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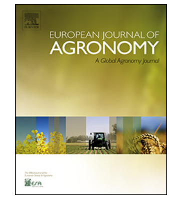

Improving productivity and increasing the efficiency of soil nutrient management on grassland farms in the UK and Ireland using precision agriculture technology

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ABSTRACT

Grass growth and utilisation on grassland farms across the UK and Ireland are below their potential, and nutrient management is sub-optimal. Excessive soil phosphorus concentrations are an issue, contributing to eutrophication of waterways, while sub-optimal soil pH due to a reduction in lime use is seen in many areas. This paper discusses the potential for introducing technology onto grassland farms, and implementing sensible farm-specific management decisions as a means of enhancing productivity and minimising the environmental impact of livestock farming. The adoption rate of Precision Agriculture (PA) technology by grassland farmers in the UK and Ireland is still relatively low, and significantly lagging behind the advances that have taken place within the arable farming community. With rapidly advancing technology and investment in research, there are now a range of soil sensors available along with technology for grass growth monitoring, yield mapping, remote sensing, satellite imagery, and devices for tracking animal movement, behaviour and feed intake. In this review paper we examine the latest technology developments specific to grassland farming and we question their suitability and 'readiness' for adoption by farmers. The review identifies the challenges that are specific to grassland such as complex soil, vegetation and climatic variables along with economic barriers that may be preventing change within the farming community in these areas.

1. Introduction

In Ireland 80% of the utilised agricultural area is permanent grassland and 65% in the UK. The mild, moist temperate climatic conditions of this region supports a prolonged grass growing season. Soils tend to be high in organic matter, temperatures are moderate and there is sufficient / high rainfall (as much as 900–2000 mm annually, the higher amounts typically across the west of Ireland). These grasslands include grazed pastures (dairy, beef and sheep) and grassland harvested for hay and silage or a combination of both. They receive high external inputs of fertiliser and disturbance (*e.g.* biomass removal, reseeding and drainage) and are typically dominated by productive forage grasses such as perennial ryegrass (*Lolium perenne*) and to a lesser extent by herbs and white clover (*Trifolium repens*). The high rainfall climate of the UK and Ireland creates specific challenges for farmers, with a tendency towards saturated soils necessitating winter livestock housing for up to 6 months of the year. Winter feed is in the form of silage (harvested from the previous summer), commonly supplemented with concentrate feed stuffs. High grass yields and good grass quality drive production, as milk yields and animal live weight gain tend to be constrained by feed energy (Taube et al., 2013).

Inorganic fertilisers (primarily nitrogen (N), phosphorus (P), potassium (K) and sulphur (S)), provide the nutrients for grass growth, along with organic applications of animal manure and slurry recycled back onto the fields. Animal manure and slurry are excellent nutrient sources, however the volume produced can sometimes be in excess of requirements, creating above-optimum nutrient concentrations within soils and contributing to potential sites of diffuse nutrient losses to the environment. While inorganic fertiliser tends to be applied as blanket applications across fields, there is a tendency for some fields to traditionally receive more organic (slurry and manure) applications than others due to their location, topography and accessibility. This, combined with the fact that animal manure itself is notoriously heterogeneous in composition, creates a situation where soil nutrient distributions and grass growth at sub-field and between-field scale can be highly variable (McCormick, 2005; Higgins et al., 2011; Bailey et al.,

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2011).

In this paper we discuss how precision technology could potentially improve the efficiency of soil nutrient management, increasing productivity and minimising nutrient surpluses and deficiencies at both a farm scale and a sub-field scale. Increasing grass growth and utilisation, optimising milk from forage, reducing the reliance on concentrate feeds and improving soil health are some of the key targets for the intensive grassland farmer. We examine the role of PA technology in helping to improve nutrient management efficiency on farms and achieve some of these targets. The paper is divided into 4 Sections:

Section 1 discusses the importance of regular monitoring of grass yield and quality and how to optimise grazing performance / silage quality

Section 2 discusses how PA technology could be employed for yield mapping and identifying fields or parts of fields that could be underperforming and requiring different management

Section 3 discusses management changes required to improve yield / grass quality, nutrient management efficiency and protect the environment

Section 4 briefly discusses issues associated with data handling and interpretation, along with social issues and barriers specific to rural dwellers within grassland farming communities in the UK and Ireland.

