-area soils located near the field borders including Mukey 403446 (Yield RMSE 4524.0 kg ha^{-1}, area = 0.5 ha), Mukey 403397 (Yield RMSE 2468.1 kg ha^{-1}; area = 1.9 ha), and Mukey 403398 (Yield RMSE 1917.2 kg ha^{-1}; area = 0.2 ha; **Table S3**). Excluding these soils from the results (4% of the field area) improved model fit ($r^2 = 0.65$; **Figure 3**) and reduced yield RMSE 1645.0 kg ha^{-1} and ROI RMSE to 21.5% (**Table 4**).

Low yields observed in the southwest corner of the field (Mukey 403351) were reportedly caused by topographical effects and a broken drainage tile, which over several years had limited infiltration and increased susceptibility to ponding and soil compaction (**Figure 2**; **Table S4**, personal communication with land manager). Interannual variation in simulated yield and ROI due to varying weather conditions, crop production costs, and maize prices were found to be consistent with observations (**Figure 4**). Low yields and corresponding ROI estimates observed in 2012 due to drought conditions were reflected in modeled outputs as well as the relatively high yields and economic return observed in 2013. However, the range of model estimates associated with 2015–2017 was found to be consistently high.

Objective 2: Evaluation of Simulated Subfield ROI Response to Variable Management

Model results were compared with corresponding experimental plot yields obtained from spatially averaged yield monitor data (**Figure 2**). Model outputs associated with the two highest N treatments tended to over-estimate observed crop productivity and corresponding ROI (**Figure 5**). Overall, the plot based yields had an RMSE of 2490.6 kg ha^{-1} (12.1% ROI) and 3075.2 kg ha^{-1} (15.4% ROI) in 2015 and 2016, respectively (**Table S5**). However, similar to observations, simulated 2015 yields showed

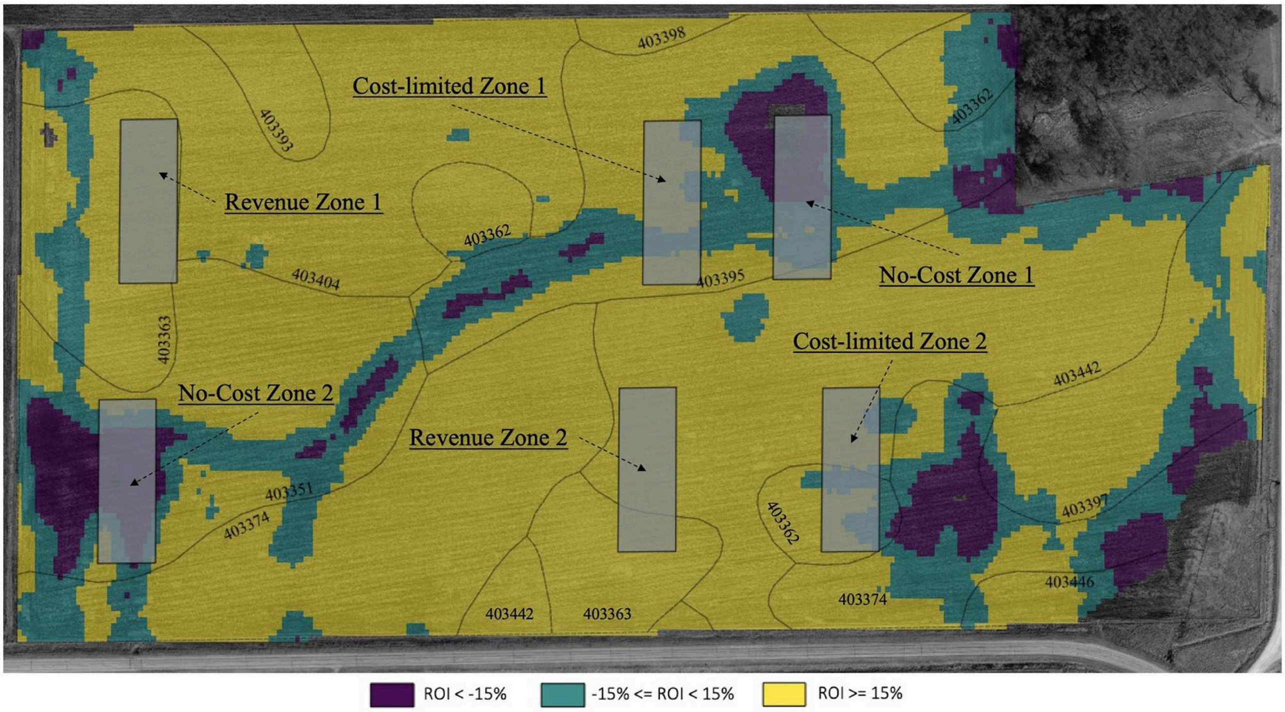

FIGURE 2 | Average 2013 and 2014 ROI map of field used to identify spatial economic zones in which N-fertilizer rate trials were performed in 2015 and 2016. SSURGO soil mapunit polygons are overlayed and labeled with unique Mukey identifier (e.g., 403442). Each soil polygon was modeled independently to determine an optimum management for that area. Boundaries defining the identified economic zones (gray areas) include two "no-cost" zones defined by an average ROI of −15.0% or less; two "cost-limited" zones with a mean annual ROI between −15.0 and 15.0%; and two "revenue" zones with a mean annual ROI >15.0% (Google imagery 2017, DigitalGlobe).

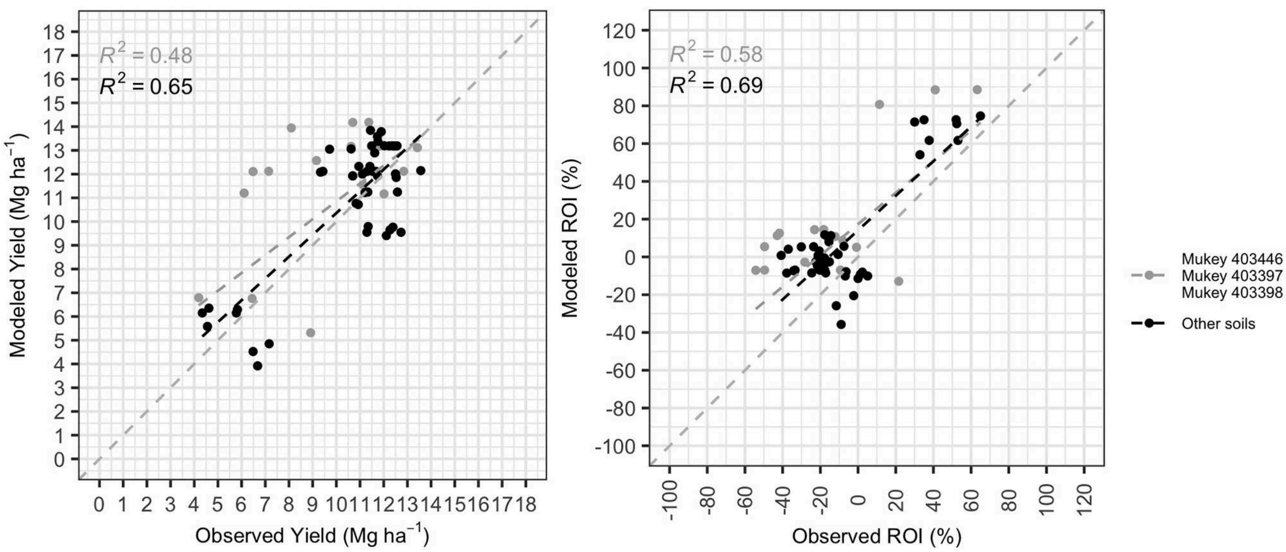

FIGURE 3 | Modeled yield and ROI values fit to observations obtained from spatially averaged precision yield monitor data. Gray data points represent data removed from soils with small areal extent located near the field boundary.

little response to N-fertilizer applications beyond the 50% of the field application rate. Contrastingly, modeled 2016 yields responded positively to increases in the early Spring N-fertilizer application (**Figure 6**). Observations in 2016 showed the highest N application rate (125% of field-scale N application) resulted in lower yields than the 50 and 100% field-scale treatments indicating the secondary spring application, following the fall manure application in 2015, may not have been necessary to maximize yield. Consequently, the highest N treatment resulted in lower observed economic return when compared with the 50 and 100% application rates, particularly in 2015 (**Figures 5**, **6**).

Simulated yield and ROI were found to have a positive response to increasing N application rates during the spring of 2016. The modeled outputs showed the yield and ROI to be more proportional to the incremental increases between N-treatments. Variance associated with the predicted yield and ROI values was found to decrease as N fertilizer rates increased to a maximum. The decreased variance across the maximum simulated N treatment plots indicated the increasing N-fertilizer rates were adequate to overcome any insufficient source of initial plant available N that is based on soil type.

The largest modeling errors were found to correspond with N treatment simulations representing plots located in areas with historically low productivity and economic return. Yield in "No-cost" zones were found to have an RMSE of 4313.6 kg ha^{-1} (21.3% ROI) compared to 1449.6 kg ha^{-1} (7.1% ROI) and 1667.6 kg ha^{-1} (8.4%) associated with "Expense-limited" and "Revenue" zones, respectively (**Figure 7**; **Table S6**).

TABLE 4 | Mean annual yield and ROI error estimates generated by the APSIM model framework based on spatially averaged precision yield monitor data.

Group	Sample size	Yield RMSE (kg ha^{-1})	Yield NRMSE (%)	ROI RMSE (%)
All Soils	66	2171.8	21.0	27.1
Excluding 403446, 403397, and 403398	48	1645.0	15.5	21.5

Objective 3: Simulated Environmental and Economic Impacts Associated With Variable Rate Seeding and N Fertilizer

Multiple seeding and N-fertilizer rate combinations were simulated across all subfield soils within the North-central Iowa field during 2015 and 2016 to identify combinations of seed and N-fertilizer inputs predicted to result in agronomic and economic optimums. A total of 4774 APSIM simulations were processed to estimate yield and ROI responses across a management decision space of 1–15 seeds per square meter and 0–150% of the field-scale N-fertilizer rate. Simulations showed a range of variability in maize yield and ROI estimates across the different soil types and years (data not shown). Modeled yield and ROI response surfaces were generated, and agronomic and economic optimums were identified from the different combinations of seeding density and N-fertilizer rates (e.g., **Figure 8**).

Modeled annual crop productivity estimates for 2015 and 2016 ranged from 2812.4 to 14055.2 kg ha^{-1} across all plots, seeding densities, and N-fertilizer rate combinations. The range of yields corresponded with a minimum ROI of −75.3% and a maximum of 1.6% (data not shown). Initial soil conditions set using SSURGO data were found

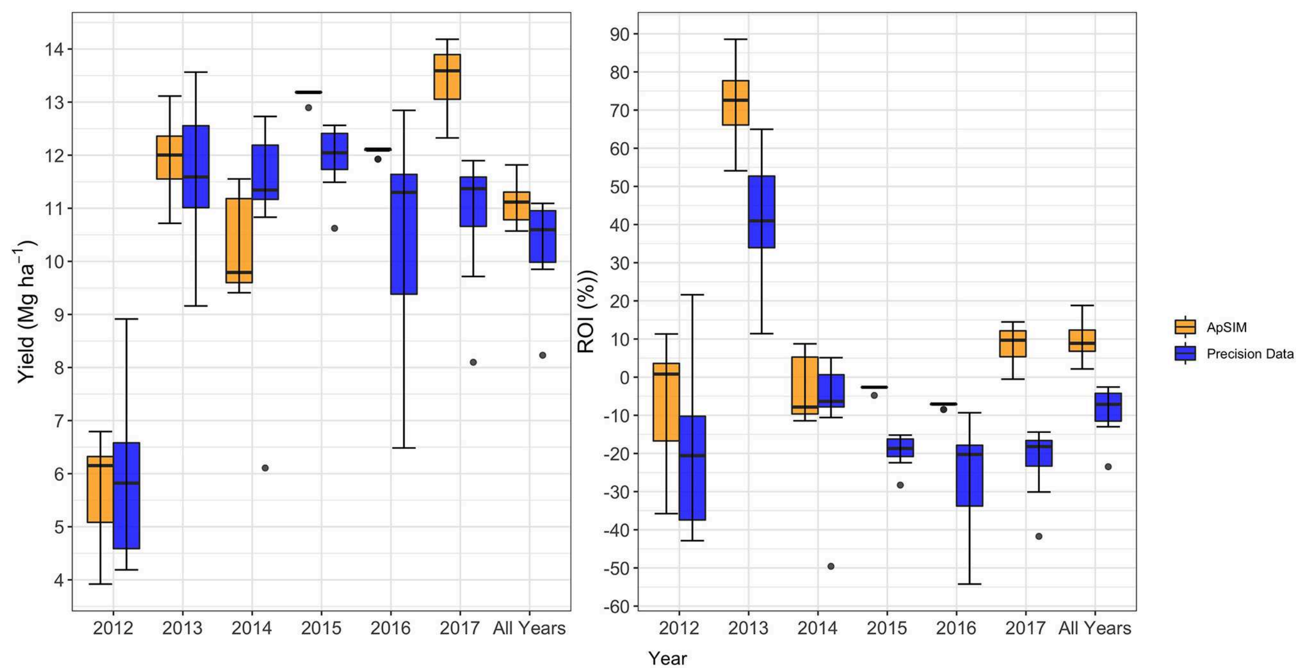

FIGURE 4 | Distribution of annual modeled and observed yield monitor data for each year of analysis. Filled boxes represent the interquartile range (IQR), end caps represent maximum and minimum and dots are outliers defined as >1.5 times the IQR.

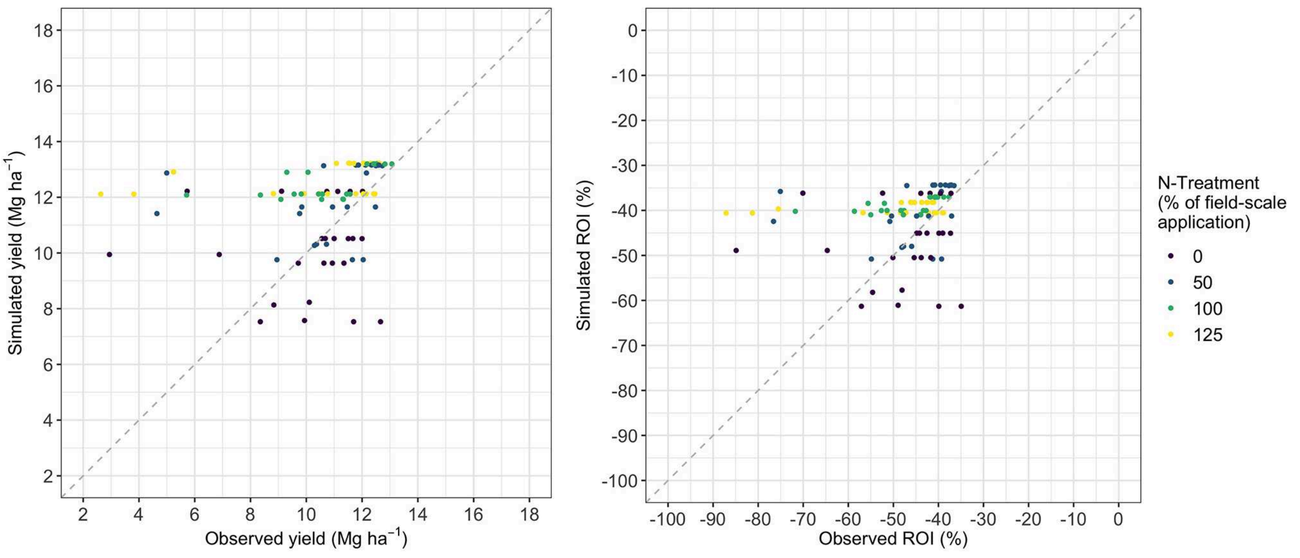

FIGURE 5 | Scatter plot of simulated and spatially averaged yield monitor data corresponding with each experimental N-treatment plot located in the northcentral Iowa field.

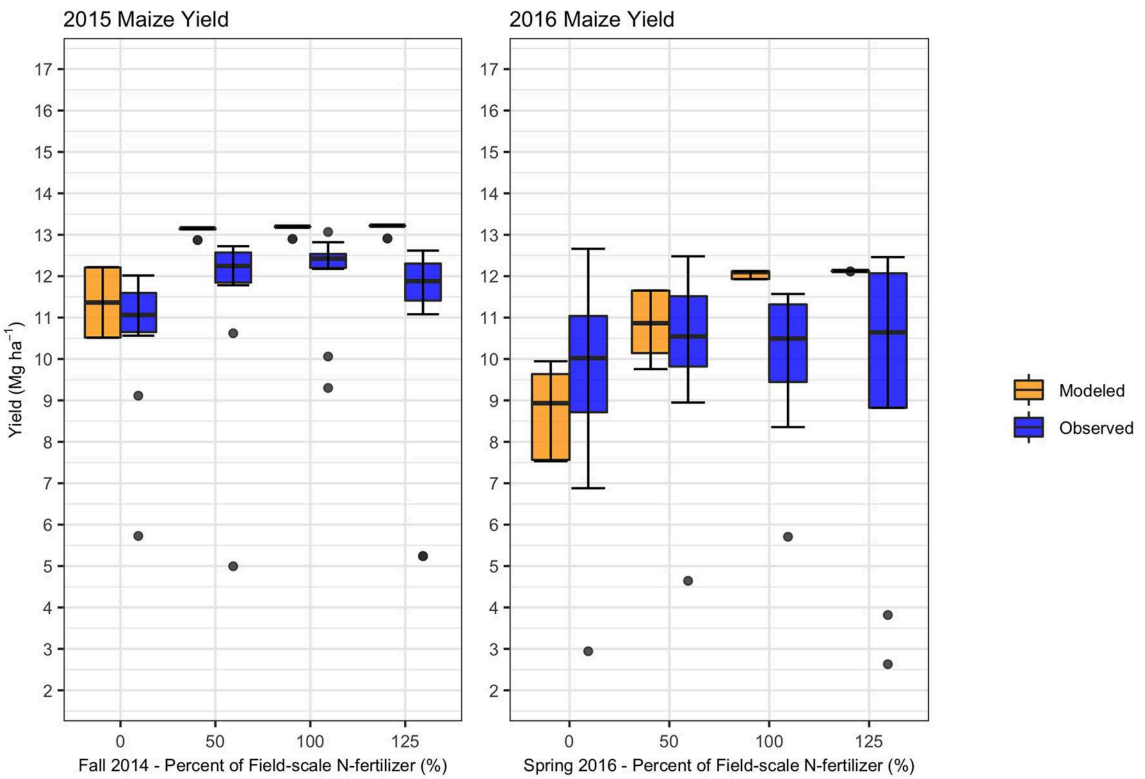

FIGURE 6 | Modeled and observed yield data associated with the four N-fertilizer treatments corresponding with 0, 50, 100, and 125% of the field-scale N-fertilizer rate applied during the fall of 2014 and the spring of 2016. Two replicates of each N-treatment were applied in randomized adjacent plots within the six zones located in an Iowa field (see **Figure 2**).

to directly influence the magnitude of the simulated maize yields, particularly at lower N-fertilizer rates (0 and 50% of field-scale). Due to relatively high input costs and low commodity prices during 2015 and 2016, a majority of modeled yield values were estimated to result in an ROI below break-even (0% ROI).