*1.1. **Section 1**: monitoring grass yield and quality and opportunities for optimising grazing performance/silage quality using PA technology*

Optimising the utilisation of grazed grass is extremely important for the grassland farmer. Grazed grassland is the least expensive feed source. If livestock fail to ingest sufficient quantities of high quality forage it will have a direct and negative impact on milk and meat outputs and farmers will be required to import expensive supplements and concentrate feeds. To optimise the utilisation of grazed grass, farmers need to be accurately measuring and forecasting grass growth in order to make timely decisions day-to-day and throughout the growing season. In Ireland, the average dairy farm utilises 7.1 t of grass dry matter (DM) /ha (Creighton et al., 2011) while more efficient farms are growing and utilising in excess of 12–14 t of grass DM/ha over a 280 day grazing season with stocking rate of over 3 cows /ha (Shalloo et al., 2011). Much can be gained from improving grass utilisation, with research findings showing that every additional ton of grass utilised per hectare could increase net profit by €180/ha (£158/ha) (Forager, 2017).

Short-term decision making on farms includes estimates and predictions of grass cover, enabling an assessment of feed availability and demand from grazing animals. Planning over the long-term includes forecasting growth potential, farm profitability, productivity and pricing, which is made more challenging by the highly variable climate within the UK and Ireland. The 'grass wedge' is a mid-season grazing decision support management tool (Macdonald et al., 2010). It is a snapshot in time of the amount of grass that is on farm and its relationship to livestock demand. It indicates the amount of feed required for a specific stocking rate, rotation length and livestock requirement, generated from weekly pasture cover estimates. From this, appropriate management strategies can be implemented such as removing pasture surpluses when there is an excess, or reducing demand by introducing supplementation when pasture is in deficit.

It is recognised that relatively few producers measure and record grass growth or set pasture cover targets for various times of the year. In a recent survey by Forager magazine, 70% of farmers never measure their grass (Forager, 2017). As a result, many farmers do not know the maximum potential or current performance of their grassland. Spatial and temporal variability in growth at sub-field and between-field scale also needs to be considered and managed appropriately. PA technology provides tools that make measuring and monitoring grass more efficient. A range of sensors are available for measuring soil, vegetation, animal and environmental data. These can be ground-level, hand-held, portable, or connected to a navigation device or farm machinery. Traditional methods of measuring grass include visual assessment, rising plate meters or electronic probes. These methods require some skill, are relatively time consuming and require to be done at least every 7–10 days during peak growth (Forager, 2017). Rising plate meters are gradually becoming more sophisticated in their function. The 'Grasshopper' by True North Technologies (http://www.moregrass.ie/) is a rising plate with +/− 1 mm accuracy, GPS engine, field and farm mapping function. The Grasshopper is operated by hand while walking across a field. It can calculate total and available cover, paddock 'wedge' i.e. amount of grass available relative to livestock demand, date and time of cover along with temperature. There is a Bluetooth connection to a phone or tablet, and a 5-hour rechargeable battery life. Attached to a farm vehicle, a 'Rapid Plate Meter' is a trailed plate meter that fits on a vehicle's drawbar and automatically records grass covers (Pasture Meters, 2019) (http://www.pasturemeters.co.uk/rapid-plate-meter/). It can record covers at vehicle speeds of up to 18 mph, reducing the time needed to walk fields with a conventional rising plate meter. Some systems can take a reading every 50 cm travelled versus 30 plus readings in a field with the rising plate meter, and so is claimed to have higher accuracy compared to the rising plate meter. Bluetooth facilitates connectivity between trailer and an Android App, avoiding the use of cables and offering flexibility in download options to other third parties and stakeholders. However, obtaining estimates of grass cover per area made by measuring grass height by eye or using a plate meter requires a trained individual and can have errors associated with it. The benefit of technology such as the rising plate meter is that, while it requires a trained individual to operate, it offers the farmer some independence and ownership of the process. Farmers can choose themselves when to complete their weekly field walk, and there is great benefit to the farmer knowing their own land and being fully involved in the processing of their own data.