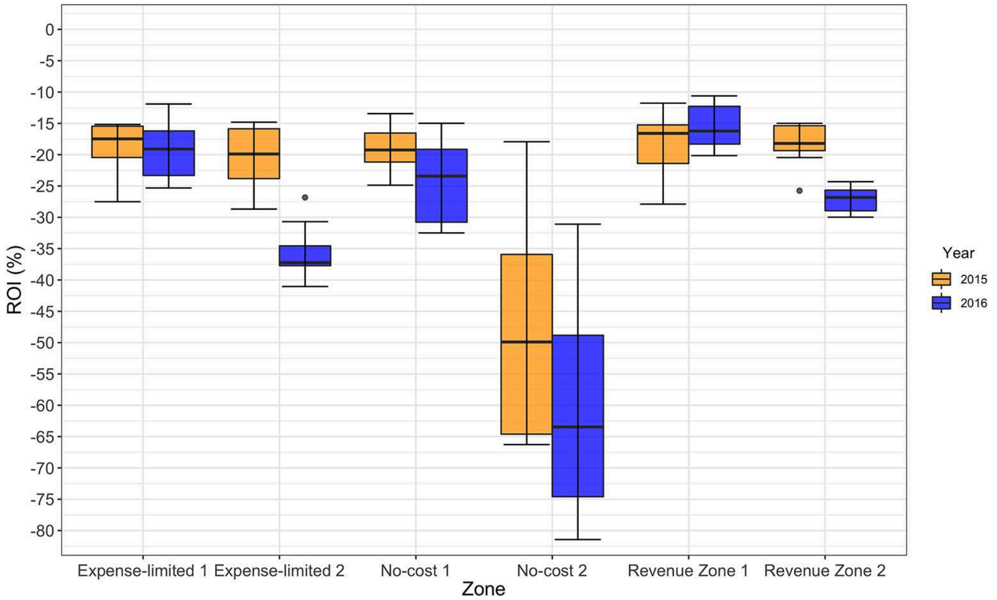

FIGURE 7 | Range of ROI values within each experimental zone during 2015 and 2016. No-cost zones were found to have the greatest range of variability resulting from the alternative N-treatments within each zone. Revenue zones were found to have the least variability compared to the No-cost and Cost-limited zones.

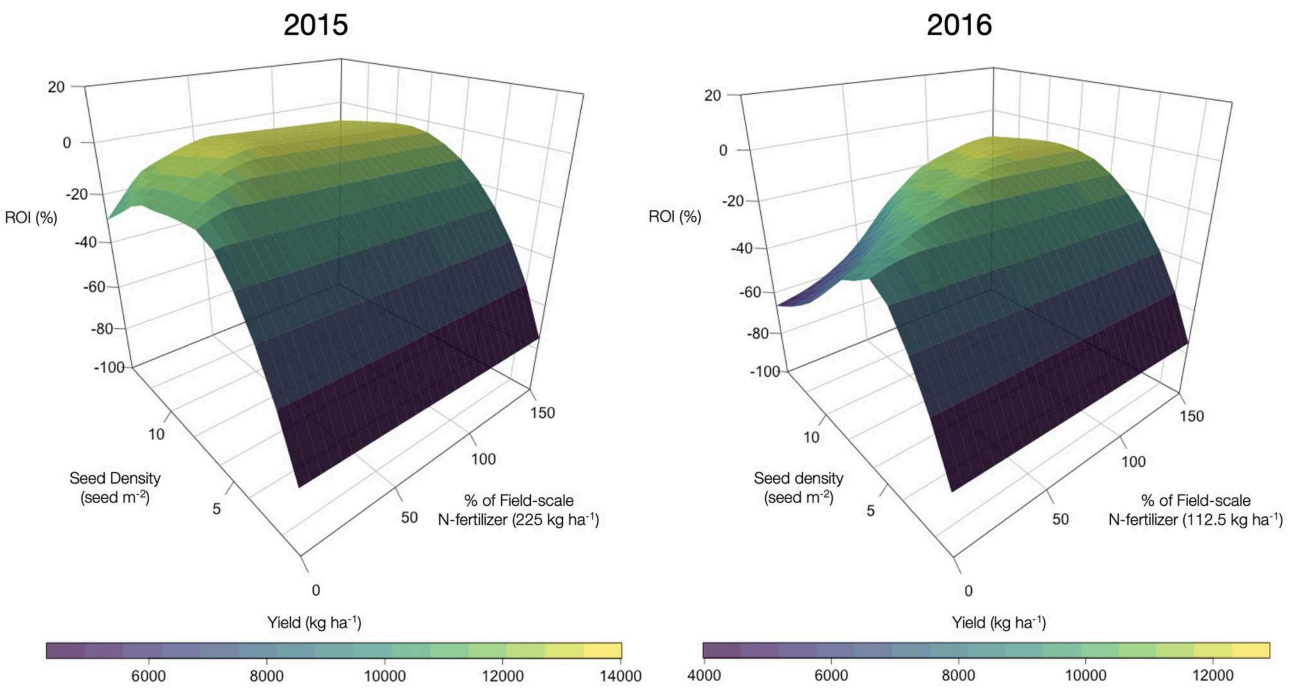

FIGURE 8 | An example of modeled yield and ROI response to variable seeding density and N-fertilizer rate combinations applied in 2015 and 2016. Data associated with the area-dominant subfield soil type within the North-central Iowa field is shown (Mukey 403374; 5.5 ha; see **Figure 2**).

In 2015, maximum yield estimates consistently corresponded with the highest seeding density (15 seed m^{-2}) and N-application rate (150% of field-scale rate; 336.8 kg ha^{-1}) for all soil types (data not shown). The economic optimum seeding density (EOSD) was also consistent across a majority of soils ranging from 8 to 9 seeds m^{-2} (**Figure 9**). Economic optimum N-fertilizer rates (EONR) in 2015 showed increased variability across the field ranging from 110 to 180 kg ha^{-1}. Although the EONR varied across the field, the maximum predicted ROI potential associated with the different soils was found to be relatively consistent, varying by 4.1%. Similar to 2015, maximum crop yields in 2016 corresponded with the greatest N-fertilizer rate (150% of field-scale rate; 168.4 kg ha^{-1}) considered within the decision space for the spring application. However, the agronomic optimum seeding rates in 2016 were more variable than 2015, ranging from 9 to 14 seeds m^{-2}. This indicated higher seeding rate scenarios were likely N-limited at the 150% field-scale application rate. As in 2015, the predicted 2016 EOSD was consistent (8–9 seed m^{-2}) and showed little variation from EOSD predictions from the previous year. N-fertilizer rates were again shown to be the main regulating input for maximizing ROI across the field.

ROI, NO_3^- leaching, and N_2O emissions differences between the agronomic and economic optimum seeding density and N-fertilizer rate scenarios were calculated to determine the range of economic and environmental outcomes that separate maximum economic return and maximum yield potential. Yield differences between the economic and agronomic maximums associated with each subfield soil polygon ranged from 423.1 to 830.5 kg ha^{-1} in 2015 and from 99.5 to 897.1 kg ha^{-1} in 2016. The yield differences corresponded with ROI gains ranging from 10.0 to 12.1% in 2015 and 0.3 to 8.0% in 2016, respectively (**Figure 10**). The yield and ROI differences between the agronomic and economic optimums were found to be driven by both changes in seeding density as well as N inputs. In cases where seeding density was the main factor separating the agronomic and economic optimum management scenarios, the shift in ROI was minor. These relatively small shifts in ROI from changes in seeding density were primarily the result of a reduced yield impact compared to the simulated changes in N-fertilizer. Additionally, the relative cost savings from the reduced seed density were minimal compared to the cost of N. An average reduction of 5 seeds m^{-2} in 2015 equated to reduced input cost of \$44.40 ha^{-1}. In terms of N, a reduction of 43.0 kg ha^{-1} would be needed to achieve an equivalent cost reduction, however, proportionally larger differences in N-fertilizer rate were estimated. An average N-fertilizer difference of 157.3 kg ha^{-1} was predicted to separate economic and agronomic optimum managements in 2015 (\$161.99 ha^{-1} in cost savings based on the average N-price in 2015), followed by an estimated 19.5 kg ha^{-1} (\$20.13 ha^{-1}) difference in N-fertilizer in 2016. The economic optimum combination of inputs was found to have an average decrease NO_3^- leaching across all soils with an average reduction of 3.7 and 1.4 kg ha^{-1} in 2015 and 2016, respectively (**Figure 11**). In addition to NO_3^- leaching, N_2O emissions showed a relative decrease when comparing the seeding and N-fertilizer rates associated with maximum yield to those associated with maximum ROI. In 2015, differences between the optimum management scenarios accounted for an average change in N_2O emissions of 14.8 kg ha^{-1}. In 2016, the N2O emissions difference between economic and agronomic optimum scenarios was 0.5 kg ha^{-1} (**Figure 11**).

DISCUSSION

Optimizing the use of input resources within cropping systems is critical to improving sustainability and increasing economic returns from farm fields. However, predicting how to best allocate input resources such as seed and N-fertilizer to maximize ROI is difficult due to many dynamic factors influencing crop productivity and variability within the cropping systems (Scharf et al., 2005; Jaynes et al., 2011; Dhital and Ruan, 2016). As a result, subfield seeding density and N-fertilizer application guidance is needed prior to upcoming cropping seasons. However, pre-season methods of determining the EONR and EOSD, such as a yield-goal approach, rely heavily on historical data and often involve estimates of interdependent factors (Sela et al., 2017). Regional MRTN tools that incorporate N-fertilizer prices and use empirical data to predict yield response to variable N-fertilizer rates provide field-scale approximations of optimums, but do not provide site-specific subfield recommendations or adjust for year-to-year variability (Sawyer et al., 2006).

Cropping system models such as APSIM are capable of predicting such site-specific subfield yield responses, however determining how these models can best be applied to provide land managers with actionable information to use within their existing management operations is difficult. The framework presented here was developed to determine if a cropping system model, coupled with publicly available data sources, could be used as a decision support tool for estimating site-specific subfield economic optimum seeding density and N-fertilizer rates. Ultimately to be adopted, the framework will need to be practical to use, requiring further development of a user-friendly interface that may need to be catered to specific regions. This study was focused on maize grown in the Midwest U.S., a region where the adoption of precision agriculture has spread rapidly (Schimmelpfennig, 2016), and hence a logical initial focus for framework development. However, the SSURGO and Daymet data sources provide coverage across the conterminous U.S. allowing the framework to be applied to a variety of cropping system locations with varying weather and soil conditions. Extending beyond our study region, there are analogous tools such as Yield Prophet (Hochman et al., 2009; McCown et al., 2009) which have been successfully implemented in wheat, barley, canola, and oat cropping systems in Australia. Additionally, alternative data sources which provide alternate global weather and soil characteristics could be integrated with the framework to further extend its use in different regions (e.g., the European Centre for Medium-Range Weather Forecasts Reanalysis (ERA) products and the European Soil Database).

The framework was applied to determine subfield EONR and EOSD combinations for a Butler, County, Iowa, U.S. cropping system field in continuous maize and demonstrated the ability of the tool to capture subfield variability of yield and ROI across multiple years (2012–2017) and weather conditions (**Figures 2**, **3**). The initial demonstration of the framework required making some assumptions about the farming operations (e.g., selling grain at peak annual price) that could be incorporated into the user interface as customizable settings. Results of the Butler County field analysis showed fair agreement with annual subfield soil-based observations obtained from area-averaged yield monitor data for the 2012–2017 growing seasons. The greatest sources of modeling error corresponded with several small-area soils along the field boundary (**Figure 2**). Yields and

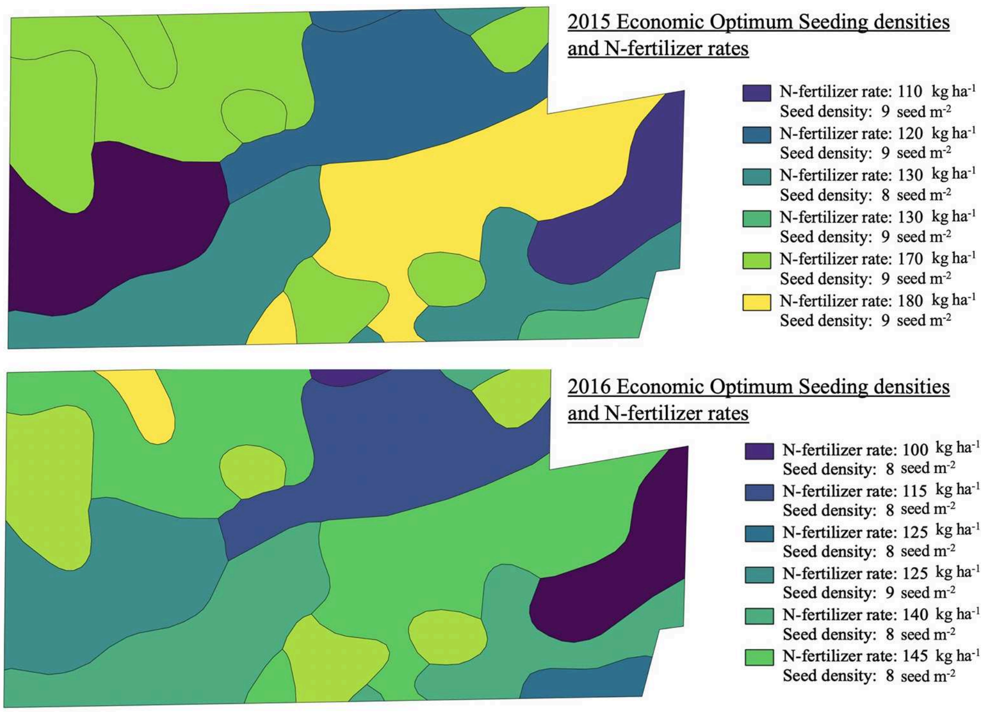

FIGURE 9 | Estimated economic optimum seeding density (EOSD) and economic optimum N-fertilizer rates (EONR) for 2015 and 2016. Management zones defined by one or more soil types sharing the same optimal combination of inputs are shown.

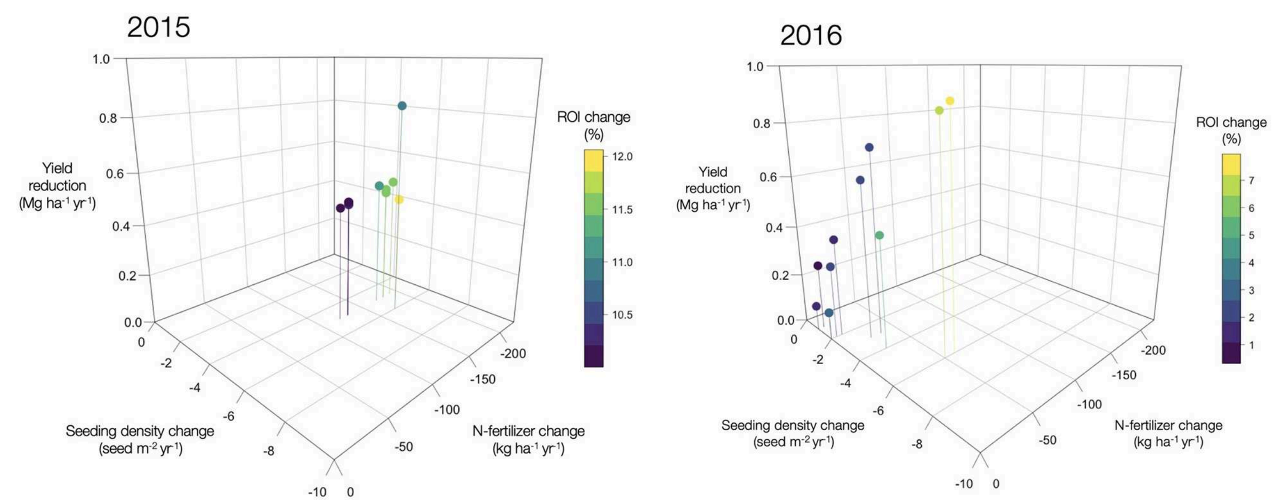

FIGURE 10 | Yield and ROI changes associated with a shift from agronomic optimum inputs to economic optimum inputs. Data points represent changes corresponding with each subfield soil types during 2015 and 2016 (**Table S7**).

ROI associated with these soils were all over-estimated compared to the observations derived from yield monitor data. Plant stresses from non-simulated factors (e.g., standing water and soil compaction) could explain model over estimation in these areas. However, due to the small size (4% of field area) and the proximity of the soils to the field boundary the increased error might be expected. Furthermore, yield monitor measurements may be artificially low near field borders (Luck and Fulton, 2004). Excluding the identified soils improved model fit to observations associated with the remaining 96% of the field area ($r^2 = 0.48$ to $r^2 = 0.65$) and reduced yield RMSE from 2171.8 to 1645.0 kg ha^{-1}.

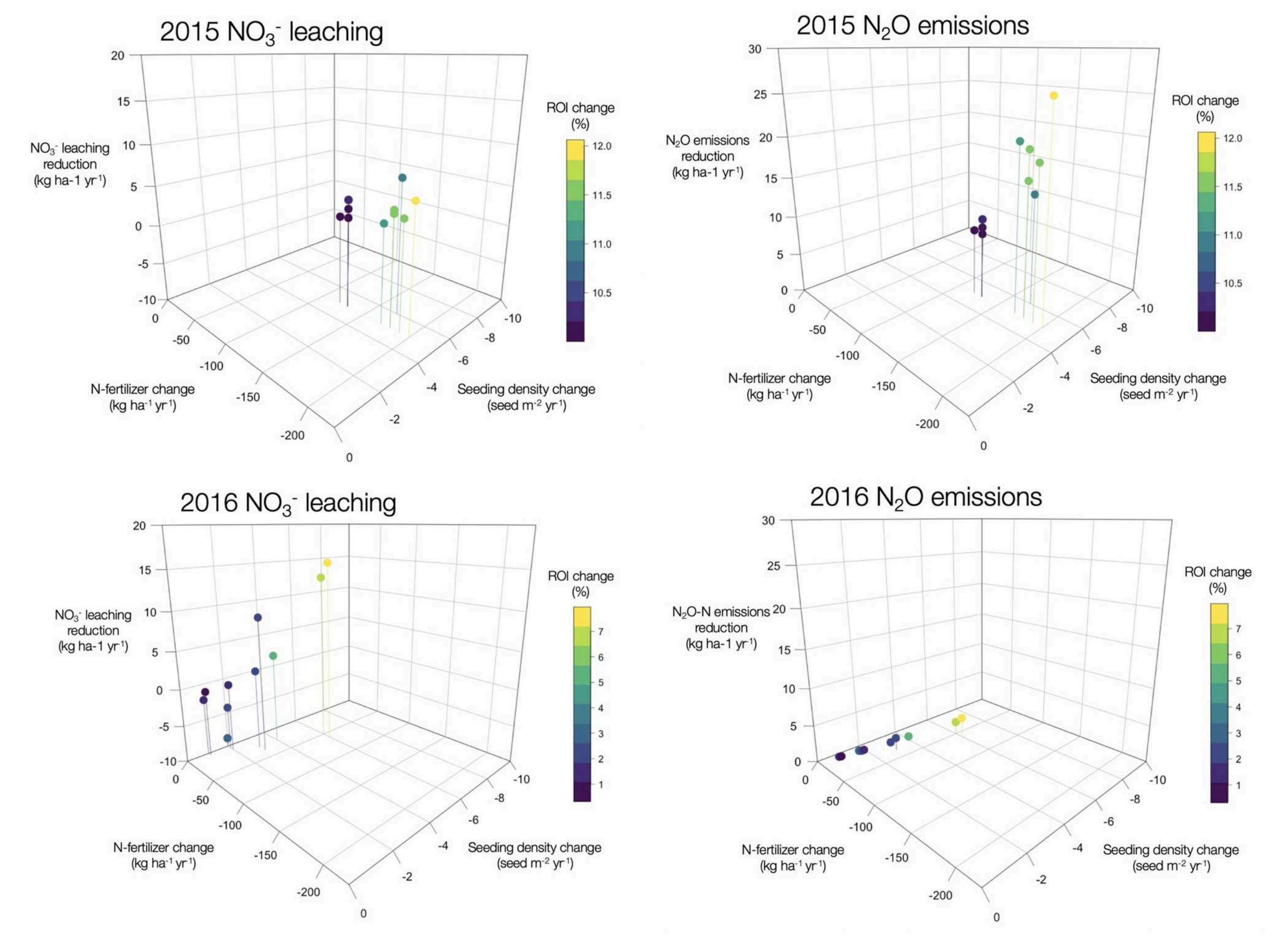

FIGURE 11 | NO_3^- leaching and N_2O emission changes associated with a shift from managing for maximum yield (agronomic optimum inputs) to managing for maximum ROI (economic optimum inputs). Data points represent changes corresponding with each subfield soil type during 2015 and 2016 (**Table S7**).