More traditional methods of measuring grass yield include destructive grass sampling coupled with weighing systems on mowers, trailers or balers (Schellberg et al., 2008; Fricke et al., 2011). Optical sensing techniques that can estimate pasture biomass levels by using a proxy such as spectral reflectance indices or plant height have recently evolved (Schaefer and Lamb, 2016). Fricke et al. (2011) used an ultrasonic sensor to determine sward heights. The prediction accuracy of forage mass from ultrasonic height measurements was promising, but Fricke et al. (2011) felt that it could be improved further by using spectral reflectance signatures in combination with the ultrasonic sensor. This is due to the complex interaction between sward structure and reflection data that exists, and is significantly affected by size, angle, surfaces of vegetation, sward type, weed abundance and growth periods, with an overestimation of forage mass more likely to occur in mature swards having low forage mass (Fricke et al., 2011).

*1.2. **Section 2** employing PA technology for yield mapping and identifying fields or parts of fields that could be underperforming and requiring different management*

Many decisions on-farm are made on a day-to-day basis in response to weather conditions and seasonal priorities. To accommodate this, sensors ideally need to operate in real-time. Yield mapping is an important component of precision management, and it can be used by the farmer to optimise the allocation of grass, as well as identifying underperforming areas where there may be soil fertility or health issues, soil compaction or areas requiring reseeding. Mapping of grass silage fields has shown extensive spatial and temporal variation in growth of up to 4 tha^{-1} (McCormick, 2005) within single fields. N mineralisation variability across fields has been shown to be an important driver of yield variability (Bailey et al., 2001; Jordan et al., 2003) and sub-optimal N fertiliser rates are suggested to be one of the main reasons for

UK grass yields (average 6–10 t/ha) being less than half of the biological potential for the UK environment (Berry et al., 2017). Berry et al (2017) found that the optimum N requirement varied substantially by up to 100 kg N/ha within a 3 ha experimental area. Variation in N optima was found to be negatively related to soil N supply and there was a good relationship between spectral reflectance indices and crop N uptake which potentially could have a role in estimating soil N supply (Berry et al., 2017). In grazed grassland, spatial and temporal variability in soil nutrients and grass yield can be even more extensive and complex, due to the heterogeneity in excreta returns to the soil by grazing animals (West et al., 1989; Bramley and White, 1991; Cuttle, 1992). In addition to this, grazing animals are notoriously selective in their feeding. They show preference for specific grass species and tend to congregate around water troughs, gateways or hedges. Management of grazed fields using precision management techniques tends not to focus on soil nutrients per se, but is generally aimed at monitoring grass intake per individual cow, in order to improve grass utilisation, milk yields and live weight gain.

Many plant sensors utilise the reflectance of light from the plant canopy. Active Optical Sensors, emit light onto the canopy and can be used independently of ambient light (Yule and Pullanagari, 2009; Jasper et al., 2009; Heege et al., 2008; Holland and Schepers, 2013), whereas Passive Optical Sensors require illumination from a separate light source, usually sunlight (Holland et al., 2012; Lamb et al., 2002). Commercial sensors incorporating active optical sensors for estimating the amount of nitrogen fertiliser required across a field include Crop-Circle™ (Holland Scientific), Greenseeker™ (Trimble) and the Yara N Sensor ALS (Yara). Active Optical Sensors have been used to monitor pasture species and growth, but the species diversity in pastures (as opposed to the commonly seen mono-species canopies of crop production) along with the presence of nitrogen fixing legumes and animal excreta, which input additional N into the system complicate the application of Active Optical Sensing within pasture systems.