Normalizing the RMSE by the mean observed yield resulted in a relative RMSE (RRMSE) of 15.5% (**Table S2**), which was similar in magnitude to a previous study examining the ability of the APSIM cropping system model to capture yield response to variable N-fertilizer rates in an Iowa maize system (Puntel et al., 2016). The RRMSE between 15 and 30% represents moderate model performance based on Yang et al. (2014). However, it is important to note the framework simulation approach was characterized by a high degree of difficulty as it runs a continuous simulation between 2012 and 2017, avoiding re-initialization of the soil data to capture year-on-year impacts on N-cycle dynamics (Constantin et al., 2011; Basso and Ritchie, 2015) related to the variable weather conditions and prior management practices. Such a modeling approach may propagate and accumulate error associated with a particular year during the full simulation period (Salo et al., 2016; Puntel et al., 2018). Based on this high level of difficulty and the resulting model performance, we believe the ability of the framework to capture subfield-scale patterns outside of a calibrated experimental setting indicates the framework to be a viable basis for an assessment tool when using public soils and weather data.

The model outputs corresponding with varying combinations of seeding density and N-fertilizer rates showed, in addition to increased ROI, managing for maximum economic return vs. maximum yield, likely provides an environmental co-benefit by reducing N-losses from NO_3^- leaching and N_2O emissions. Daily outputs from the analysis showed modeled N_2O emissions were driven by interannual conditions that resulted in several periods during the growing season each year in which conditions favored denitrification (data not shown). Alternatively, the daily outputs showed a majority of NO_3^- leaching to have occurred during the fall of 2015 into the spring of 2016. This indicated the fall manure application in 2015 was susceptible to high rates of NO_3^- leaching. The economic and environmental co-benefit associated with strategically targeting management practices to subfield zones supports similar findings in Muth (2014) and Brandes et al. (2016), which have noted a correlation between environmental and economic performance in cropping systems. Such a relationship presents a financial incentive for adopting the economically optimum inputs, even at the cost of potential yield. A comparison of the predicted economic and agronomic optimums performed in this analysis showed the importance of managing the balance between seeding density and reduced N-fertilizer rates. The dual benefit of increased economic return and reduced environmental impacts may be sufficiently appealing to incentivize adoption by land managers, especially relative to regulatory actions by governments (Arbuckle, 2013; Kalcic et al., 2014).

The modeled relationship between maximum yield and maximum ROI was shown to reinforce aggregated empirical findings that are used in MRTN tools such as the Corn Nitrogen Rate Calculator (CRNC) (Sawyer et al., 2006). A small yield response was observed in 2015 when the primary source of N to the field was varied (224.5 kg ha^{-1} in the Fall 2014) indicating that some N-stress occurred at the lower rates of 0 and 50% of the field-scale N application. The long history of manure amendment prior to the 2012 start of the analysis has likely resulted in a large stock of organic N sources within the soil profile of the North-central Iowa field. A calibration approach, such as the one used in Puntel et al. (2016), based on previous knowledge of the system including the C:N ratio of the crop residues could be used to improve the predictive capability of the framework for future years.

The accuracy and usefulness of the tool could also be improved with more information and site-specific data sources. For example, relatively low yield observations in the southwest corner of the Iowa maize field were reported by the land manager to be the result of a broken tile drain and water infiltration issues (personal communication). Such information was not captured in the simulations when using only the public data sources to drive predictions. As a result, the variable N-treatment zone (*No-cost 1*) located in this area was found to correspond with the greatest modeling errors [yield and ROI RMSE of 4313.6 kg ha^{-1} and 21.3%, respectively (**Table S6**)], compared to the other variable N-treatment zones. For example, expense-limited zones showed the least error with a yield RMSE of 1449.6 kg ha^{-1} and ROI RMSE of 7.1%. Therefore, a real world application of the framework could be improved with some familiarity with the field being analyzed beyond crop, weather, and soil conditions. Calibration of the framework using historical precision yield data and initialization of simulated soil properties including initial $NO_3{}^-$ and NH_4^+ concentrations would also likely improve model performance. Such calibrations could be used to account for residual N within the soil in amounts adequate to offset any N-limitations that may occur in lower N-treatment plots. However, the ability and motivation of the land manager to take the steps to obtain the necessary site-specific measurements may not be likely in some cases (Schimmelpfennig, 2016). In practice, there will be a range of potential users of the framework with varying levels of access to site-specific data and precision equipment/technology. Further calibration of the framework to provide more accurate predictions may represent a second phase in the analysis process after initially using the framework to highlight areas of the field that are not likely to respond to changes in management practices (e.g., "*No-cost*" zones). The second "calibrated" phase would then focus on areas of field where the model has shown to provide a yield response similar to historical observations. We envision the framework being applied in the following manner:

(1) Perform initial baseline assessment of field using historical management practices (i.e., seeding rate, N-fertilizer rates, tillage), public soils data, and public weather data.
(2) Compare predicted baseline yield values to historical precision yield data to identify areas of the field where the framework provides satisfactory agreement with observations (e.g., NRMSE $\leq$ 30%).
(3) Use framework to determine optimum seeding density and N-fertilizer application rates to the areas identified as satisfactory in Step 2 (standard management for remaining areas).

The result of this second phase would then be used to guide subfield management of seeding and N-fertilizer rates for the sub-field areas that have not been excluded in the "*No-cost*" zones. These zones should be prioritized for the enrollment of conservation programs or targets for perennial energy crops (Brandes et al., 2016). Further testing on additional independent sites will strengthen the predictive ability of the framework for supporting future application decisions.

CONCLUSIONS

Optimizing the use of input resources within cropping systems is critical to reducing nutrient losses improving sustainability, and increasing economic return from cropping system fields. However, predicting how to best allocate input resources within a field is difficult due to the spatial and temporal variability of weather, soils, and management practices within the systems. By leveraging publicly available field-to-subfield data sources, cropping system models may provide a valuable decision support tool for predicting site specific yield, ROI, and environmental impacts on which farmers could base management decisions. The developed framework provides a basis for a subfield decision support tool for estimating economically optimum seeding densities and N-fertilizer rates. An application of the framework to predict annual yield and ROI outcomes in a maize cropping system found the framework effectively captured subfield variability of the observed crop productivity. These results support that this framework could potential be used to increase both economic and environmental performance in relatively well performing zones. Our analysis also indicated that poor performing zones are unlikely to be profitable at any realistic combination of the key inputs studied, suggesting that these areas may be targets for alternative cropping systems (e.g., perennial grasses). $NO_3{}^-$ leaching and N_2O emissions differences between economic and agronomic optimum yields reinforces a correlation between maximum profitability and improved environmental performance. Further development of the integrated modeling approach to simulate perennial grasses and utilize more site-specific data may increase the accuracy and robustness of the framework. Integrating the use of additional precision agriculture data layers including as-applied nutrient applications, as-planted seeding data, gridded soil sampling, elevation data, and remote sensed layers could provide the necessary increase in spatial resolution needed to extend the process-based modeling framework as a more practical decision making resource.

DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/**Supplementary Material**.

AUTHOR CONTRIBUTIONS

GM and AV developed research idea, performed modeling study, and drafted manuscript. EH assisted with interpretation of data. SA assisted with model parameterization. ML assisted with modeling study design. All co-authors reviewed and contributed to the final manuscript.

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SUPPLEMENTARY MATERIAL

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REFERENCES

Adamchuk, V. I., Dobermann, A., and Ping, J. (2004). *Precision Agriculture: Listening to the Story Told by Yield Maps*. Lincoln, NE: University of Nebraska-Lincoln Extension.

Arbuckle, J. G. (2013). Farmer attitudes toward proactive targeting of agricultural conservation programs. *Soc. Nat. Resour.* 26, 625–641. doi: 10.1080/08941920.2012.671450

Banger, K., Yuan, M., Wang, J., Nafziger, E. D., and Pittelkow, C. M. (2017). A vision for incorporating environmental effects into nitrogen management decision support tools for US maize production. *Front. Plant Sci.* 8:1270. doi: 10.3389/fpls.2017.01270

Basso, B., Benjamin, D., Davide, C., Andrea, P., Francesco, M., Sartori., et al. (2016). Environmental and economic benefits of variable rate nitrogen fertilization in a nitrate vulnerable zone. *Sci. Total Environ*. 545–546, 227–235. doi: 10.1016/j.scitotenv.2015.12.104

Basso, B., and Ritchie, J. T. (2015). "Simulating crop growth and biogeochemical fluxes in response to land management using the SALUS model," in *The Ecology of Agricultural Landscapes: Long-Term Research on The Path to Sustainability*, eds S. K. Hamilton, J. E. Doll, and G. P. Robertson (New York, NY: Oxford University Press), 252–274.

Bobryk, C. W., Myers, D. B., Kitchen, N. R., Shanahan, J. F., Sudduth, K. A., Drummond, S. T., et al. (2016). Validating a digital soil map with corn yield data for precision agriculture decision support. *Agron. J.* 108, 957–965. doi: 10.2134/agronj2015.0381

Brandes, E., McNunn, G. S., Schulte, L. A., Bonner, I. J., Muth, D., Babcock, B. A., et al. (2016). Subfield profitability analysis reveals an economic case for cropland diversification. *Environ. Res. Lett*. 11:014009. doi: 10.1088/1748-9326/11/1/014009

Constantin, J., Beaudoin, N., Laurent, F., Cohan, J. P., Duyme, F., and Mary, B. (2011). Cumulative effects of catch crops on nitrogen uptake, leaching and net mineralization. *Plant Soil*. 341, 137–154. doi: 10.1007/s11104-010-0630-9

Dhital, S., and Ruan, W. R. (2016). Variability in optimum nitrogen rates for maize. *Agron. J.* 108, 2165–2173. doi: 10.2134/agronj2016.03.0139

Fleming, K. L., Westfall, D. G., Wiens, D. W., and Brodahl, M. C. (2000). "Evaluating management zone technology and grid soil sampling for variable rate nitrogen application," in *Proceedings of the 5th International Conference on Precision Agriculture* (Bloomington, MN), 16–19. doi: 10.1023/A:1011481832064

Gao, F., Anderson, M., Daughtry, C., and Johnson, D. (2018). Assessing the variability of corn and soybean yields in central Iowa using high spatiotemporal resolution multi-satellite imagery. *Remote Sens*. 10:1489. doi: 10.3390/rs10091489

Hochman, Z., Van Rees, H., Carberry, P. S., Hunt, J. R., McCown, R. L., Gartmann, A., et al. (2009). Re-inventing model-based decision support with Australian dryland farmers. 4. Yield Prophet helps farmers monitor and manage crops in a variable climate. *Crop Pasture Sci.* 60, 1057–1070. doi: 10.1071/CP09020

Holland, K. H., and Schepers, J. S. (2010). Derivation of a variable rate nitrogen application model for in-season fertilization of corn. *Agron. J.* 102, 1415–1424. doi: 10.2134/agronj2010.0015

Holzworth, D. P., Neil, I. H., Peter, G., Zurcher, E. J., Herrmann, N. I., Mclean, G., et al. (2014). Environmental Modelling & Software APSIM e Evolution towards a new generation of agricultural systems. *Environ. Model. Softw*. 62, 327–350. doi: 10.1016/j.envsoft.2014.07.009

Hong, N., White, J. G., Weisz, R., Crozier, C. R., Gumpertz, M. L., and Cassel, D. K. (2006). Remote sensing-informed variable-rate nitrogen management of wheat and corn: agronomic and groundwater outcomes. *Agron. J.* 98, 327–338. doi: 10.2134/agronj2005.0154

Jaynes, D. B., Kaspar, T. C., and Colvin, T. S. (2011). Economically optimal nitrogen rates of corn: management zones delineated from soil and terrain attributes. *Agronomy J*. 103, 1026–1035. doi: 10.2134/agronj2010.0472

Jin, Z., Archontoulis, S. V., and Lobel, D. B. (2019). How much will precision nitrogen management pay off? An evaluation of simulating thousands of corn fields over the US Corn-Belt. *Field Crops Res.* 240, 12–22. doi: 10.1016/j.fcr.2019.04.013

Johanns, A. (2019). *Iowa Cash Corn and Soybean Prices*. Ames, IA: Iowa State University Extension – Ag Decision Maker.

Johanns, A., and Plastina, A. (2019). *Historical Costs of Crop Production*. Ames, IA: Iowa State University Extension – Ag Decision Maker.

Kalcic, M., Prokopy, L., Frankenberger, J., and Chaubey, I. (2014). An in-depth examination of farmers perceptions of targeting conservation practices. *J. Environ. Manage.* 54, 795–813. doi: 10.1007/s00267-014-0342-7

Kitchen, N. R., Sudduth, K. A., Drummond, S. T., Scharf, P. C., Palm, H. L., Roberts, D. F., et al. (2010). Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization. *Agron. J.* 102, 71–84. doi: 10.2134/agronj2009.0114

Licht, M. A., Lenssen, A. W., and Elmore, R. W. (2017). Corn (*Zea mays* L.) seeding rate optimization in Iowa, USA. *Precision Agric*. 18, 452–469. doi: 10.1007/s11119-016-9464-7

Link, J., Graeff, S., Batchelor, W. D., and Claupein, W. (2006). Evaluating the economic and environmental impact of environmental compensation payment policy under uniform and variable-rate nitrogen management. *Agric. Syst.* 91, 135–153. doi: 10.1016/j.agsy.2006.02.003

Long, D. S., Whitmus, J. D., Engel, R. E., and Brester, G. W. (2015). Net returns from terrain-based variable-rate nitrogen management on dryland spring wheat in Northern Montana. *Agron. J.* 107, 1055–1067. doi: 10.2134/agronj14.0331

Luck, J. D., and Fulton, J. P. (2004). *Precision Agriculture: Best Management Practices for Collecting Accurate Yield Data and Avoiding Errors During Harvest.* Lincoln, NE: University of Nebraska-Lincoln Extension.

Maestrini, B., and Basso, B. (2018). Predicting spatial patterns of within-field crop yield variability. *Field Crops Res.* 219, 106–112. doi: 10.1016/j.fcr.2018.01.028

Martinez-Feria, R. A., Castellano, M. J., Dietzel, R. N., Helmers, M. J., Liebman, M., Huber, I., et al. (2018). Linking crop- and soil-based approaches to evaluate system nitrogen-use efficiency and tradeoffs. *Agric. Ecosyst. Environ*. 256, 131–143. doi: 10.1016/j.agee.2018.01.002

McCown, R. L., Carberry, P. S., Hochman, Z., Dalgliesh, N. P., and Foale, M. A. (2009). Re-inventing model-based decision support with Australian dryland farmers. 1. Changing intervention concepts during 17 years of action research. *Crop Pasture Sci.* 60, 1017–1030. doi: 10.1071/CP08455

Morris, T. F., Murrell, T. S., Beegle, D. B., Camberato, J. J., Ferguson, R. B., Grove, J., et al. (2018). Strengths and limitations of Nitrogen rate recommendations for corn and opportunities for improvement. *Agron. J.* 110, 1–37. doi: 10.2134/agronj2017.02.0112

Muth, D. (2014). Profitability versus environmental performance: are they competing? *J. Soil Water Conserv*. 69, 203–206. doi: 10.2489/jswc.69.6.203A

Ordóñez, R. A., Castellano, M. J., Hatfield, J. L., Helmers, M. J., Licht, M. A., Liebman, M., et al. (2018). Maize and soybean root front velocity and maximum depth in Iowa, USA. *Field Crops Res.* 215, 122–131. doi: 10.1016/j.fcr.2017.09.003

Paz, J. O., Batchelor, W. D., Babcock, B.A, Colvin, T. S., Logsdon, S. D., Kaspar, T. C., et al. (1999). Model-based technique to determine variable rate nitrogen for corn. *Agric. Syst.* 61, 69–75. doi: 10.1016/S0308-521X(99)00035-9

Plastina, A. (2018). *Estimated Costs of Crop Production in Iowa*. Ames, IA: Iowa State University Extension – Ag Decision Maker.

Puntel, L. A., Pagani, A., and Archontoulis, S. V. (2019). Development of a nitrogen recommendation tool for corn considering static and dynamic variables. *Eur. J. Agron.* 105, 189–199. doi: 10.1016/j.eja.2019.01.003

Puntel, L. A., Sawyer, J. E., Barker, D. W., Dietzel, R., Poffenbarger, H., Castellano, M. J., et al. (2016). Modeling long-term corn yield response to nitrogen rate and crop rotation. *Front. Plant Sci.* 7, 1–18. doi: 10.3389/fpls.2016.01630

Puntel, L. A., Sawyer, J. E., Barker, D. W., Thorburn, P. J., Castellano, M. J., Moore, K. J., et al. (2018). A systems modeling approach to forecast corn economic optimum nitrogen rate. *Front. Plant Sci.* 9:436. doi: 10.3389/fpls.2018.00436

Raun, W. R., Solie, J. B., Johnson, G. V., Stone, M. L., Mullen, R. W., Freeman, K. W., et al. (2002). Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agron. J.* 94, 815–820. doi: 10.2134/agronj2002.8150

Salo, T. J., Palosuo, T., Kersebaum, K. C., Nendel, C., Angulo, C., Ewert, F., et al. (2016). Comparing the performance of 11 crop simulation models in predicting yield response to nitrogen fertilization. *J. Agric. Sci*. 154, 1218–1240. doi: 10.1017/S0021859615001124

Sawyer, J., Nafziger, E., Randall, G., Bundy, L., Rehm, G., and Joern, B. (2006). *Concepts and Rationale for Regional Nitrogen Guidelines for Corn*. Ames, IA: Iowa State University Extension.

Sawyer, J. E., and Mallarino, A. P. (2008). *Using Manure Nutrients for Crop Production.* Ames, IA: Iowa State University Extension.

Sawyer, J. E., and Nafziger, E. D. (2005). "Regional approach to making nitrogen fertilizer rate decisions for corn," in *Agronomy Conference Proceedings and Presentations* (Des Moines, IA), 37. doi: 10.31274/icm-180809-823

Scharf, P. C., Kitchen, N. R., Sudduth, K. A., Davis, G., Hubbard, V. C., and Lory, J. A. (2005). Field-scale variability in optimal nitrogen fertilizer rate for corn. *Agron. J.* 97, 452–461. doi: 10.2134/agronj2005.0452

Schimmelpfennig, D. (2016). *Farm Profits and Adoption of Precision Agriculture, ERR-217.* U.S. Department of Agriculture, Economic Research Service.

Sela, S., van Es, H. M., Moebius-Clune, B. N., Marjerison, R., Melkonian, J., Moebius-Clune, D., et al. (2016). Adapt-N outperforms grower-selected nitrogen rates in northeast and midwestern united states strip trials. *Agron. J.* 108, 1726–1734. doi: 10.2134/agronj2015.0606

Sela, S., van Es, H. M., Moebius-Clune, B. N., Marjerison, R., Moebius-Clune, D., Schindelbeck, R., et al. (2017). Dynamic model improves agronomic and environmental outcomes for maize nitrogen management over static approach. *J. Environ. Qual.* 46:311–319. doi: 10.2134/jeq2016.05.0182

Solie, J. B., Monroe, A. D., Raun, W. R., and Stone, M. L. (2012). Generalized algorithm for variable-rate nitrogen application in cereal grains. *Agron. J.* 104, 378–387. doi: 10.2134/agronj2011.0249

Stefanini, M., Larson, J. A., Lambert, D. M., Yin, X., Boyer, C. N., Scharf, P., et al. (2018). Effects of optical sensing based variable rate nitrogen management on yields, nitrogen use and profitability for cotton. *Precision Agric*. 20, 591–610. doi: 10.1007/s11119-018-9599-9

Thornton, M. M., Thornton, P. E., Wei, Y., Mayer, B. W., Cook, R. B., and Vose, R. S. (2018). *Daymet: Annual Climate Summaries on a 1-km Grid for North America, Version 3.* Oak Ridge, TN: ORNL DAAC.

Tremblay, N., Wang, Z., Ma, B. L., Belec, C., and Vigneault, P. (2009). A comparison of crop data measured by two commercial sensors for variable-rate nitrogen application. *Precision Agric.* 10, 145–161. doi: 10.1007/s11119-008-9080-2

Walters, C. G., Shumway, C. R., and Huggins, D. R. (2017). Impacts of terrain attributes on economics and the environment: costs of reducing potential nitrogen pollution in wheat production. *Agric. Econ*. 48, 143–152. doi: 10.1111/agec.12321

Woli, K. P., Burras, C. L., Abendroth, L. J., and Elmore, R. W. (2014). Optimizing corn seeding rates using a field's corn suitability rating. *Agron. J.* 106, 1523–1532. doi: 10.2134/agronj14.0054

Yang, J. M., Yang, J. Y., Liu, S., and Hoogenboom, G. (2014). An evaluation of the statistical methods for testing the performance of crop models with observed data. *Agric. Syst*. 127, 81–89. doi: 10.1016/j.agsy.2014.01.008

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Innovation Uncertainty Impacts the Adoption of Smarter Farming Approaches

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There are increasing opportunities to use smart farming technologies for improved management of farming systems. However, there is limited understanding of how the potential can be translated into effective use in the farming sector. Previous studies have highlighted the role that uncertainty plays in technological innovation systems. In this paper, we present the results of an international survey investigating the impact of innovation uncertainty on adoption of a smart farming technology, automatic milking systems (AMS). The objective of this study was to review adoption of AMS internationally and propose lessons for developing institutional knowledge and effective networks of practice in emerging smart farming innovation systems. We used an online survey of AMS experts globally and received 81 completed survey responses. The main countries represented were Canada, The Netherlands, USA, Denmark, and the UK. Respondents identified a range of adoption trends in their country and some of the reasons behind these adoption profiles were suppression of uptake due to low milk prices, financial markets, and issues with early installations and perceptions of these issues by other farmers. In terms of the impact of uncertainty, technological uncertainty was historically an important issue around the early development of AMS, with decommissioning occurring in some cases due to perceived technology issues. Political uncertainty also impacted adoption, with implications of food safety regulations or rules around herd testing systems. Our study highlighted the potential impact of negative experiences associated with new technologies from farmers who struggle with the adaptation process as such occurrences may act to stall the uptake of smart farming technologies. If public policy organizations are to realize the desired impacts of smart farming technology, there needs to be greater focus on understanding where (and which) technologies can have an actual impact on farm as opposed to technologies that only create greater farmer distrust and uncertainty. Our study highlights that to reduce uncertainty with emerging smart technologies, greater public and private R&D collaboration is required to foster knowledge development and exchange.

Keywords: automatic milking systems, innovation uncertainty, dairy, smart farming, advisors

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INTRODUCTION

There are increasing opportunities to use smart farming technologies for improved management of farming systems (Shepherd et al., 2018). Potential management improvements are related to enhanced collection of data to manage animals, plants, and the wider farming environment (Eastwood et al., 2017a). However, there is limited understanding of how the potential can be translated into widespread adoption in the farming sector, which has been slow to date (Gargiulo et al., 2018). The uptake of smarter farming approaches often represents more than a "plug and play" process for farmers (Jago et al., 2013). Successful use of these new tools depends on aspects of technology fit-for-purpose, on-farm adaptation, learning about data-driven decision-making, and social learning within a farmer's network of practice (Eastwood et al., 2012; Rose et al., 2016; Higgins et al., 2017; Klerkx et al., 2019). To turn the opportunity of smarter farming into a reality on-farm, we need to better understand the wider issues affecting a farmer's investment decision making (Rutten et al., 2018).

Previous studies have highlighted the role that uncertainty plays in the functioning of technological innovation systems. For example, Meijer et al. (2007b) identified the importance of technological, resource, competitive, supplier, consumer, and political uncertainty. The use of farm system-changing smart farming technologies such as automatic milking systems (AMS) [see Rodenburg (2017) for a description of AMS technology] requires not only a reconfiguration of farming practice, but also in the systems that operate around the farmer, for example, knowledge of veterinarians on how to maintain reproductive performance under AMS or structural changes to herd testing protocols (Svennersten-Sjaunja and Pettersson, 2008; Hansen, 2015; Rodenburg, 2017). The success of an innovation system can depend on minimizing the uncertainty around the innovation (Meijer et al., 2007b; Kuehne et al., 2017). Poor or haphazard innovation system reconfiguration can increase the uncertainty that farmers or their advisors have about a technology and impact on its successful uptake and implementation.

Within this context, the objective of this current study was to understand drivers for adoption of AMS internationally and propose lessons for developing institutional knowledge and effective networks of practice in emerging smart farming innovation systems. In this paper, we present the results of an international survey investigating the impact of innovation uncertainty within AMS support networks across different institutional environments. First, we outline the conceptual framework based around innovation uncertainty, and then we present the methods and results of the survey and discuss them in relation to the conceptual framework. The novel contribution of this paper is 2-fold: first, it adds to knowledge of the specific factors influencing farmer adoption of smarter farming technologies such as AMS, and second, it adds to the limited literature that empirically explores the role of various factors of uncertainty in technological innovation systems.

CONCEPTUAL FRAMEWORK

Adoption of agricultural technologies has been extensively studied and perspectives vary from a diffusion of innovations perspective (Rogers, 1962) to the more holistic concepts of agricultural innovation systems (Klerkx et al., 2010). The agricultural innovation systems (AIS) approach considers the role of institutional change within agricultural innovation and potential benefits from different ways of organizing within such systems (Morriss et al., 2006; Klerkx et al., 2010). Successful agricultural innovations depend on factors such as technology development, institutional change, supply chain reorganization, market development, and creating societal acceptance (Klerkx et al., 2010). The AIS concept has value as an analytical framework to "improve everyday innovation capacity" (Spielman and von Grebmer, 2006). One feature of AIS is the role of uncertainty in the uptake and use of technologies. Meijer et al. (2007b) identify six forms of uncertainty that might occur: technological, resource, competitive, supplier, consumer, and political. Individuals (including farmers or service providers) within AIS may have little ability to influence the uncertainty existing around an innovation. Uncertainty within innovation systems can potentially reduce the uptake of a technology, affect its integration into the farm system or industry, and can prevent some actors from engaging in the innovation system (Meijer et al., 2007b).

While the sources of uncertainty cited by Meijer et al. (2007b) focus on the formation of innovation projects, and in particular the impact on entrepreneurial action, the framework could be applied to the actions of farmers and advisors in respect to new system-changing innovations such as AMS. An ongoing process of AMS innovation could therefore be viewed as dependent on not just the technology or its developers, but also the farmers, distributors, milk companies, researchers, consultants, and regulatory agencies that also operate in the AMS space. Through the AIS approach, the actors involved in an innovation system can be identified, along with possibilities for different ways of organizing the actors. Innovation systems analysis can highlight the development of agency in actors and the reduction of uncertainty in the environment in which the actors operate.

Uncertainty surrounding a smart farming innovation can occur during the early development phase, including uncertainty related to available support and finance, and around best practice when using the technology. While innovation developments are rarely associated with low uncertainty, too much uncertainty can cause stagnation in respect to the ongoing innovation process, or lead to "failure" of an innovation (Kuehne et al., 2017). Meijer et al. (2007b) describes a framework for analyzing "perceived uncertainty" in the early stage of an innovation (**Figure 1**). Few empirical studies have applied the innovation uncertainty framework to case studies (Meijer et al., 2007a; Roper and Tapinos, 2016); therefore, the novelty of our study is in relation to both the empirical survey of uncertainty factors and explaining longitudinal adoption trends.

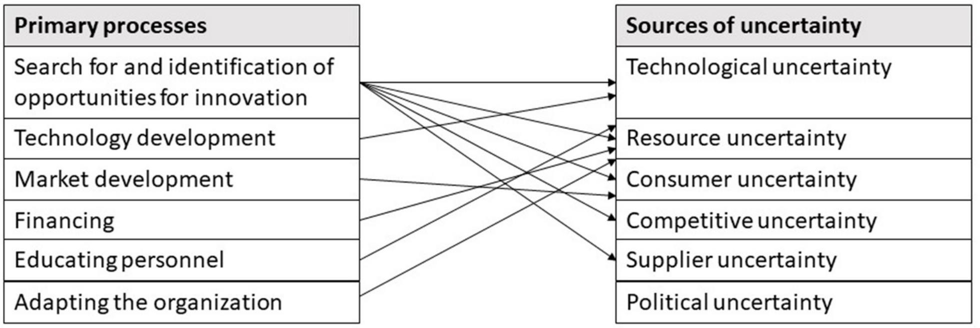

FIGURE 1 | How the primary processes are linked to six sources of uncertainty (adapted from Meijer et al., 2006).

ADOPTION OF AMS IN DIFFERENT DAIRY FARMING COUNTRIES

AMS involve the milking of dairy cows without human labor and are based on robotics and sensor technology. Since the first commercial AMS units were installed on a dairy farm in The Netherlands in 1992, there has been a range of adoption rates across different dairy farming countries. No single organization maintains statistics of the milking installations across different countries, and the information is held tightly by AMS retailers; however, some publications have provided data on installations over the last two decades (de Koning, 2010; Barkema et al., 2015; Tse et al., 2017). By 2015, there was up to 25,000 dairy farms using AMS worldwide, with the technology most popular in The Netherlands and Scandinavia (Rodenburg, 2017).

In the current paper, we focus on the "box-type" AMS rather than the robotic rotary systems that are also commercially available. In **Table 1**, we present data drawn from several sources to highlight the AMS adoption trends in dairy-producing countries where there were sufficient data from 2002 to 2018. Through to 2018, Iceland and Sweden had the greatest percentage of farms using AMS, at around 30% of farms, followed by another cluster of countries between 20 and 25% including Denmark, The Netherlands, Norway, Belgium, and Switzerland (Hogenkamp, 2018; Sigurdsson et al., 2019; Vik et al., 2019). Less data are published for other dairy countries; however, Canada (7% of farms) has seen a steady increase in installations (Tse et al., 2017). Limited data are available for the UK and USA; however, it is estimated that around 7% of farms in the UK (Hogenkamp, 2018) and 3% of farms in USA were using AMS by 2018 (Reed, 2018). There are few farms using AMS in Australia or NZ (<1% of farms). Interestingly, the data show that, in recent years, the percentage of farms using AMS in Denmark has peaked and is now declining, in part due to increasing farm sizes making other milking parlors more cost-effective (Sigurdsson et al., 2019).

TABLE 1 | Automatic milking system adoption rates from 2002 to 2018 in several dairy producing countries (% of total farms in each country, rounded to nearest 0.5%).

Country	2002	2006	2010	2014	2018	Increase since 2010 (%)
Denmark	2.2	8	22.5	24	22	−2
The Netherlands	2	4	11	18	23	109
Germany	∼0	0.5	2	6.5	15	650
Norway	∼0	1	6.5	13.5	23	254
Sweden	1	5	13	23	30	131
Canada	∼0	0.5	2	5	11.5	475

Sources: Barkema et al. (2015), Hansen (2015), Tse et al. (2017), CDIC (2019), and Vik et al. (2019).

METHODS

An online survey was designed to capture processes around AMS uptake, through three phases of the adoption process: (1) when farmers are initially thinking of investing in AMS, (2) when farmers have made the decision to invest, and (3) after they have installed and are using the AMS. The survey was conducted online via the SurveyMonkey™ platform. Closed questions were primarily used, with the number of open-ended questions limited to minimize survey length (Bryman, 2001). There were 116 questions, including demographic questions and questions on the role of the respondents and their organization in AMS development and extension, respondents' experience with AMS adoption, and patterns of AMS adoption in their country. In the current paper, we focus on a subset relevant to innovation uncertainty. The questions were developed based on AMS-related studies that had been published prior to survey design (Meskens et al., 2001; Shephard, 2004; Svennersten-Sjaunja and Pettersson, 2008; de Koning, 2010; Khanal et al., 2010). Below, we discuss the drivers for selecting AMS-related questions for each of the innovation uncertainty factors. The survey respondent answers to the questions are then listed in **Table 2**.

Technological Uncertainty

Uncertainty around the characteristics of an innovation, related infrastructural implications, the level of adaptation required, and the impact on future options are all aspects of technological uncertainty (Meijer et al., 2007b; Klerkx et al., 2010; Tomy and Pardede, 2018). Relevant factors to AMS could be the support available to farmers when making investment decisions, the

TABLE 2 | Survey questions asked in relation to the six forms of uncertainty within innovation systems [adapted from Meijer et al. (2007b)].

Uncertainty factor (Meijer et al., 2007b)	Explanation	Potential factors associated with AMS (from literature review)	Relevant statements in survey
Technological uncertainty	- Characteristics of the innovation (costs and performance) - Relation between the innovation and the infrastructure in which it is embedded - Uncertainty to what extent adaptations to the infrastructure are needed - Possibility of choosing alternative (future options)	- Technological lock-in (impact on ability to expand herd) - Transition time for cows to adapt to the new system	- Farmers are well-supported when making an AMS investment decision - Farmers understand the challenges specific to farming with AMS - Farmers understand the implications of expanding their herd size in an AMS farming system - Technological development of AMS includes a feedback loop to capture knowledge gained by farmers
Resource uncertainty	- The amount and availability of raw material, human and financial resources - How to organize the innovation process (in-house or external R&D?)	- Obtaining finance for AMS when banks are unsure of the technology - Uncertainty around future milk price - Pricing of secondhand AMS units, and ability to sell on a secondhand market	- Farmers understand the issues involved with reverting from AMS back to conventional milking (CMS) - Farmers are confident about the process for getting finance to invest in AMS - Farmers can easily determine the depreciation value for AMS units - There is certainty around the potential secondhand value of AMS units - Farmers can be confident in choosing a milk price value to use in budgets for AMS investment - It is easy to find people (staff) who suit an AMS farm - Farmers are aware of potential changes to farm staff roles and skills in an AMS farm
Competitive uncertainty	- Behavior of (potential or actual) competitors and the effects of this behavior	- Impact of competition between AMS dealers - How companies describe a competitor's product - Ability of farmers to obtain independent advice	- When deciding which AMS units to purchase, farmers can obtain sufficient knowledge about features of different AMS products from company sales staff - Farmers can easily obtain independent advice prior to an AMS investment - Support is available for farmers through industry extension programs
Supplier uncertainty	- Actions of suppliers (timing, quality, and price of delivery)	- Access to quality and timely service - An understanding of ongoing costs associated with AMS	- There is a ready supply of AMS units to supply market demand - Farmers are aware of the after-sales technical service they will receive from their AMS supplier (e.g., breakdowns) - Farmers are aware of the after-sales learning support they will receive their AMS supplier (i.e., how to run a dairy farm using AMS) - Farmers are aware of where to go for advice on running their AMS farm
Consumer uncertainty	- Consumer preferences with respect to the innovation - Consumer characteristics - Long-term development of the demand over time	- Understanding the type of farmer who matches well with AMS farming systems - Clarity on the long-term demand would help other manufacturers invest in AMS	- The types of farmers suited to AMS are well-known by the industry - The future pattern of AMS adoption is certain - Technological development of AMS is well-matched with farmer requirements - The capacity of farmers to succeed with AMS is considered in the sale process
Political uncertainty	- Current policy (interpretation or effect of policy, lack of regulation), future changes in policy, reliability of government	- Regulation over milk quality and food safety - General public support for AMS - Not so much political as agri-food regulatory	- Current regulations (e.g., milk quality, food safety) act to make farming with AMS easier - Farmers are aware of regulations that specifically relate to use of AMS - Farmers know how to comply with regulations relevant to AMS - Public sector financial incentives have increased AMS adoption - Public sector learning support has helped farmers learn to use AMS - The dairy community is well-aware of potential future regulations related to AMS

degree of technological lock-in (including the ability to expand herd sizes), and the specific challenges of adapting farming systems to AMS.

Resource Uncertainty

This factor focuses on the availability of resources, such as human, financial, and material, and also encompasses organization of the process of innovation (Meijer et al., 2007b). The uncertainty around forecasting resources and capital required for the innovation involves factors such as availability of knowledge and skills, required R&D expenditure, and potential revenue streams (Tomy and Pardede, 2018). In an AMS context, resource uncertainty could relate to the ability to get finance for the AMS investment, uncertainty around milk price and its impact on viability, along with other factors such as uncertain pricing of secondhand AMS technology and how to revert to previous milking methods.

Competitive Uncertainty

The behavior of competitors in the innovation system can affect its success (Meijer et al., 2007b). Factors behind this uncertainty can include level of market share, the impact of leading competitors, and the type of competition in the market (Tomy and Pardede, 2018). This relates to the competition between retailers of AMS technology (i.e., is there sufficient competition in a market dominated by two main players?) and how each competitor might refer to each other's product. We assessed this by asking questions around the availability of independent advice on technology, the adequacy of advice provided by technology retailers, and what industry support was available to farmers.

Supplier Uncertainty

This source of uncertainty relates to perceptions around the reliability of the supplier (Meijer et al., 2007b). In respect to AMS, we asked questions around the availability of AMS technology (was there sufficient supply to match demand), the access that farmers had to back-up service for both technical and learning support, and whether farmers knew where to access advice about farming with AMS.