To aid interpretation of sensor data, the spectral reflectance of vegetation at certain wavelengths (red and near infrared for example) have been translated into indices such as the normalised difference vegetation index (NDVI), simple ratio (SR), and soil adjusted vegetation index (SAVI) to name a few (Trotter et al., 2010). The simple ratio (SR, Jordan, 1969) has been successfully used to predict yield parameters of crops such as dry matter content, shoot dry weight, fresh matter yield, N content and above ground N uptake (Kipp et al., 2012). NDVI can provide a robust spectral indication of the greenness of the vegetation and its nitrogen content (Ramoelo et al., 2012), as well as soil cover and leaf area index. The chlorophyll content of leaves provides a good representation of the capacity of the leaf to absorb photosynthetically active radiation, and is strongly correlated with the intensity of light reflectance and absorption. Flynn et al. (2008) used a ground-based sensor to calculate the NDVI and investigate the within-field variability in pasture biomass. They found that NDVI showed a good correlation with biomass ($r^2 = 0.68$) (and therefore plant N content) and with the results from the rising plate meter ($r^2 = 0.54$). Careful calibration of commercial sensors at individual field or sub-field scale are necessary in order to minimise errors in estimates of green biomass. Regional calibration rather than a single overall calibration was found necessary by Andersson et al. (2017) in an investigation of relationships between pasture biomass and measures of height and NDVI in Australian pastures using a Trimble® GreenSeeker handheld active optical sensor.

The wavelength position of the so-called red edge inflexion point (REIP) of the spectral signature has been shown to be highly correlated with the nitrogen nutrition index (NNI) of crops on which the REIP has been determined. Mistele and Schmidthalter (2008) suggested that the REIP would be a useful indicator of N-uptake in grassland, particularly when tractor-mounted and taken quickly and non-destructively. Such application could help guide N applications and lower uncertainty in the amount of N to apply. The speed of data collection is particularly important, due to a small shift in REIP values between biomass samplings, so field spectrometers need to be calibrated according to the given field conditions (Mistele and Schmidhalter, 2008). Calibration procedures would require considerable expertise and training in order to be completed correctly, along with interpretation of the data. However while these techniques are useful for research, it has been suggested that it is questionable whether hyperspectral remote sensing above canopies would provide data manageable by farmers (Possoch et al., 2016). For PA to be implemented successfully researchers and technology providers need to collaborate in order to produce user-friendly solutions that are scientifically robust. This will take time, and will be a continual process of learning and development as technology advances.

1.2.1. The challenges of Remote Sensing (RS) for PA management of grassland

Remote Sensing (RS) using satellite or aerial imagery is a useful method or acquiring large amounts of data over time (Wachendorf et al., 2017) particularly for sites that are possibly isolated or difficult to access. Observations of canopy development across time and space can be integrated into crop growth models to provide estimates of biomass production at fine scales (Campos et al., 2017). Grassland vegetation characteristics such as standing biomass, canopy characteristics, biomass production (Maselli et al., 2003), sward height, floristic composition (Feilhauer et al., 2013), grazed grassland and area of soil cover (Zha et al., 2003) have been mapped at large spatial scales in many regions across the world. Different sensor specifications are required to enable collection of usable data, depending on the application scale. Data from Landsat TM/MSS, SPOT, AVHRR, MODIS and RapidEye® sensors are most commonly used for mapping land use cover change at large spatial scales. For agricultural management, sensors with high spatial and temporal resolution are more effective, for example GeoEye® and RapidEye®. These provide imagery with a higher spatial resolution and revisit time, thereby permitting the detection of spatio-temporal patterns at scales closer to that of field surveys.

Integrating multispectral and multitemporal RS data with local knowledge and simulation models has been successfully demonstrated as a valuable approach to identifying and monitoring a wide variety of agriculturally related characteristics (Yiran et al., 2012; Oliver et al., 2010) including soil pH (Roelofsen et al., 2015). With all RS, it is essential to have high quality ground truthed data for cross validation. Ali et al. (2016) reviewed the application of satellite RS for grassland and its transition from grassland mapping to grassland / pasture monitoring and management. While Ali et al. (2016) acknowledge the evolution in the use of satellite data that has taken place in recent years, more high quality calibration and validation data is still required. The low spatial resolution of many instruments is still an issue and precludes their use at fine spatial field scales. Overcoming cloud contamination is a requirement, but the development of hypertemporal satellite data gives value, particularly for times series generation. The launch of new satellites such as GeoEye: 1.35 m resolution, 3 days revisit time) RapidEye (6.5 m resolution, 5.5 days revisit time) and QuickBird (2.4 m resolution, 1–3.5 days revisit time) offers more field-scale application for managed grasslands. Ali et al. (2016) also believe that a better understanding of microwave imagery would produce more products suitable for cloudy regions. Many managed grassland fields are small in size. The average field size in Northern Ireland for example is 1.2 ha (DAERA, 2018), but on single farms there is extensive variability, with neighbouring fields commonly ranging between 1 and 5 ha in size (McCormick, 2005). Very high spatial resolution imagery is therefore required in order to determine inter- and intra-field variations.