Consumer Uncertainty

Consumer uncertainty concerns the preferences consumers might have for an innovation, the characteristics of consumers, and the development of demand for the technology (Meijer et al., 2007b). It also includes factors associated with knowledge of consumer acceptance of the technology, and the potential changes in demographics of the target population and therefore potential market size (Tomy and Pardede, 2018). These features are more applicable to entrepreneurs looking to work with consumers (farmers) rather than the consumers themselves. Therefore, for this factor, we asked industry-related questions such as uncertainty around future patterns of AMS adoption, the nature of technological development, whether farmer ability to succeed was included in the design and sale process, and the fit of AMS with farmer typologies. This is one aspect of the framework that potentially has less applicability when taking the farmer perspective in an AMS innovation system.

Political Uncertainty

The policy environment can have a major impact on the innovation process, for example, the interpretation of policy, existence of regulations, and uncertainty regarding government and policy changes (Meijer et al., 2007b). It also includes the potential impact of government support for the innovation, the impact of exchange rates, and taxation that may relate to the innovation (Tomy and Pardede, 2018). In respect to AMS, this may include the implications of milk quality and food safety regulations, general political and community support for AMS, the awareness of regulations, and the existence of incentives.

The survey design incorporated the framework derived from Meijer et al. (2007b) and Klerkx et al. (2010) to assess the impact of uncertainty in the AMS innovation system. For each of the uncertainty factors, a series of statements were developed by the project team (**Table 2**), and participants were asked to indicate to what extent they agreed or disagreed with each statement, based on a five-point Likert scale from 1 = strongly disagree to 5 = strongly agree.

A pilot of the survey was run with five experienced AMS researchers from New Zealand, The Netherlands, USA, England, and Australia. Feedback from the pilot group was incorporated into the final survey design. Participants in the full survey were chosen to represent a range of those in the network of practice of AMS farmers internationally including: AMS researchers, technology developers, and sales/support representatives. Actors in the research and service/support sectors were targeted primarily due to language differences across the countries surveyed. The project team decided that people from these sectors were more likely to engage and complete the extensive English-based survey. The survey was therefore designed for these actors to use their knowledge of both farmer experiences, and innovation system-wide issues, to answer the questions posed.

Contacts were sourced initially through researcher networks, and then a snowball method was used (Bryman, 2001). The study was approved by the University of Melbourne Human Research Ethics Committee (HREC), and a plain language statement outlining the project aims, funders, use of data, and key contacts was provided on the opening survey page. If participants consented to participate, they were invited to click "next" to enter the survey.

The survey weblink was sent out twice to those on the contact list. Results were exported as a.csv file and imported into Microsoft Excel™ Data were reviewed for quality and completeness and any erroneous responses were removed. The data were analyzed for interactions using multivariate statistics, but no strong associations were found; therefore, we focused the analysis on counts and summary statistics.

RESULTS

In this section we outline the key results, beginning with an overview of the survey participant demographics, their experience and opinions related to AMS, and finally the results of questions related to the uncertainty factors.

Survey Participants

There were 84 survey responses of which three were removed due to incomplete responses; therefore, 81 responses were used in the analysis. The major countries represented were Canada (24), The Netherlands (14), USA (10), Denmark (7), and the UK/Ireland (6). Other countries represented were Germany (4), Sweden (3), Israel (2), Norway (2), and Switzerland (2). There was one representative from each of Finland, France, Ireland, New Zealand, India, Iceland, and Japan. The respondents were primarily male (89%) and 63% were aged 35–54.

There was a range among respondents when it came to their day-to-day experience with AMS farmers with 27 stating it was "a major part of my job," 27 said it was "often part of my job," and 26 a "small part of my job." There was a similar mix in respect to years of experience that respondents had with AMS farms and farmers with 27 having over 10 years' experience, 27 had 5–10 years' experience, and 27 had <5 years' experience. There were 36 respondents from AMS retailers and 45 respondents not from AMS retailers (36 from public or industry funded research and advisory organizations, and 9 from privately funded advisors or consultants). In answering the survey questions, the respondents drew from experience that ranged from working with 1 farm to 1,000 farms. Most respondents interacted with between 20 and 100 farmers. The responses for each country, grouped by role (retailer vs. non-retailer) and experience, are shown in **Table 3**.

Of non-retailer respondents who were in a publicly funded research/advisory position, or identified as consultants, most were aligned with research. Many also provided general farm management advice to farmers and to a lesser extent helped farmers before and after AMS installation. Providing technical support was generally a small part of their role.

Survey Responses

How Respondents Perceived Their Role in the AMS Innovation System

The AMS retailer representatives who completed the survey primarily described their role as helping farmers learn to use AMS, along with providing technical support. A smaller part of their jobs in general was actively selling AMS or installing the equipment. They indicated that the organization they worked for had a wider role from installing equipment, providing pre-sale and after-sales support. In terms of their AMS skill base, the company representatives indicated they learned slightly more through practical experience and interacting with farmers than via specific training. They were generally happy with their skill levels but felt they could learn more about farm management. The roles of non-retailers were less focused on technical support, and more on delivering AMS-related research and development knowledge, providing farmers with support prior to AMS investment, and providing general farm management advice. Few non-retailers (22%) had been specifically trained in supporting farmers using AMS, compared to 77% of retailers. Around half of non-retailers (49%) agreed that they were happy with their skills and knowledge related to AMS, compared to 71% of retailers. Both cohorts agreed they learned through interacting with AMS farmers (non-retailers 86% and retailers 91%). Additionally, they also agreed that they needed to learn more about farm management associated with AMS (non-retailers 67% and retailers 71%).

Respondents were asked about their opinions of the impact and future role of AMS in the dairy sector (**Table 4**). Most (87%) agreed that AMS required farmers to make significant changes to their farm systems, and responses were relatively consistent between retailers and non-retailers. Respondents also agreed (80%) that AMS represented the biggest transformation in dairy farming in the last 50 years. When asked if AMS would become the dominant milk harvesting method, most agreed (69%), and more retailers strongly agreed (53% compared with 30%).

Perceptions on AMS Investment, Past, and Future

The most significant reasons for past AMS investment by farmers were identified as reducing total farm labor, reducing hours spent milking, more family time, and to reduce physical work. Improving milk quality, increasing production, and sustaining the farm business were not seen as overly important. Main reasons for farmers *not* investing were identified by respondents to be the cost of technology and to a lesser extent issues around herd expansion, difficulty obtaining finance, fit with farm system, and experiences of other farmers. Less of an issue were farmer perceptions of management issues during transition and availability of advice for farmers during the investment decision.

Respondents noted some decommissioning of AMS farms, although most respondents classified it as a "rare" occurrence. Countries where more than 10 decommissioned AMS farms had been observed included Denmark, The Netherlands, and the UK but this needs to be viewed in the context of the total number of AMS units in these countries and their position as sites of early adoption in the 1990s before the technology was mature. Reasons for decommissioning suggested by respondents included economic factors leading to bankruptcy (farm or company), initial lack of knowledge about using AMS and availability of support, initial technology issues (mostly in the 1990s), need for large herd flexibility, and lack of fit with farmers (incompatible expectations or skills). Specific comments of respondents highlighted the range in adoption trajectories in the first 10–15 years of AMS use (i.e., up to 2010). Below, we outline comments of respondents from The Netherlands (a mature market) and Canada (an emerging market) in relation to the adoption trajectories.

In The Netherlands, a mature AMS market at the time of surveying, respondents identified that in the early installations, there were technical problems and skepticism among farmers that automated milking was possible. Factors that led to greater uptake were more trust in the technology, a period of higher milk prices, the ability to have increased work flexibility, and more understanding among farmers of how to run AMS-based farm systems. There were up to five different AMS suppliers in The Netherlands. Comments made by some respondents were as follows:

TABLE 3 | Number of respondents by country where they are primarily based compared to role and years of experience with AMS.

	Canada	USA	The Netherlands	Denmark	UK/Ireland	Other	Total
Role							
Retailer	21	8	5	0	2	0	36
Non-retailer	3	2	9	7	5	19	45
Total	*24*	*10*	*14*	*7*	*7*	*19*	*81*
Years of experience working with AMS							
Less than 5	10	3	6	1	3	4	27
5 to 10	12	5	2	3	1	4	27
More than 10	2	2	6	3	3	11	27
Total	*24*	*10*	*14*	*7*	*7*	*19*	*81*

TABLE 4 | Respondent opinions regarding the impact of AMS on dairy farming. Results are presented as percentages, with retailer, non-retailer in brackets, respectively.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Impact of AMS on dairy farming					
Requires farmers to make significant farming system changes	0 (0,0)	7 (11,5)	6 (3,9)	28 (31,25)	59 (55,61)
AMS is the biggest transformation in dairy farming in the last 50 years	1 (0,2)	11 (8,14)	8 (11,5)	33 (28,37)	47 (53,42)
I expect AMS to become the dominant method of harvesting milk	1 (3,0)	14 (8,18)	16 (22,11)	29 (14,41)	40 (53,30)

TABLE 5 | Respondent opinions regarding the future adoption of AMS from 2011 to 2015, presented as percentages.

	All respondents	All retailer	All non-retailer	Canada	USA	The Netherlands	Denmark	UK/Ireland
Decreasing	1.3	0	2.3	0	0	0	14.3	0
Steady at current rate	13.0	5.9	18.6	8.7	0	16.6	28.6	14.3
Increasing	62.3	58.8	65.1	60.7	50	66.7	57.1	57.1
Rapidly increasing	23.4	35.3	14.0	30.4	50	16.7	0	28.6

"At the moment approximately 1 out of 2 new [milking] machines is an AMS, quite popular among the family farms. Larger farms (>200 cows) often decide to have a rotary parlor or large rapid exit side by side or herringbone parlors." (Netherlands, non-retailer)

"In the first 5–10 years, AMS was bought mainly by early adopters, sometimes farmers who were very interested in the technology. In the recent decade this changed to farmers interested in optimizing individual cow management by using this technology." (Netherlands, non-retailer)

In Canada, an emerging AMS market at the time of surveying, respondents noted a pattern of some installations, then a "tapering off" or some deinstallation, followed by a more rapid increase around the time of the survey. This was for a variety of reasons including after-sales service quality, poor understanding of the farm systems (in particular feeding) changes required, and farm economic issues. There were three different AMS suppliers in Canada. Comments made by some respondents were as follows:

"In the beginning we did not understand robotic milking correctly in Canada. We had to learn how to be successful. Robots were pulled out and this slowed the sales process for about three years. Robot knowledge then became better and the units themselves continued to progress. We now know that robotics work. We also know that it only works with some farmers and we have to be very careful who we sell to." (Canada, retailer)

"The first robots were pulled out because we did not understand robotic milking fully. A learning curve had to happen and feeding strategies in Canada needed to be implemented to make sure the robots ran successfully" (Canada, retailer)

We also asked questions about predictions for future adoption and the predicted adoption trajectories are presented in **Table 5**. Across all respondents, 62% of respondents thought AMS uptake in their country would increase over the next 5 years, and another 23% thought it would rapidly increase. There was more confidence in the level of increased AMS adoption among retailers in comparison to non-retailers, with 35 and 14% expecting a rapid increase, respectively. Expectations of a rapid increase were also greater in the emerging markets of Canada and USA, when compared with the more mature markets of Denmark and The Netherlands. Increased labor costs were seen as a major future driver, along with increased confidence in AMS. Possible factors holding back AMS use was incompatibility with increased herd size and fluctuations in milk price or the farm economic environment.

Comments of respondents from The Netherlands (mature market) indicated that future adoption would be driven by higher farm labor costs, a desire to maintain family farming, and well-being factors. One limitation to adoption identified in The Netherlands was farm expansion, with herds of over 200 cows seen as a point where farmers considered other milking technologies such as a rotary or herringbone parlor. Canadian respondents felt that there would be more installations in the future. The reasons behind this were related to generational change on farm (younger farmers would invest in AMS to have more social time), it has become more reliable and trusted among farmers, and a lack of available agricultural workforce. One respondent noted that "With new anti-expansion quota policies several larger dairies are now considering robots as well."

Role of Innovation Uncertainty on AMS Adoption Trends

Responses to survey questions related to different uncertainty factors are summarized in **Table 6** and displayed in **Figures 2–4**. The results are summarized across all respondents, by role, and by country. The countries listed represent those with the most responses in the survey, and show mature AMS markets (The Netherlands, Denmark) and emerging markets (UK/Ireland, USA, Canada). Below, each individual factor is numbered and we refer to them in the text from F1 to F28.

Technological uncertainty

There were four questions related to technological uncertainty. Retailers were more positive when scoring these factors (average 3.9), compared with non-retailers (3.4), with the most divergence regarding whether farmers were well-supported when deciding to invest in AMS. The most agreement between these groups was in relation to farmers understanding the farm system challenges associated with AMS, with both cohorts being less positive for this factor (3.2 and 3.4). In terms of responses from different countries, respondents from The Netherlands and Canada had the most positive responses (4.0 and 3.8, respectively) with a 3.0 average for UK respondents. The UK respondents did not agree that farmers were well-supported in making investment decisions (2.3) or that farmers understood the challenges of AMS (2.8)—particularly compared with Dutch responses to these factors, 3.8 and 4.0, respectively.

Competitive uncertainty

Retailers and non-retailers provided the same average responses to the competitive uncertainty factors (3.2), but there was divergence among the individual factors, for example F6 where retailers agreed (4.5) that farmers can obtain sufficient knowledge about different AMS features, whereas non-retailers were more neutral (3.3). Conversely for F7, retailers (2.0) did not think support was available through industry extension initiatives, while non-retailers were more neutral (2.7). In respect to responses by country, UK respondents again were less positive on average (2.6), with The Netherlands most positive (3.8). The mature markets (The Netherlands 4.3, Denmark 4.3) agreed that farmers could easily obtain independent AMS advice (F5), compared with neutral responses from emerging markets (UK 2.7, USA 2.7, Canada 3.1). There was a similar trend for F7 on industry extension initiatives.

Consumer uncertainty

Retailers were more positive about the two consumer uncertainty factors (F8 and F9) than non-retailers, particularly in relation to whether the capacity for farmers to succeed with AMS was considered in the sale process. Additionally, respondents from countries in mature AMS markets provided overall neutral (3.0) responses while emerging markets showed a higher level of agreement with both factors (USA 4.2, Canada 3.6).

Resource uncertainty

There were seven factors related to resource uncertainty, and the average response for all respondents was neutral (3.1), with limited difference in the average between non-retailers and retailers. Dutch respondents (3.6) were slightly more positive than respondents from other countries. In terms of the individual factors, retailers (3.9) and non-retailers (2.5) differed most about whether farmers could confidently choose a milk price for their budgets. Overall, there was most disagreement (2.7) that farmers understood about reverting back to conventional milking, with respondents from UK/Ireland providing a rating of 2.3. Dutch respondents agreed most strongly that farmers were confident about getting finance (3.9), could determine depreciation values (4.0), were certain around secondhand AMS markets (4.0), and were aware of staff roles with AMS (4.0). Respondents from Denmark (1.6), UK/Ireland (1.8), and USA (2.0) most strongly disagreed that farmers could be confident on milk prices for their budgeting.

Supplier uncertainty

Retailers agreed more strongly with the factors related to supplier uncertainty, with an average rating of 4.2 compared with 3.4 for non-retailers. There was most divergence about whether farmers were aware of after-sales service by AMS suppliers (retailer 4.5, non-retailer 3.6) and the learning support they will receive from AMS suppliers (retailer 4.0, non-retailer 2.7). UK/Ireland respondents provided the lowest average rating (3.1) to supplier factors and, along with Dutch respondents, gave a low rating for farmer knowledge of learning support they would receive from AMS providers (2.8 UK/Ireland, 2.6 Netherlands). The most agreement for individual factors were from Danish respondents who felt there was a ready supply of AMS units (4.7) and Dutch respondents who agreed strongly that farmers were aware of the technical service they would receive (4.8).

Political uncertainty

The factors associated with political uncertainty were rated the lowest of all the uncertainty areas at an average rating of 2.5. There was little difference between retailers (2.4) and non-retailers (2.6). The lowest rated individual factor was F26, that public sector financial incentives have increased AMS adoption. On average, respondents from most countries disagreed that current regulations acted to make farming with AMS easier (F23), in particular USA (1.7) and UK/Ireland (2.5). Respondents across role and different countries were all neutral as to whether farmers were aware of regulations relating to AMS use (F24). While respondents from Denmark agreed (3.6) that the dairy community was aware of future regulations related to AMS (F28),

TABLE 6 | Average responses to questions for the six innovation uncertainty categories, by role and country (scale of 1–5 where 1 = strongly disagree, 5 = strongly agree).

	All	Responses by role		Responses by country				
		Retailer	Non-retailer	The Netherlands	Denmark	UK/Ireland	USA	Canada
All factors ("F1-28")		3.8	3	3.5	3.1	2.8	3.1	3.3
Technological uncertainty								
1. Farmers are well-supported when making a decision about AMS investment	3.6	4.3	3.2	3.8	3.6	2.3	3.6	4.2
2. Farmers understand the challenges specific to farming with AMS	3.3	3.2	3.4	4.0	3.3	2.8	2.9	3.2
3. Farmers understand the implications of expanding their herd size in an AMS farming system	3.7	4.0	3.5	4.2	3.1	3.3	3.5	4.1
4. Technological development of AMS includes a feedback loop to capture knowledge gained by farmers	3.8	4.1	3.7	3.9	4.0	3.3	4.4	3.6
Average for factor	*3.6*	*3.9*	*3.4*	*4.0*	*3.5*	*3.0*	*3.6*	*3.8*
Competitive uncertainty								
5. Farmers can easily obtain independent advice prior to an AMS investment	3.4	3.1	3.6	4.3	4.3	2.7	2.7	3.1
6. When deciding which AMS units to purchase, farmers can obtain sufficient knowledge about features of different AMS products from company sales staff	3.8	4.5	3.3	4.3	2.6	3.2	4.4	4.4
7. Support is available for farmers through industry extension programs	2.5	2.0	2.7	2.8	3.7	2.0	2.0	2.0
Average for factor	*3.2*	*3.2*	*3.2*	*3.8*	*3.5*	*2.6*	*3.0*	*3.2*
Consumer uncertainty								
8. The capacity of farmers to succeed with AMS is considered in the sale process	3.3	3.8	2.9	2.8	2.7	3.8	4.2	3.4
9. The future pattern of AMS adoption is certain	3.4	3.9	3.1	3.3	3.3	3.2	4.2	3.7
Average for factor	*3.4*	*3.9*	*3.0*	*3.0*	*3.0*	*3.5*	*4.2*	*3.6*
Resource uncertainty								
10. Farmers understand the issues involved with reverting from AMS back to conventional milking (CMS)	2.7	2.7	2.6	2.6	3.1	2.3	3.0	2.7
11. Farmers are confident about the process for getting finance to invest in AMS	3.1	3.4	3.0	3.9	2.6	2.3	2.1	3.8
12. Farmers can easily determine the depreciation value for AMS units	2.8	3.1	2.7	4.0	2.9	3.5	2.8	2.6
13. There is certainty around the potential secondhand value of AMS units	3.1	3.0	3.1	4.0	2.7	3.8	2.7	2.8
14. Farmers can be confident in choosing a milk price value to use in budgets for AMS investment	3.0	3.9	2.5	3.2	1.6	1.8	2.0	4.5
15. It is easy to find people (staff) who suit an AMS farm	3.0	3.0	2.9	3.8	2.6	2.2	2.6	3.0
16. Farmers are aware of potential changes to farm staff roles and skills in an AMS farm	3.8	4.0	3.7	4.0	4.0	3.8	3.7	3.9
Average for factor	*3.1*	*3.3*	*2.9*	*3.6*	*2.8*	*2.8*	*2.7*	*3.3*
Supplier uncertainty								
18. There is a ready supply of AMS units to supply market demands	4.1	4.4	3.9	3.9	4.7	3.3	4.2	4.3
19. Farmers are aware of the after-sales TECHNICAL SERVICE they will receive from their AMS supplier	3.9	4.5	3.6	4.8	3.3	3.2	4.2	4.4
20. Farmers are aware of the after-sales LEARNING SUPPORT they will receive from their AMS supplier	3.2	4.0	2.7	2.6	3.4	2.8	3.4	3.9
21. Farmers are aware of where to go for advice on running their AMS farm	3.7	4.1	3.4	4.1	3.7	3.0	3.9	3.9
Average for factor	*3.7*	*4.2*	*3.4*	*3.9*	*3.8*	*3.1*	*3.9*	*4.1*
Political uncertainty								
23. Current regulations (e.g., milk quality, food safety) act to make farming with AMS easier	2.4	2.5	2.3	2.7	3.3	2.5	1.7	2.6

(Continued)

TABLE 6 | Continued

	All	Responses by role		Responses by country				
		Retailer	Non-retailer	The Netherlands	Denmark	UK/Ireland	USA	Canada
24. Farmers are aware of regulations that specifically relate to use of AMS	2.9	2.9	2.8	3.0	2.9	3.0	2.9	2.9
25. Farmers know how to comply with regulations relevant to AMS	2.9	2.9	2.9	3.4	2.6	2.8	2.9	3.1
26. Public sector financial incentives have increased AMS adoption	2.1	1.8	2.3	2.8	1.7	1.8	1.4	2.1
27. Public sector learning support has helped farmers learn to use AMS	2.3	2.1	2.5	2.9	2.4	1.8	2.0	2.3
28. The dairy community is well aware of potential future regulations related to AMS	2.5	2.3	2.6	2.4	3.6	2.5	2.0	2.4
Average for factor	*2.5*	*2.4*	*2.6*	*2.9*	*2.7*	*2.4*	*2.2*	*2.5*

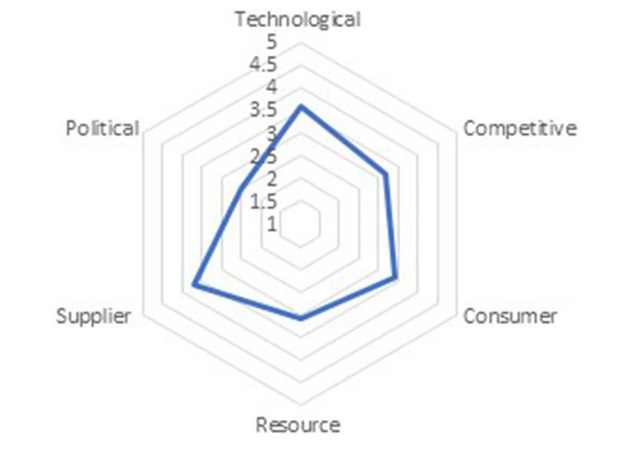

FIGURE 2 | Average factor scores for the six uncertainties across all responses (scale of 1–5 where 1 = strongly disagree, 5 = strongly agree).

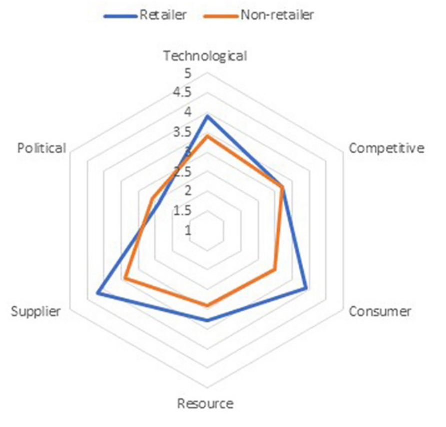

FIGURE 3 | Average factor scores for the six uncertainties across roles (retailer and non-retailer) (scale of 1–5 where 1 = strongly disagree, 5 = strongly agree).

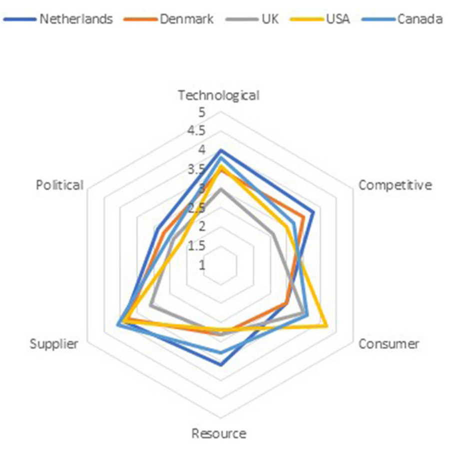

FIGURE 4 | Average factor scores for the six uncertainties across countries (scale of 1–5 where 1 = strongly disagree, 5 = strongly agree).

respondents from all other countries disagreed (2.0–2.5). On average, respondents from USA disagreed the most (2.2) with the factors related to political uncertainty.

DISCUSSION

In this paper, we aimed to understand the impact of innovation uncertainty adoption of AMS internationally and propose lessons for developing institutional knowledge and effective networks of practice in emerging smart farming innovation systems.

Major Themes Associated With Predicted AMS Adoption

Survey responses in this current study indicated a range of influences on potential AMS adoption. While historical adoption had been negatively influenced by financial factors such as low milk prices and the 2008 financial crisis, there were examples of technological uncertainty affecting early installations and perceptions of these issues by other farmers. Respondents identified some examples of decommissioning, which created a level of uncertainty in the local farming population about the suitability of AMS. Farmers in early adopting countries (e.g., The Netherlands and Denmark) had some issues with learning to use AMS successfully, in some cases farmer skills and perceptions did not fit with AMS. The historical adoption factors associated with AMS identified in our study, such as reducing total farm labor, reducing hours spent milking, more family time, and reducing physical work, are supported by several authors (de Koning, 2010; Jacobs and Siegford, 2012; Hansen, 2015; Rodenburg, 2017; Vik et al., 2019).

In our study, we examined the predicted AMS adoption and the potential reasons for this among a group of experts. Almost all respondents predicted increased AMS adoption, with almost a quarter predicting a rapid increase. Understandably, this expectation of a rapid increase was higher among those selling AMS technology. Analyzed by country, respondents expected a slower adoption rate in Denmark and The Netherlands, when compared with Canada and USA. The data presented in **Table 1** mostly agree with these predictions. Danish AMS installations have not increased from 2010 to 2018, and in recent years have actually decreased. However, installations in The Netherlands and Sweden doubled from 2010 to 2018, and there have been dramatic increases in countries such as Germany (650%), Canada (475%), and Norway (250%)—albeit off a relatively low 2010 base. Of the emerging markets in our survey, USA still shows a low level of adoption, with an estimated 3% of farms. This could be primarily due to the farm system types and sizes employed there, and relatively low labor costs. The number of large farms has previously been highlighted as a barrier to AMS adoption in USA by Jacobs and Siegford (2012), and increased farm size is also having an impact in countries such as Denmark and Norway (Sigurdsson et al., 2019; Vik et al., 2019). However, the information presented in our survey adds weight to the need for alternative automated milking approaches for larger farm systems, such as robotic rotaries and stand-alone robotic cup attachment systems that work in rotary parlors. We further explore the potential reasons for the different adoption trajectories in section The Impact of Uncertainty on AMS Adoption below.

The Impact of Uncertainty on AMS Adoption

Respondents were most positive toward factors associated with *technological* and *supplier* uncertainty. This indicates that at the time of the survey, the AMS technology was relatively mature and reliable, but in some countries, the knowledge associated with AMS use in different farm systems was not so developed. In this study, respondents felt that farmers were well-supported when making AMS investment decisions but were not always certain of the implications AMS had on farm systems challenges such as expanding their herd size, or reverting back to a conventional milking system (Hansen, 2015). The survey results therefore provide insights into the development and potential future adoption of AMS, including the need for greater certainty around issues of technological lock-in (where farmers face difficulties reversing technology investment decisions) and the forms of after-sales support required (for example, managing the farm systems changes related to AMS use).

There was most potential uncertainty around *political* factors, with ratings lowest among USA respondents. The political environment can have a large impact on innovations such as AMS through even apparently minor regulations or policies. One example highlighted in comments by respondents was food safety regulations in Europe requiring a person to be present at milking, which was not feasible under the 24 h milking cycle of AMS. Altering these regulations can take considerable effort and can act to discourage farmers. Other institutional arrangements can also be affected, for example, herd test protocols that require two milk samples at 12 h intervals have had impacts on the ability of AMS farmers to participate in herd improvement schemes (Eastwood et al., 2017b). Political factors have also been highlighted as driving industry structural change that can impact smart farming adoption such as AMS (Vik et al., 2019).

Respondents perceived a lack of awareness among farmers as to future regulations that may have an impact on AMS use and felt that farmers were moderately aware of the current regulations that are related to AMS use. There was a strong perception that current regulations did not act to make farming with AMS easier. There was also a perception that financial incentives at an industry level had not played a role in the uptake of AMS. In terms of the role of public and industry good organizations, respondents identified a lack of industry-level extension programs related to AMS use but perceptions were mixed as to whether there was a role for the dairy industry or public organizations in the learning support space. Smart farming technology is dominated by commercial interests, which has been shown to have implications for private and public R&D roles in terms of supporting adoption (Eastwood et al., 2017b; Klerkx et al., 2019). This tension was also highlighted by respondents in factors related to *competitive* uncertainty, with an indication that sourcing independent advice on AMS technology was difficult for farmers in the emerging markets of Canada, USA, and the UK. Farmer uncertainty about adopting AMS and the lack of service providers for technical support were also found to be an issue in USA by Jacobs and Siegford (2012).

Responses related to supplier uncertainty highlighted differences between retailers and non-retailers. Retailers were much more positive that farmers were receiving good technical and learning support. The ratings showed that while farmers could be certain about the extent of technical support they will receive, they may be less aware of the learning support available from their retailer. This retailer focus on technical support is common in the smart farming domain (Eastwood et al., 2016). However, this can be compensated by farmers having access to AMS farming system advice from other agents in the innovation system, but these skills take time to build. For example, a network of farm system advisors took two decades to develop in The Netherlands, primarily because a certain AMS market size was needed to make it worthwhile for advisory firms to upskill (Eastwood et al., 2017b).

When investing in smart farming technology, farmers need a clear value proposition and business case, which in turn requires more transparent sharing of financials and robot performance by farmers and retailers (Rojo-Gimeno et al., 2019). In terms of our factors related to resource uncertainty, respondents perceived relative certainty for farmers accessing finance for AMS, but that ascertaining the depreciation value of the technology was more difficult. This was more of an issue in the emerging markets, as the mature markets had more knowledge of AMS performance, and potentially more experience with use of secondhand AMS units. Additionally, in some countries, the uncertainty around future milk prices could impair the ability to create robust investment cases for smart technologies. It is interesting to note that AMS retailers indicated much more confidence in predicting milk prices than non-retailers, potentially indicating undue optimism in the sales process.

Usefulness of the Perceived Uncertainty Framework

The framework of Meijer et al. (2007b) provided a good lens with which to look at the AMS issues internationally. While most of the factors of uncertainty were relevant to the "farmer as entrepreneur" perspective adopted in our analysis, some of the factors relate better to other actors in the network. For example, consumer uncertainty relates more to technology providers and their uncertainty of the farmers' needs or to consultants and their uncertainty whether there is a business case for them to become involved. Use of the framework highlighted clear differences between technology retailers in specific aspects, and therefore, the framework could be used with other smart farming technologies to assess where potential issues occur between retailer and non-retail actors.

Difficulties we encountered with an empirical investigation using the framework factors involved first determining robust factors that related to each area of uncertainty. While we developed these within the research team, and tested them in a pilot, they would benefit from further refinement subsequent to this study. Additionally, with such survey methods in a niche research area, achieving sufficient responses is difficult. In our study, we concentrated on results from countries with the most respondents, but further empirical studies using this framework would benefit from greater targeting of respondents.

Implications for Minimizing Uncertainty Related to Smart Technologies in Agriculture

This current study indicates some lessons for the configuration of smart farming innovation systems. In the case of AMS, the dominant forms of uncertainty uncovered across all respondents were in the resource and political domains, a finding supported by another study of uncertainty in technological start-ups (Tomy and Pardede, 2018). In particular, we identify a need for further discussion regarding the role of private providers of advice to farmers, and the related role of public or industry good AMS support programs. Our study indicates that development of commercial roles for consultants in providing advice to AMS farmers took some time to occur in the established markets in Europe, a finding supported by Eastwood et al. (2017b). In relation to smart farming technologies generally, the potential role of farm advisors in reducing innovation uncertainty has been highlighted in other studies (Ayre et al., 2019; Eastwood et al., 2019). There exists a significant opportunity for farm advisors to support farmers, so they get the most from their technology investments, requiring more focus from public R&D in the smart farming domain.

Our survey results highlighted a difference in perceptions between technology retailers and other actors in the technological innovation system, particularly around factors related to supplier and consumer uncertainty. The smart farming domain is dominated by private R&D (Eastwood et al., 2017b; Klerkx et al., 2019) and therefore the pressures of being first to market, providing a return on agtech venture capital, and achieving sufficient sales in a niche market can lead to ambitious marketing. This may result in development of smart technologies without a full understanding of market (farmer) needs (i.e., consumer uncertainty) and lack of focus on after-sales service that helps farmers integrate the technology into their farming system context (i.e., supplier uncertainty). It is therefore vital that commercial interests, farm advisors, and public R&D actors foster a collaborative approach to development and support of smart farming technologies (Ayre et al., 2019; Phillips et al., 2019). The need for collaborative approaches is especially the case where technologies are brought together in platforms (e.g., via artificial intelligence) to solve dynamic and complex agricultural problems (Hermans et al., 2019).

We identified an impact of immature AMS technology being marketed to farmers, and AMS technology being sold to farmers who did not have the capability or mindset to adapt their farm systems to suit. This resulted in instances of decommissioning, or reverting to conventional milking technology, and had a subsequent impact on farmer (and advisor) confidence in the technology. This experience highlights an important consideration for smart farming innovation uncertainty. Agricultural NGOs and governments are increasingly viewing smart farming as a tool for improvements in productivity and sustainability of agriculture. However, our study highlighted the potential impact of negative experiences associated with new technologies from farmers who struggle with the adaptation process as such occurrences may act to stall the uptake of smart farming technologies. If public policy organizations are to realize the desired impacts of smart farming technology, there needs to be greater focus on understanding where (and which) technologies can have an actual impact on farm (Shepherd et al., 2018), as opposed to technologies that only create greater farmer distrust and uncertainty (Jakku et al., 2018; Klerkx et al., 2019).

Limitations of the Approach

The approach used in this paper involved an online survey with a targeted snowball method where domain experts were first identified and then asked to distribute the survey among their networks. The target population (researchers and professionals with knowledge of AMS) was relatively small and dominated by commercial technology and service providers who are often difficult to access in research projects.

This research represented an exploratory approach to use the innovation uncertainty framework to describe major influences on AMS adoption in different countries. The questions were developed by the project team, and tested in a pilot survey, and therefore represent a best design of the appropriate questions. However, the questions could be open to interpretation of individual participants.

CONCLUSIONS

In this paper, the concept of perceived uncertainty in innovation systems was used to examine the adoption of automated milking systems, a smart farming technology. The major drivers for farmers adopting AMS included reducing total farm labor, hours spent milking, and the amount of physical work, while also having more family time. Adoption was perceived to be negatively impacted by the cost of technology and issues around future herd expansion, difficulty obtaining finance, fit with farm system, and negative experiences of other farmers. This study adds to limited literature focused on empirical analysis of the role of uncertainty in using factors associated with perceived uncertainty; we were able to analyze the AMS innovation system across different countries and institutional contexts and use this to determine implications for smart farming technology adoption. We highlighted perceived impacts of political uncertainty, and the impact of technological uncertainty around not only immature smart farming technologies but also the on-farm adaptation that such technologies can require. We also suggest that to reduce uncertainty with emerging smart technologies, greater effort is required to foster knowledge development and exchange. In emergent markets for smart farming technologies, there is a public or industry-good role in delivering broad knowledge development and capability building programs focused on key actors such as nutritionists, veterinarians, banking finance representatives, and agricultural consultants.

DATA AVAILABILITY STATEMENT

Restrictions apply to the datasets: The datasets for this article are not publicly available to protect the anonymity of respondents. Requests to access the datasets should be directed to Callum R. Eastwood, callum.eastwood@dairynz.co.nz.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Human Ethics Advisory Group—The University of Melbourne. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

Research method and data collection were undertaken by CE. Data analysis, writing, and revision of the manuscript were undertaken equally by CE and AR.

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REFERENCES

Ayre, M., Mc Collum, V., Waters, W., Samson, P., Curro, A., Nettle, R., et al. (2019). Supporting and practising digital innovation with advisers in smart farming. *NJAS-Wagen. J. Life Sci.* 90:100302. doi: 10.1016/j.njas.2019.05.001

Barkema, H. W., von Keyserlingk, M. A. G., Kastelic, J. P., Lam, T. J. G. M., Luby, C., Roy, J. P., et al. (2015). Invited review: changes in the dairy industry affecting dairy cattle health and welfare. *J. Dairy Sci.* 98, 7426–7445. doi: 10.3168/jds.2015-9377

Bryman, A. (2001). *Social Research Methods.* Oxford: Oxford University Press.

CDIC (2019). *Dairy Barns by Type in Canada*. Canadian Dairy Information Centre. Available online at: https://www.dairyinfo.gc.ca/index_e.php?s1=dff-fcil&s2=farm-ferme&s3=db-el (accessed December 1, 2019).

de Koning, K. (2010). "Automatic milking - common practice on dairy farms," *in The First North American Conference on Precision Dairy Management* (Toronto, ON).