Optical RS is used to discriminate between different vegetation types and measure productivity. Vegetation indices that combine reflectance values at two or more wavelengths are required, accentuating particular features of the spectral signature, such as greenness, water content or light use efficiency (Song et al., 2013). The red edge, where there is a rapid increase in reflectance from the red to NIR reflectance (around 680–730 nm) has been shown to have a strong correlation with the grass chlorophyll content of the canopy, and of the leaves (Pinar and Curran, 1996). RapidEye® is the first high-resolution multispectral satellite system that operationally provides a red edge channel. Schuster et al. (2012) reported that this enables higher classification accuracy for managed grassland types (Hollberg and Schellberg, 2017). Ideally a time series of imagery acquired through a growing season is most beneficial in terms of providing maximum information on yields and management effects such as grazing, cutting and fertilisation timing. This is particularly important in grassland areas due to the huge temporal differences in plant phenology and farm management (*e.g.* grazing and mowing activities). Acquiring a multi-temporal image series is more effective than using single data acquisitions (Kasischke et al., 1997; Pierce et al., 1998; Ranson and Sun, 1994). The availability of images at times that are important for decision making is essential.

Ali et al. (2016) emphasised the potential offered by microwave spaceborne instruments which measure the strength of the back-scattered signal from the surface under almost all weather and light conditions, allowing frequent repeat measurements throughout the growing season. Microwave instruments such as Synthetic Aperture Radar (SAR) instruments offer a number of different acquisition modes, with different polarisations, incidence angles and orbital directions (ascending/descending) and may be a means of providing information useful for site specific management. Until recently Optical Earth Observation data would have been unable to match the frequency of changes in grass dry matter accumulation when fields are in constant grazing rotation. Sentinel-1 (SAR) is able to provide free dual-polarisation images at a farm scale every 2 days, although the resolution may not be sufficiently adequate for finer scale field monitoring. As an example of SAR applications, changes in soil moisture content can result in large changes in radar backscatter. Barrett et al. (2014) used the Essential Climate Variable Soil Moisture product (Liu et al., 2012) to provide an estimate of the soil moisture conditions on SAR acquisition dates. Although a number of limitations and constraints relating to the microwave domain exist, such as the difficulty distinguishing between the signal response associated with the vegetation cover, from moisture and other conditions, microwave instruments have potential. SAR data are almost independent of weather and illumination conditions, and this makes their use for operational purposes especially appealing. SAR is therefore an important alternative or complementary data source for areas with persistent cloud cover such as in the UK and Ireland. RS is one of the most rapidly developing areas of PA management. While currently the most appropriate application of RS is in monitoring over large spatial and temporal scales, rapidly developing devices such as SAR could enable future field-scale monitoring at a frequency that facilitates on-farm decision support.

1.2.2. The powerful nature of Digital Image Analysis (DIA)

Digital Image Analysis (DIA) assists with the interpretation of images obtained from RS. DIA is able to estimate biomass and distinguish individual plant species based on characteristic shape, colour and texture (Wachendorf et al., 2017). It has the potential to support the identification of plant species required for example, for site-specific weed control in grassland swards (Gebhardt et al., 2006). Digital Image Analysis includes close range imagery using digital photographs, and any kind of remotely sensed and geographically referenced pixel based information. Distinguishing between species and identifying features and characteristics in grasslands can be complex due to diversity of optical plant properties within a mixed sward, such as leaf colour and shape, overlapping of leaves and tillers, shades on leaves and soil, as well as the non-uniform soil background (Gebhardt et al., 2006; Wachendorf et al., 2017). Gebhardt et al. (2006) successfully used digital image processing to identify the occurrence of the broad-leaved dock (*Rumex obtusifolius* L., *R.o.*) in complex mixtures of perennial ryegrass, *R.o.* and other herbs. Spectral data is very sensitive to the stage of crop maturity at the date of image acquisition. Gebhardt and Kühbauch (2007) found that detection rates decreased when classifying the later stages of growth, and recommended that image classification should take place early in the growing season. Close range digital imaging can be used to identify open spaces within swards, such as areas where damage has been caused by machinery or grazing. It can also facilitate a higher detection rate and quality of processed object features by producing near-ground imagery.