Eastwood, C. R., Ayre, M., Nettle, R., and Dela Rue, B. (2019). Making sense in the cloud: farm advisory services in a smart farming future. *NJAS-Wagen. J. Life Sci.* 90:100298. doi: 10.1016/j.njas.2019.04.004

Eastwood, C. R., Chapman, D. F., and Paine, M. S. (2012). Networks of practice for co-construction of agricultural decision support systems: case studies of precision dairy farms in Australia. *Agric. Syst.* 108, 10–18. doi: 10.1016/j.agsy.2011.12.005

Eastwood, C. R., Jago, J. G., Edwards, J. P., and Burke, J. K. (2016). Getting the most out of advanced farm management technologies: roles of technology suppliers and dairy industry organisations in supporting precision dairy farmers. *Anim. Prod. Sci.* 56, 1752–1760. doi: 10.1071/AN141015

Eastwood, C. R., Klerkx, L., Ayre, M., and Dela Rue, B. (2017a). Managing socio-ethical challenges in the development of smart farming: from a fragmented to a comprehensive approach for responsible research and innovation. *J. Agric. Environ. Ethics Online Early.* 32, 741–768. doi: 10.1007/s10806-017-9704-5

Eastwood, C. R., Klerkx, L., and Nettle, R. (2017b). Dynamics and distribution of public and private research and extension roles for technological innovation and diffusion: case studies of the implementation and adaptation of precision farming technologies. *J. Rural Stud.* 49, 1–12. doi: 10.1016/j.jrurstud.2016.11.008

Gargiulo, J. I., Eastwood, C. R., Garcia, S. C., and Lyons, N. A. (2018). Dairy farmers with larger herd sizes adopt more precision dairy technologies. *J. Dairy Sci.* 101, 5466–5473. doi: 10.3168/jds.2017-13324

Hansen, B. G. (2015). Robotic milking-farmer experiences and adoption rate in Jæren, Norway. *J. Rural Stud.* 41, 109–117. doi: 10.1016/j.jrurstud.2015.08.004

Hermans, F., Geerling-Eiff, F., Potters, J., and Klerkx, L. (2019). Public-private partnerships as systemic agricultural innovation policy instruments – assessing their contribution to innovation system function dynamics. *NJAS-Wagen. J. Life Sci.* 88, 76–95. doi: 10.1016/j.njas.2018.10.001

Higgins, V., Bryant, M., Howell, A., and Battersby, J. (2017). Ordering adoption: materiality, knowledge and farmer engagement with precision agriculture technologies. *J. Rural Stud.* 55, 193–202. doi: 10.1016/j.jrurstud.2017.08.011

Hogenkamp, W. (2018). *Groei Melkrobot Verschilt Sterk Per Land. Melkvee100plus*. Available online at: https://www.melkvee100plus.nl/Artikelen/Automatisering/2018/4/Groei-melkrobot-verschilt-sterk-per-land-277025E/?intcmp=navigatiepijlen (accessed April 29, 2018).

Jacobs, J. A., and Siegford, J. M. (2012). Invited review: the impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *J. Dairy Sci.* 95, 2227–2247. doi: 10.3168/jds.2011-4943

Jago, J., Eastwood, C. R., Kerrisk, K., and Yule, I. (2013). Precision dairy farming in Australasia: adoption, risks and opportunities. *Anim. Prod. Sci.* 53, 907–916. doi: 10.1071/AN12330

Jakku, E., Taylor, B., Fleming, A., Mason, C., Fielke, S., Sounness, C., et al. (2018). "If they don't tell us what they do with it, why would we trust them?" Trust, transparency and benefit-sharing in Smart Farming. *NJAS-Wagen. J. Life Sci.* 90:100285. doi: 10.1016/j.njas.2018.11.002

Khanal, A. R., Gillespie, J., and MacDonald, J. (2010). Adoption of technology, management practices, and production systems in US milk production. *J. Dairy Sci.* 93, 6012–6022. doi: 10.3168/jds.2010-3425

Klerkx, L., Aarts, N., and Leeuwis, C. (2010). Adaptive management in agricultural innovation systems: the interactions between innovation networks and their environment. *Agric. Syst.* 103, 390–400. doi: 10.1016/j.agsy.2010.03.012

Klerkx, L., Jakku, E., and Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: new contributions and a future research agenda. *NJAS-Wagen. J. Life Sci.* 90:100315. doi: 10.1016/j.njas.2019.100315

Kuehne, G., Llewellyn, R., Pannell, D. J., Wilkinson, R., Dolling, P., Ouzman, J., et al. (2017). Predicting farmer uptake of new agricultural practices: a tool for research, extension and policy. *Agric. Syst.* 156, 115–125. doi: 10.1016/j.agsy.2017.06.007

Meijer, I. S. M., Hekkert, M. P., and Koppenjan, J. F. M. (2007a). How perceived uncertainties influence transitions; the case of micro-CHP in the Netherlands. *Technol. Forecast. Soc. Change.* 74, 519–537. doi: 10.1016/j.techfore.2006.02.007

Meijer, I. S. M., Hekkert, M. P., and Koppenjan, J. F. M. (2007b). The influence of perceived uncertainty on entrepreneurial action in emerging renewable energy technology; biomass gasification projects in the Netherlands. *Energy Policy.* 35, 5836–5854. doi: 10.1016/j.enpol.2007.07.009

Meijer, I. S. M., Hekkert, M. P., Faber, J., and Smits, R. (2006). Perceived uncertainties regarding socio-technological transformations: towards a framework. *Int. J. Foresight Innovat. Policy* 2, 214–240. doi: 10.1504/IJFIP.2006.009316

Meskens, L., Vandermersch, M., and Mathijs, E. (2001). *Implication of the Introduction of Automatic Milking on Dairy Farms Literature Review on the Determinants and Implications of Technology Adoption*. Leuven: Departement of Agricultural and Environmental Economics, Katholieke Universiteit.

Morriss, S., Massey, C., Flett, R., Alpass, F., and Sligo, F. (2006). Mediating technological learning in agricultural innovation systems. *Agric. Syst.* 89, 26–46. doi: 10.1016/j.agsy.2005.08.002

Phillips, P. W. B., Relf-Eckstein, J.-A., Jobe, G., and Wixted, B. (2019). Configuring the new digital landscape in western Canadian agriculture. *NJAS-Wagen. J. Life Sci.* 90:100295. doi: 10.1016/j.njas.2019.04.001

Reed, E. (2018). *The Cow-Milking Robots Keeping Small Farms in Business*. The Atlantic. Available online at: https://www.theatlantic.com/business/archive/2018/10/young-dairy-farmers/567937/ (accessed October 11, 2018).

Rodenburg, J. (2017). Robotic milking: technology, farm design, and effects on work flow. *J. Dairy Sci.* 100, 7729–7738. doi: 10.3168/jds.2016-11715

Rogers, E. M. (1962). *Diffusion of Innovations*. New York, NY: Free Press of Glencoe.

Rojo-Gimeno, C., van der Voort, M., Niemi, J. K., Lauwers, L., Kristensen, A. R., and Wauters, E. (2019). Assessment of the value of information of precision livestock farming: a conceptual framework. *NJAS-Wagen. J. Life Sci.* 90:100311. doi: 10.1016/j.njas.2019.100311

Roper, S., and Tapinos, E. (2016). Taking risks in the face of uncertainty: an exploratory analysis of green innovation. *Technol. Forecast. Soc. Change.* 112, 357–363. doi: 10.1016/j.techfore.2016.07.037

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., et al. (2016). Decision support tools for agriculture: towards effective design and delivery. *Agric. Syst.* 149, 165–174. doi: 10.1016/j.agsy.2016.09.009

Rutten, C. J., Steeneveld, W., Oude Lansink, A. G. J. M., and Hogeveen, H. (2018). Delaying investments in sensor technology: the rationality of dairy farmers' investment decisions illustrated within the framework of real options theory. *J. Dairy Sci.* 101, 7650–7660. doi: 10.3168/jds.2017-13358

Shephard, R. (2004). *Automatic Milking System (AMS) Research Applicable to the Australian Dairy Industry*. Ellinbank, VIC: National Milk Harvesting Centre.

Shepherd, M., Turner, J. A., Small, B., and Wheeler, D. (2018). Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture' revolution. *J. Sci. Food Agric.* doi: 10.1002/jsfa.9346. [Epub ahead of print].

Sigurdsson, S., Hettasch, T., Gretarsson, S., Kromann, H., Manninen, E., Nyman, K., et al. (2019). "Development of AMS in the Nordic countries, 1998-2018," in *IDF 2019 Mastitis Conference* (Denmark: Copenhagen).

Spielman, D., and von Grebmer, K. (2006). Public–private partnerships in international agricultural research: an analysis of constraints. *J. Technol. Transf.* 31, 291–300. doi: 10.1007/s10961-005-6112-1

Svennersten-Sjaunja, K. M., and Pettersson, G. (2008). Pros and cons of automatic milking in Europe. *J. Anim. Sci.* 86, 37–46. doi: 10.2527/jas.2007-0527

Tomy, S., and Pardede, E. (2018). From uncertainties to successful start ups: a data analytic approach to predict success in technological entrepreneurship. *Sustainability* 10:602. doi: 10.3390/su10030602

Tse, C., Barkema, H. W., DeVries, T. J., Rushen, J., and Pajor, E. A. (2017). Effect of transitioning to automatic milking systems on producers' perceptions of farm management and cow health in the Canadian dairy industry. *J. Dairy Sci.* 100, 2404–2414. doi: 10.3168/jds.2016-11521

Vik, J., Stræte, E. P., Hansen, B. G., and Nærland, T. (2019). The political robot – the structural consequences of automated milking systems (AMS) in Norway. *NJAS-Wagen. J. Life Sci.* 90:100305. doi: 10.1016/j.njas.2019.100305

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What Are the Implications of Digitalisation for Agricultural Knowledge?

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In this perspective paper we consider the implications of a digital transformation for agricultural knowledge, a subject which hitherto has received limited attention. We raise critical questions about how digital agriculture will intersect with established modes of knowing and decision-making. We also consider the implications for the wider Agricultural Knowledge and Innovation System (AKIS), specifically the roles and capabilities of those who provide advice to farmers, as well as those responsible for data analytics, and the organizations and institutions that link and support them. We conclude that new data driven processes on farm, as well as the changing AKIS dynamic under digital agriculture, bring new demands, relations and tensions to agricultural decision-making, but also create opportunities to foster new learning by harnessing synergies in the AKIS.

Keywords: digital agriculture, agricultural knowledge and innovation system, knowledge, smart farming, farmer, big data

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INTRODUCTION

It is generally agreed that digital agriculture[1] will deliver a step change in efficiency, productivity and sustainability at the farm level and across the value chain (Aubert et al., 2012; Wolfert et al., 2017). Sensing systems and associated analytics can provide producers with better information to make more timely decisions with more predictable outcomes, while automating tasks using sensing technologies and machine learning can increase reliability. Rapid developments in the Internet of Things (IoT), cloud computing, robotics and Artificial Intelligence are accelerating the transition to smart farming and the promotion of big data and precision agriculture to improve agri-food sustainability. The expectation is that smart farming approaches will ultimately improve knowledge about an individual enterprise, or via efficient sharing and learning from data from multiple enterprises (Robertson et al., 2018).

However, although this "fourth agricultural revolution" brings the promise of multiple gains, it also brings with it technical, social, economic, ethical and practical questions, with significant implications for how commercial agriculture is structured, practiced and governed. Research to date is only just exploring the full ramifications of this so called "disruptive innovation" in relation to these aspects (Bronson and Knezevic, 2016; Jakku et al., 2016; Carolan, 2018; Klerkx et al., 2019; Rotz et al., 2019). One question that is not being fully addressed, however, is: what are the implications of digitalisation for agricultural knowledge?

[1] Digital agriculture typically involves both the collection and analysis of data to improve both on-farm and off-farm decision (Leonard et al., 2017), although here we refer to different forms of digitalisation in agricultural production systems.

Digital applications and platforms have the potential to dramatically change the way knowledge is processed, communicated, accessed and utilized. For farmers, digital applications will provide decision-making capabilities that were previously not possible, potentially leading to radical changes in farm management (Sonka, 2014; Wolfert et al., 2017). As smart machines and sensor networks increase on farms and farm data grow in quantity and scope, farming processes will become increasingly data-driven and data-enabled (Wolfert et al., 2017). This raises critical questions about how digital agriculture will require new capabilities, support decision-making and interact with, and potentially disrupt, established modes of knowledge processing.

There are significant implications for the whole Agricultural Knowledge and Innovation System (AKIS)[2], specifically the roles and capabilities of farmers, those who provide advice to farmers, as well as those responsible for data analytics, and the organizations and institutions that link and support them.

These considerations are important if we are to enable digital agriculture to be effectively implemented.

DIGTIAL AGRICULTURE AND KNOWLEDGE PROCESSES

Our understanding of knowledge in agriculture has evolved from regarding it as a transferable commodity to something more diffuse emerging out of technical and social interactions. This understanding underpins the AKIS concept and the multiple knowledge generation, exchange and utilization processes operating interactively between the heterogenous actors involved (Klerkx et al., 2012). Analysis of the potential impact of digital agriculture on the AKIS to date has tended to follow a supply-orientated narrative, examining, for example: digital services in extension (Steinke et al., 2020), social media usage, digital literacy and access (Bronson and Knezevic, 2016); and adoption of technologies (Pierpaoli et al., 2013; Barnes et al., 2019; Lowenberg-DeBoer and Erickson, 2019). Whilst these perspectives are insightful, we argue that digital agriculture requires us to fundamentally rethink these knowledge processes and to reflect on the consequences of a shift toward data-driven processes.

This perspective piece refers especially to conventional agricultural systems and draws on research primarily from developed countries. In this brief discussion inevitably we have to use shorthand terms for the different AKIS actors: farmers, advisers, researchers, etc. We acknowledge that these groups are not homogeneous and we know that farmers' interactions with, and access to, digital agriculture differs significantly depending on multiple farm, farmer and wider enabling factors (Barnes et al., 2019; Vecchio et al., 2020).

[2]The AKIS concept refers to complex arrangements and interactions between actors, knowledge organizations (agricultural research, extension, and education organisations) as well as the informal networks of heterogeneous actors (supply chains, policy makers etc).

DIGITAL AGRICULTURE, FARMER KNOWLEDGE, AND DECISION-MAKING

Decision Support - Analytical Capabilities

Digital agriculture offers the ability to utilize technology to convert precise data into actionable knowledge to drive and support complex decision-making on-farm and along the value chain. The promise is that, whilst past sources of knowledge were based on general knowledge often derived from research experiments, smart technologies will be able to offer on-farm, local-specific information to farmers (Poppe et al., 2015). As such, digital agriculture reflects a shift from generalized management of farm resources toward highly optimized, individualized, real-time, hyper-connected and data driven management (Van Es and Woodard, 2017).

Of the three pillars of digital agriculture: robotics, sensors, and Big Data analytics platforms, the latter is critical. The large amounts of data being currently generated on farms by, for example, yield monitors, are of little value unless they can be turned into useful decision support tools for farmers (Janssen et al., 2017; Weersink et al., 2018).

However, some scholars suggest that our capacity to collect large amounts of data outstrips our ability to convert it into usable information. Data analytics[3] and decision support are fundamental for fully-enabled digital agriculture, but to date the interpretation and use of data from smart technologies is not matching expectations (Leonard et al., 2017; Weersink et al., 2018) and the capability to effectively analyse these data to achieve promised improvements is limited.

Whilst there is evidence of uptake of GPS technologies that simplify the work (e.g., auto-steer systems) or passively collect data (e.g., yield monitors) (Lowenberg-DeBoer and Erickson, 2019), they signify "embodied-knowledge technologies" (Griffin et al., 2017) that require no additional skills to capture their value; in other words, they rely on the knowledge that farmers already possess regarding how to operate their machinery. This is distinct from the information-intensive technologies which use data collected from the farm as input into a decision support system that generates a prescription for the variable inputs. This distinction, some argue, explains the low uptake of variable-rate (VR) technologies which require new skills and decision-making models compared to the widespread adoption of GPS automated steering systems, yield monitors, and grid soil sampling (Weersink et al., 2018). Barnes et al. (2019) for example in a recent European survey noted this distinction in adoption patterns. Capalbo et al. (2017) point to the many cases where VR application of nutrients continues to be based on simple rule-of-thumb or empirical approaches.

Overall, it is felt that the difficulty of constructing, maintaining, analyzing, and sharing such data limits the opportunity to derive effective decision rules with high information value to producers Weersink et al. (2018). Given this, there is still a heavy reliance on the user to interpret the data. Studies have also found an increased learning load for farmers from using digital agriculture tools and the need to invest in

[3]Analytics is the capability available to analyse data (Shepherd et al., 2018)

human capital (Van Es and Woodard, 2017; Eastwood et al., 2019).

Apart from the difficulty of providing decision support, farmers, advisers and researchers are finding it hard to manage, interpret, or make use of their data as a result of their volume and complexity (Van Es and Woodard, 2017). Typically farmers do not need high frequency and precise data for every decision (Robertson et al., 2018) and have limited capacity to deal with data complexity (Lioutas et al., 2019).

Despite these challenges, there are multiple examples of technologies available, from farm management software solutions (e.g., AGERmetrix and FieldView^{TM} in USA and Agrivi in UK) to decision support tools (e.g., FieldNET Advisor^{TM} in the USA) (Kamilaris et al., 2017; Saiz-Rubio and Rovira-Más, 2020), that show how analytic capabilities are advancing.

However, limited decision support continues to reduce farmers' ability to meet the new demands of digital agriculture and can present significant adoption hurdles (Pierpaoli et al., 2013; Knierim et al., 2018). Whilst we cannot characterize the complex implementation problems of digital agriculture as solely due to limited capabilities in analytics and data use (Lowenberg-DeBoer and Erickson, 2019), it is evident that the optimism for digital agriculture is not yet matched by analytic capability within the AKIS.

Disruptions To Farmer Knowledge and Decision-Making

Although there is a suggestion that skilled agricultural workers have the highest probability of automation compared to other workers (Nedelkoska and Quintini, 2018), the extent to which this will support or replace decisions in farming depends on the technology. Sensors provide raw data (e.g., weather data), and smart devices (robotic vehicles, drone mounted cameras) will allow sophisticated farm management advice (Walter et al., 2017), while smart systems have the capability to execute autonomous actions (Budaev et al., 2019). For the former, human interpretive skills for decision making are still important, but for the latter the role of humans in analysis and planning is increasingly assisted by machines.

The nature and extent to which the human role shifts in the "sense–analyse–act" cycle in achieving actionable knowledge is debated. Whilst many agree that farmers' knowledge is not about to be replaced by algorithms, it is suggested that their involvement will be at a much higher intelligence level, leaving most operational activities to machines (Wolfert et al., 2017). This distinction between strategic and tactical action releases the farmer from mundane day-to-day monitoring although it also removes the opportunity for observational knowledge which contributes to experiential learning.

There is a perceived risk of increasing reliance on technical experts and the technology resulting in a loss of tacit knowledge if the cognitive processing of information is delegated to machines or algorithms (Jago et al., 2013; Shepherd et al., 2018). Arguably the farmers' experiential knowledge acquired over the years is at risk (Moschitz and Stolze, 2018). However, the opportunity for farmers to acquire a better knowledge of their production sites and thus gain greater certainty when making decisions increases (Rösch and Dusseldorp, 2007). The use of digital technologies, such as sensors for monitoring animal behavior, can arguably also replace the lost knowledge of older generations (Moschitz and Stolze, 2018). Furthermore, new systems are expected to support handling a higher complexity as well as an increased local adaptation which may be beyond individual experiential knowledge (Aubert et al., 2012).

More fundamentally, decision-making and experiential processing commonly applied on farm have been supported in the past with descriptive and diagnostic tools and models explaining what and why things have happened. Digital agriculture heralds an era where these learning opportunities will be potentially diminished, in which the "what is known" is prioritized over the "capacity to know."

With respect to decision making, new sources of data are seen to create the opportunity to inform and drive a change in decision making from one that is typically characterized as being highly intuitive to one that is data driven and processed in real-time (Xin and Zazueta, 2016). This, many argue, requires a change in the mode of working for many farmers, transitioning from experiential decision-making to data-driven processes (Eastwood and Kenny, 2009; Nuthall and Old, 2018). However, in reality many farmers have been transitioning toward more data-driven decision-making processes for some time, integrating different information sources and drawing on different levels of analysis, using, for example, precision agriculture and DSS.