1.2.3. What about unmanned aerial vehicles (UAVs) (drones)?

Airborne platforms at low altitudes, such as Unmanned Aerial Vehicles (UAVs), provide a platform for rapidly developing sensor technology, allowing aerial imagery of fields using a range of passive panchromatic multispectral and hyperspectral sensors covering different wavelengths (visible, near infrared and thermal). They can also support active sensors such as LiDAR. UAVs are evolving rapidly both technically and with regard to regulations, and are now widely available. They are relatively low cost, light weight, and are less hindered by cloud cover compared to other satellite devices. Their ability to minimize pixel size to as little as a few millimetres, along with the miniaturization of on board sensors has resulted in an explosion in their potential application (Huang et al., 2013; Zhang and Kovacs, 2012). The potential use of UAVs within intensive grassland farming has yet to be fully explored, but their ability to generate very high resolution (2–10 cm) farm-level imagery within time frames of a few minutes to a few hours offers great scope and potential (Chen et al., 2004). Geipel and Korsaeth (2017) used airborne imaging spectroscopy for in-season grassland yield estimation using powered partial least squares regression and linear regression models based on selected vegetation indices and plant height. Distinct reflectance differences between grass types and clover and the highest prediction accuracies were achieved by means of powered partial least squares (relative errors of prediction from 9.1–11.8%).

Crop surface models can be generated using a series of acquired images. This requires the mosaicking of collected images, point cloud generation and digital surface model export (Bendig et al., 2014). Bareth et al (2015) captured a number of RGB images from a flying altitude of approximately 20 m above ground, producing a set of multiple overlapping images, containing at least 15.000 pixels for each of the 25 experimental plots in the study. Bareth et al. (2015) hypothesised that a UAV-based crop surface model approach is transferrable to grassland ecosystems and that crop surface model-derived plant height can be used as a measure to estimate yield. LiDAR has the ability to extend spatial analysis to a third dimension. LiDAR uses pulses of radar light directed towards objects and measures the time required for the pulse to return to the sensor. Despite its success in monitoring forest biomass, fewer studies have demonstrated the application of LiDAR to estimate temperate grassland biomass (Wachendorf, 2017).

1.3. Section 3 Management changes required to improve yield/grass quality, nutrient management efficiency and protect the environment

All farm businesses are different in terms of size, structure, type of livestock, etc. In the Irish National Farm Survey in 2015, the farmers who were ranked in the top 20% of producers in terms of profit per hectare, were shown to be the farms that utilised more grass, had lower costs and a greater net margin (Forager, 2017). Some farms are growing 10 t/ha while other farms are growing 18 t/ha. Some farms are utilising 2 t/ha while other farms are utilising 12–14 t/ha. Much of this is due to management. An individual farmer needs to assess (i) what strategies could potentially be employed on their farm to increase grass yield and optimise stocking rate and (ii) how can they best forecast grass growth to inform timely decisions throughout the grazing season. Here we assess where PA could have a potential role in aiding some of these decisions.

Shalloo et al. (2011) highlighted grassland management, soil fertility and national reseeding levels as having a strong influence on overall pasture production in Ireland. There are areas of grassland farming that could be vastly improved with the aid of data informed decision making. The implementation of PA is applicable to all farmers, at whatever scale and extent they require / desire / can afford in order to improve their own farming business. This could be simply the implementation of weather data such as temperature and rainfall to inform and improve management decisions such as silage cutting and fertilisation dates. It also includes the collection of soil and field data such as growth stage, grass condition, and farm data such as stocking levels and outputs. The degree of implementation of PA technology should be farm specific and outcome specific. The needs of the intensive dairy farmer aiming to improve milk yields would be very different from the aims of the part-time upland beef and sheep farmer, but all can benefit from the implementation of different forms of PA. Improvements in grassland management, particularly at the 'fringes' of the grass growing season, offer the possibility of extending the grazing season by a number of weeks.

Less than 10% of farmland in Northern Ireland has an up-to-date soil analysis (Gilliland, 2016). Inadequate soil fertility can be extremely detrimental to grass productivity. While soil analysis remains the most accurate methods of determining soil nutritional status, the time required and cost involved in extracting soil samples from fields in the numbers required to adequately map spatial and temporal variability, is cost-prohibitive for the majority of grassland farmers (McCormick, 2005). Provided they are accurate and the data correctly interpreted, soil sensors can be labour saving and a useful management tool, often providing more timely results (Sudduth et al., 2017). Hand-held sensors such as soil moisture probes have the advantage of being portable and provide instant readings. A recent paper by Smolka et al (2017) presented a mobile sensor for on-site analysis of soil sample extracts. If successful, this device could be used to detect the primary plant nutrients in their available form, at a fraction of the time and cost associated with traditional laboratory soil analysis. The device scanned ion concentrations within liquid samples, using a microfluidic chip in which the sample ions are separated in an electric field by capillary electrophoresis, and the individual ion concentrations are moved past a detector one after another and the conductivity recorded. The sensor was particularly appropriate for the analysis of NO_3, NH_4, K and PO_4. and followed on from previous studies exploring the potential for on-the-go soil sampling for nitrate using electrochemical sensor platforms (Adsett et al., 1999) and ion-selective electrodes (Shaw et al., 2013). Ion-selective electrodes are relatively cheap and simple to use. It has also been suggested that in-situ sensor networks may enable a step away from predetermined N recommendations (Defra, 2010) to a more dynamic system that responds in real-time to changes in growing conditions (Shaw et al., 2013). In-situ sensors would also provide data at significantly higher temporal resolution and so negate the need for repeated, costly sampling throughout the year.

Bulk apparent soil electrical conductivity (EC_a) sensors respond to multiple soil properties, including clay content, water content (Pedrera-Parrilla et al., 2016) and salinity, and mobile measurements of EC_a have become widely used to map soil variability (Sudduth et al., 2017). McCormick (2003, 2005) measured soil apparent electrical conductivity (EC_a) in grassland fields in Northern Ireland. EC_a could be measured cheaply and rapidly and was found to be related to a large number of soil properties. The greatest potential use of EC_a scanning is in the survey of spatial soil variability, and delineating potential site-specific management zones. This in turn would allow for better resource allocation and long-term management planning.

Large volumes of data can be collected using sensors. Translating this data into meaningful management decisions is a challenge. Since 1999 there have been massive improvements in the accuracy and miniaturization of Global Navigation Satellite System (GNSS) technology. GNSS technology facilitates the linkage of data to specific geographical coordinates (geo-referencing). Global Positioning Systems (GPSs) are now commonly used on farms for auto-steer systems and the production of geo-referenced information *e.g.* yield mapping. GNSSs attached to soil and crop sensors will enable auto guidance in machinery along with soil and crop monitoring at fine spatial scales.

Auto-steer and controlled traffic farming systems guide machinery along repeatable tracks in fields with accuracy, thereby reducing errors and fatigue, and increasing the timeliness of operations. By confining vehicles to a minimal area of traffic lines, unnecessary crop damage can be avoided and soil compaction reduced. Grass yield reductions as a consequence of soil compaction imparted by passing vehicles can be as much as 74% (Hargreaves et al., 2017) along with a reduction in silage clover content (Alvemar et al., 2017). Controlled Traffic Farming Systems, by reducing damage to soil structure and grass swards, can achieve a yield increase of 13.5% (Hargreaves et al., 2017). Alvemar et al (2017) highlighted that although there can potentially be significant economic benefits for farmers converting to a Controlled Traffic Farming System, uncertainties still exist, such as initial fixed investment costs and uncertainty on yield returns.

Variable Rate Fertiliser Applicators are now available that are able to vary nutrient application rates in real-time while moving across fields. Real-time sensors (enabled using GNSS technology) scan the crop, and signals are sent straight to the fertiliser applicator indicating the nutrient requirements at the time of scanning. The benefits of variable rate applications are most likely to be seen in fields where there is marked spatial heterogeneity in yield and / or soil properties. Provided nutrients are one of the limiting yield factors, areas of lower yield may benefit from additional fertiliser. In such cases, application rate and timing are very important, so as not to increase the risk of nutrient losses to the environment, especially in areas of either heavy waterlogged or light sandy soils. In some areas the yield improvement will be small, and may not justify the effort involved in managing the inputs.