Insights from studies of DSS, reveal that they largely support, rather than replace, the decision maker; that farmers use DSS, not in a deterministic way to provide specific answers, but as learning tools (McCown, 2001; Baars, 2011; Lindblom et al., 2017). Experience with participatory design of DSS suggests that, a better appreciation of how farmers build tacit knowledge, the mind's store of decision rules and background information through repeated experience, may improve decision support for digital agriculture. In particular, understanding how this experiential processing can combine with analytical processing, where information is obtained through statistical description (Marx et al., 2007); Hansen et al. (2019), can help to overcome difficulties at the interface between data and decision-making. Working with farmers in developing technologies can also address the limited opportunities product developers have to ground truth information (Kamilaris et al., 2017). Although there are few examples yet of co-created digital technologies there is acknowledgment that farm management and information systems require a user-centric approach (Fountas et al., 2015; Van Es and Woodard, 2017).

THE CHANGING AKIS DYNAMIC UNDER DIGITAL AGRICULTURE

Farmers draw on multiple sources of knowledge and innovation support services in the AKIS (regulators, supply chain actors, conservation experts, NGOs, policy makers), however, for many, farmer networks and farm advisers remain key. Evidence to date of the impacts of digital agriculture suggest potential shifts in these knowledge relationships.

Enabling or Disrupting Farmers' Knowledge Networks

Informal networks, between farmers and often including other actors, are one of main knowledge exchange mechanisms in farming communities which lead to learning and innovation (Leeuwis and Aarts, 2011; Ingram, 2015). The extent to which digital agriculture will disrupt or enable these network processes is an important consideration. Proposed smart systems, which promise to take and learn the best practices from advanced precise farmers, formalize and transfer their knowledge and support to other farmers in everyday decision making (Budaev et al., 2019) could arguably replace interpersonal networks. However, the potential for digital technologies to support collaborative knowledge creation has also been identified (Eastwood et al., 2012). ICT enables farmers to exchange information, benchmark their production against others, establish cooperation and peer review, and maybe even develop informal information systems that can complement more formal information systems (Wolfert et al., 2017). Many farmers have started to mobilize and organize themselves (e.g., in cooperatives, online communities) to create and share know-how, technologies and experiences, and big data understanding (Kamilaris et al., 2017; Carolan, 2018). Distributed sensing systems can form the basis for knowledge platforms for social learning (Robertson et al., 2018).

Innovation Support Services

With respect to support services, farm advisers have always been important as interpreters of data and information. The digitalisation of expert knowledge into decision support tools or via artificial intelligence has the potential to disrupt advisory services and change the adviser's role (Wolfert et al., 2017). Digital agriculture tools can provide farmers with analytical power and access to information previously unavailable (Ayre et al., 2019). This may mean advisers need to reassess their capabilities, practices, services and skills as they respond to new demands (Eastwood et al., 2017; Rijswijk et al., 2018). They may also need to create new networks with technology providers and R & D (Lundström and Lindblom, 2018). Although there is a potential role for technology suppliers to take on greater advisory support for farmers and act as knowledge "translators," they can often lack the farm systems expertise or knowledge networks to adequately support on-farm use (Eastwood et al., 2016). To address this problem, researchers propose a co-development approach for building the capability to use digital agriculture tools (Eastwood et al., 2019).

New Entrants and Changing Roles

The emergence of new suppliers of equipment, software and services, business models and networks creates a new dynamic within the incumbent AKIS. The public and private sector generally operate together to establish a wide variety of data, knowledge and institutional arrangements that together constitute "a decision making infrastructure" that supports management in agriculture (Capalbo et al., 2017). This is evolving under digital agriculture with new disruptive entrants (e.g., digital technology companies) and various models of development and investment appearing, including new business models that challenge incumbent forms (Phillips et al., 2019). The changing roles of old and new software suppliers and the emerging landscape of data-driven initiatives, with the prominent role of big tech and data companies and research universities has been observed (Keogh and Henry, 2016; Van Es and Woodard, 2017; Wolfert et al., 2017). The dynamic between the new and established players is often framed by discussions of private-public data accessibility, ownership and governance (Bronson and Knezevic, 2016; Jakku et al., 2016); however, issues of knowledge are also key, and are redefining AKIS boundaries. The tensions and synergies between these new entrants and those in public bodies and universities are of particular interest. The former have limited understanding of agronomic principles but excellent market access, while the latter have the expertise and institutional learning which has provided the foundations for understanding the processes driving agricultural systems, through decades of experimental research and sophisticated modeling (enabling diagnostic understanding).

The opportunities for combining their different analytics are highlighted by Antle et al. (2017, p. 258) who point to synergies between the modeling community, which is strong on analytical capability, and the developers of user-related farm-level products. Harnessing big data and the analytical powers of models can also lead to what Capalbo et al. (2017) referred to as a virtuous circle which builds on both and will allow a new generation of models and decision support.

At a more fundamental level the arrival of new analytics raises the questions about knowledge and data-driven processes. Established R&D institutions applied analytical techniques associated with descriptive and diagnostic analytics which led to the effective application of what Sonka (2014) calls "Small Data." An important question for Sonka is: "how can the best aspects of the Small Data system be linked to the application of Big Data technologies?" Whilst he acknowledges that knowing, at increasing levels of precision, "what" happened in the field or in animal facilities does have value, he argues that knowing "why" is also key to agricultural applications.

This shift in analytics also has the potential to significantly impact the AKIS in other ways, moving us from "hindsight" to "foresight" (Shepherd et al., 2018). Digitizing agriculture will take these systems to predictive (what will happen) and prescriptive (how can we make it happen) analytics, which are future focused. This development again raises questions about where our understanding of the mechanisms underpinning these predictions and prescriptions lies.

CONCLUSION

New data-driven processes on farm as well as the changing AKIS dynamic under digital agriculture brings new demands, relations and tensions. However, there is also great potential to both build on established ways of knowing and to foster new learning by harnessing synergies.

Morakanyane et al. (2017, p. 437) defined digital transformation "as an evolutionary process that leverages digital capabilities and technologies to create value." We would argue that these capabilities are crucial and extend beyond the digital domain *per se* to the knowledge capabilities of all actors in the AKIS. Enhancing capabilities at every level, from the farm and adviser level, to new technology and software providers and established researchers, will be important if digital technologies are to achieve their full value. Equally facilitating opportunities for combining different analytic approaches and capabilities should be supported. Fostering co-learning and collaboration in implementing new technologies should be an important strand for future development and research.

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JI prepared the main draft. DM contributed material and ideas and edited the text.

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REFERENCES

Antle, J. M., Basso, B., Conant, R. T., Godfray, H. C. J., Jones, J. W., Herrero, M., et al. (2017). Towards a new generation of agricultural system data, models and knowledge products: design and improvement. *Agric. Syst.* 155, 255–268. doi: 10.1016/j.agsy.2016.10.002

Aubert, B. A., Schroeder, A., and Grimaudo, J. (2012). IT as enabler of sustainable farming: an empirical analysis of farmers' adoption decision of precision agriculture technology. *Decis. Support Syst.* 54, 510–520. doi: 10.1016/j.dss.2012.07.002

Ayre, M., Mc Collum, V., Waters, W., Samson, P., Curro, A., Nettle, R., et al. (2019). Supporting and practising digital innovation with advisers in smart farming. *NJAS-Wagen. J. Life Sci*. 90–91:100302. doi: 10.1016/j.njas.2019.05.001

Baars, T. (2011). Experiential science; towards an integration of implicit and reflected practitioner-expert knowledge in the scientific development of organic farming. *J. Agric. Environ. Ethics* 24, 601–628. doi: 10.1007/s10806-010-9281-3

Barnes, A., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., et al. (2019). Exploring the adoption of precision agricultural technologies: a cross regional study of EU farmers. *Land Policy* 80, 163–174. doi: 10.1016/j.landusepol.2018.10.004

Bronson, K., and Knezevic, I. (2016). Big data in food and agriculture. *Big Data Soc.* 3:2053951716648174.

Budaev, D., Lada, A., Simonova, E., Skobelev, P., and Travin, V. (2019). Conceptual design of smart farming solution for precise agriculture. *Manag. App. Complex Syst.* 13, 309–316. doi: 10.2495/DNE-V13-N3-309-316

Capalbo, S. M., Antle, J. M., and Seavert, C. (2017). Next generation data systems and knowledge products to support agricultural producers and science-based policy decision making. *Agric. Syst.* 155, 191–199. doi: 10.1016/j.agsy.2016.10.009

Carolan, M. (2018). *The Politics of Big Data: Corporate Agri-Food Governance Meets "Weak" Resistance*. Routledge: Agri-environmental Governance as an Assemblage. 195–212.

Eastwood, C., Ayre, M., Nettle, R., and Rue, B. D. (2019). Making sense in the cloud: farm advisory services in a smart farming future. *NJAS-Wagen. J. Life Sci*. 90–91:100298. doi: 10.1016/j.njas.2019.04.004

Eastwood, C., and Kenny, S. (2009). Art or science?: heuristic versus data driven grazing management on dairy farms. *Exten. Farming Syst. J.* 5, 95–102. Available online at: https://search.informit.com.au/documentSummary;dn=722662138426388;res=IELHSS

Eastwood, C., Rue, B. D., and Gray, D. (2017). Using a network of practice approach to match grazing decision-support system design with farmer practice. *Anim. Prod. Sci*. 57, 1536–1542. doi: 10.1071/AN16465

Eastwood, C. R., Chapman, D. F., and Paine, M. S. (2012). Networks of practice for co-construction of agricultural decision support systems: Case studies of precision dairy farms in Australia. *Agric. Syst*. 108, 10–18. doi: 10.1016/j.agsy.2011.12.005

Eastwood, C. R., Jago, J. G., Edwards, J. P., and Burke, J. K. (2016). Getting the most out of advanced farm management technologies: roles of technology suppliers and dairy industry organisations in supporting precision dairy farmers. *Anim. Prod. Sci*. 56, 1752–1760. doi: 10.1071/AN141015

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., et al. (2015). Farm management information systems: current situation and future perspectives. *Comput. Electron. Agric.* 115, 40–50. doi: 10.1016/j.compag.2015.05.011

Griffin, T. W., Miller, N. J., Bergtold, J., Shanoyan, A., Sharda, A., and Ciampitti, I. A. (2017). Farm's sequence of adoption of information-intensive precision agricultural technology. *Appl. Eng. Agric.* 33, 521–527. doi: 10.13031/aea.12228

Hansen, J. W., Vaughan, C., Kagabo, D. M., Dinku, T., Carr, E. R., Körner, J., et al. (2019). Climate services can support african farmers' context-specific adaptation needs at scale. *Front. Sust. Food Syst.* 3, 1–16.

Ingram, J. (2015). Framing niche-regime linkage as adaptation: an analysis of learning and innovation networks for sustainable agriculture across Europe. *J. Rural Stud.* 40, 59–75. doi: 10.1016/j.jrurstud.2015.06.003

Jago, J., Eastwood, C., Kerrisk, K., and Yule, I. (2013). Precision dairy farming in Australasia: adoption, risks and opportunities. *Ani. Prod. Sci.* 53, 907–916. doi: 10.1071/AN12330

Jakku, E., Taylor, B. M., Fleming, A., Mason, C., and Thorburn, P. J. (2016). *Big Data, Trust and Collaboration: Exploring the Socio-Technical Enabling Conditions for Big Data in the Grains Industry*. Brisbane, QLD: CSIRO, 34.

Janssen, S. J., Porter, C. H., Moore, A. D., Athanasiadis, I. N., Foster, I., Jones, J. W. et al. (2017). Towards a new generation of agricultural system data, models and knowledge products: information and communication technology. *Agric. Syst.* 155, 200–212. doi: 10.1016/j.agsy.2016.09.017

Kamilaris, A., Kartakoullis, A., and Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.* 143, 23–37. doi: 10.1016/j.compag.2017.09.037

Keogh, M., and Henry, M. (2016). *The Implications of Digital Agriculture and Big Data for Australian Agriculture*. Sydney, NSW: Australian Farm Institute.

Klerkx, L., Jakku, E., and Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: new contributions and a future research agenda. *NJAS-Wagen. J. Life Sci.* 90–91:100315. doi: 10.1016/j.njas.2019.100315

Klerkx, L., Van Mierlo, B., and Leeuwis, C. (2012). "Evolution of systems approaches to agricultural innovation: concepts, analysis and interventions," in *Farming Systems Research into the 21st Century: the New Dynamic,* eds I. Darnhofer, D. Gibbon, and B. Dedieu (Dordrecht: Springer), 457–483.

Knierim, A., Borges, F., Kernecker, M. L., Kraus, T., and Wurbs, A. (2018). "What drives adoption of smart farming technologies? Evidence from a cross-country study," in *13th European International Farming Systems Association (IFSA) Symposium, Farming systems: Facing Uncertainties and Enhancing Opportunities, 1-5 July 2018* (Chania: International Farming Systems Association).

Leeuwis, C., and Aarts, N. (2011). Rethinking communication in innovation processes: creating space for change in complex systems. *J. Agric. Educ. Exten.* 17, 21–36. doi: 10.1080/1389224X.2011.536344

Leonard, E., Rainbow, R., Laurie, A., Lamb, D., Llewellyn, R., Perrett, E., et al. (2017). *Accelerating Precision Agriculture to Decision Agriculture: Enabling*

Digital Agriculture in Australia (Narrabri, NSW: Cotton Research and Development Board).

Lindblom, J., Lundström, C., Ljung, M., and Jonsson, A. (2017). Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precis. Agric.* 18, 309–331. doi: 10.1007/s11119-016-9491-4

Lioutas, E. D., Charatsari, C., La Rocca, G., and De Rosa, M. (2019). Key questions on the use of big data in farming: an activity theory approach. *NJAS-Wagen. J. Life Sci.* 90–91:100297. doi: 10.1016/j.njas.2019.04.003

Lowenberg-DeBoer, J., and Erickson, B. (2019). Setting the record straight on precision agriculture adoption. *Agron. J.* 111, 1552–1569. doi: 10.2134/agronj2018.12.0779

Lundström, C., and Lindblom, J. (2018). Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to foster farming practices: the case of CropSAT. *Agric. Syst.* 159, 9–20. doi: 10.1016/j.agsy.2017.10.004

Marx, S. M., Weber, E. U., Orlove, B. S., Leiserowitz, A., Krantz, D. H., Roncoli, C., et al. (2007). Communication and mental processes: experiential and analytic processing of uncertain climate information. *Global Environ. Chang.* 17, 47–58. doi: 10.1016/j.gloenvcha.2006.10.004

McCown, R. (2001). Learning to bridge the gap between science-based decision support and the practice of farming: evolution in paradigms of model-based research and intervention from design to dialogue. *Aust. J. Agric. Res.* 52, 549–572. doi: 10.1071/AR00119

Morakanyane, R., Grace, A. A., and O'Reilly, P. (2017). Conceptualizing digital transformation in business organizations: a systematic review of literature. *InBled eConference*, 21.

Moschitz, H., and Stolze, M. (2018). "How can we make sense of smart technologies for sustainable agriculture? A discussion paper," in *International Farming Systems Association 13th European IFSA Symposium* (Chania: International Farming Systems Association).

Nedelkoska, L., and Quintini, G. (2018). Automation, skills use and training. *OECD Social, Employment and Migration Working Papers* (202).

Nuthall, P., and Old, K. (2018). Intuition, the farmers' primary decision process. A review and analysis. *J. Rural Stud.* 58, 28–38. doi: 10.1016/j.jrurstud.2017.12.012

Phillips, P. W., Relf-Eckstein, J.-A., Jobe, G., and Wixted, B. (2019). Configuring the new digital landscape in western canadian agriculture. *NJAS-Wagen. J. Life Sci.* 90–91:100295. doi: 10.1016/j.njas.2019.04.001

Pierpaoli, E., Carli, G., Pignatti, E., and Canavari, M. (2013). Drivers of precision agriculture technologies adoption: a literature review. *Proc. Technol.* 8, 61–69. doi: 10.1016/j.protcy.2013.11.010

Poppe, K., Wolfert, J., Verdouw, C., and Renwick, A. (2015). A european perspective on the economics of big data. *Farm Policy J.* 12, 11–19.

Rijswijk, K., Klerkx, L., and Turner, J. (2018). "Digitalisation of agricultural knowledge providers: the case of New Zealand," in *European International Farm Systems Association Symposium* (Chania: International Farming Systems Association), 1–5.

Robertson, M., Moore, A., Henry, D., and Barry, S. (2018). Digital agriculture: what's all the fuss about? Available online at: https://blog.csiro.au/digital-agriculture-whats-all-the-fuss-about/

Rösch, C., and Dusseldorp, M. (2007). Precision agriculture: how innovative technology contributes to a more sustainable agriculture. *GAIA-Ecol. Perspect. Sci. Soc.* 16, 272–279. doi: 10.14512/gaia.16.4.9

Rotz, S., Duncan, E., Small, M., Botschner, J., Dara, R., Mosby, I., et al. (2019). The politics of digital agricultural technologies: a preliminary review. *Sociol. Ruralis* 59, 203–229. doi: 10.1111/soru.12233

Saiz-Rubio, V., and Rovira-Más, F. (2020). From smart farming towards agriculture 5.0: a review on crop data management. *Agronomy* 10:207. doi: 10.3390/agronomy10020207

Shepherd, M., Turner, J. A., Small, B., and Wheeler, D. (2018). Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture' revolution. *J. Sci. Food Agric.* doi: 10.1002/jsfa.9346. [Epub ahead of print].

Sonka, S. (2014). Big data and the ag sector: more than lots of numbers. *Int. Food Agribus. Manag. Rev.* 17, 1–20. doi: 10.22004/ag.econ.163351

Steinke, J., van Etten, J., Müller, A., Ortiz-Crespo, B., van de Gevel, J., Silvestri, S., et al. (2020). Tapping the full potential of the digital revolution for agricultural extension: an emerging innovation agenda. *Int. J. Agricu. Sust.* 1–17. doi: 10.1080/14735903.2020.1738754

Van Es, H., and Woodard, J. (2017). Innovation in agriculture and food systems in the digital age. *The Global Innovation Index 2017: Innovation Feeding the World* (Ithaca, NY; Fontainebleau; Geneva). 97–104.

Vecchio, Y., Agnusdei, G. P., Miglietta, P. P., and Capitanio, F. (2020). Adoption of precision farming tools: the case of italian farmers. *Int. J. Environ. Res. Public Health* 17:869. doi: 10.3390/ijerph17030869

Walter, A., Finger, R., Huber, R., and Buchmann, N. (2017). Opinion: smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. U.S.A.* 114, 6148–6150. doi: 10.1073/pnas.1707462114

Weersink, A., Fraser, E., Pannell, D., Duncan, E., and Rotz, S. (2018). Opportunities and challenges for big data in agricultural and environmental analysis. *Ann. Rev. Resour. Econ.* 10, 19–37. doi: 10.1146/annurev-resource-100516-053654

Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M.-J. (2017). Big data in smart farming–a review. *Agric. Syst.* 153, 69–80. doi: 10.1016/j.agsy.2017.01.023

Xin, J., and Zazueta, F. (2016). Technology trends in ICT–towards data-driven, farmer-centered and knowledge-based hybrid cloud architectures for smart farming. *Agric. Eng. Int. CIGR J.* 18, 275–279.

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