Along with inorganic fertilisers, animal slurry is also an essential nutrient source for intensive grassland. Schellberg and Lock (2009) presented a technique which allows site-specific application of slurry to grassland based on pre-defined application maps. The system consisted of a valve controlling flow rate by an on-board PC. During operation, flow rate was measured and scaled against set point values given in an application map together with the geographic position of the site. Site-specific slurry applications could contribute significantly to the mitigation of local nutrient surpluses and loss on the one hand as well as deficiency of nutrients on the other.

Where fields or areas of fields are underperforming, reseeding may be required. Figures from the Recommended Grass and Clover Lists 2017/18 (British Grassland Society, 2018) show that by not reseeding, farmers could miss out on grass worth around £340/t on a two-cut silage system, based on a grass value of £140/t dry matter. Changes in management such as an increased frequency of silage cutting can lead to better quality silage, lower bought-in feed costs and improved performance from forage. Adopting new thinking can reap rewards for farmers and bolster production potential (Forager, 2018).

In addition, a number of environmental issues currently exist within the UK and Ireland of which nutrient losses from agriculture are a major contributing factor. The loss of phosphorus and nitrogen from fields and farm yards through leaching and overland flow has contributed to the eutrophication of fresh water bodies. Greenhouse gas emissions such as nitrous oxide and methane from fertiliser and animal manure applications are a major problem, as is ammonia from cattle housing and land spreading. Improving the precision and efficiency of soil nutrient management can play an important role in minimising nutrient surpluses (McCormick et al., 2009) and reducing the risk of nutrient loss to the environment, either to waterways of through gaseous emissions.

1.4. ***Section 4*** *Data handling and interpretation, along with social issues and barriers specific to rural dwellers within grassland farming communities in the UK and Ireland*

The rapid development of ICT-based sensor technologies in recent years, along with dedicated software that enables real-time soil and crop sensing, and provision of data for application maps or decision support systems (DSS) is a great support in terms of progressing PA. The advancement of the internet and the proliferation of smart phones has created opportunities for the development and use of decision support tools that are web enabled (Crowley et al (2013). As well as facilitating decision making, the inclusion of a data storage function dramatically increases their functionality (Hanrahan et al., 2017). One of the greatest challenges with PA is the generation of large amounts of data that needs to be standardised and processed for application across systems. For example, the production of as-applied maps that are user-friendly and which farmers can interpret and base management decisions on. Accurately interpreting the data output from sensors and PA technology still requires a large amount of research and development. For technical solutions to be of benefit they need to be applied and developed further in association with current management regimes. This is a complex procedure and requires the support of farmers, cooperatives, scientists and the private sector to effectively collaborate and co-create knowledge. Data management and compatibility are currently some of the main limitations to handling data generated by sensors. Data sharing due to non-standard software and data formatting are also big issues. The quality of the data collected (spatial and temporal) is important, and perhaps now we need to focus research and technology development efforts into data interpretation and appropriate application within grassland systems.

Data ownership is a sensitive issue, particularly if a number of bodies become involved in data collection and management decisions such as contractors, farm advisors and technology providers. The full benefits of many PA tools for grassland have yet to be demonstrated, and many of the tools that are currently available are not user-friendly. In future there may be more emphasis on the Internet of Things (IoT), which is the interconnection of uniquely identifiable embedded computing devices within the existing Internet infrastructure. This would theoretically make it possible to connect all devices that are available on the farm, in order to facilitate decision making. Wireless Sensor Networks and Smartphone Apps offer notable future potential. The ‘cloud’, provides solutions for data storage, data sharing and data exchange. Currently, different systems tend to be isolated and there is poor data communication on and between farms. Farming ‘in the cloud’ is based on internet storage sites rather than relying on storage devices such as USB sticks and flash cards.

Research and development are moving now into the development of web-based decision support tools using legacy and seasonal satellite data, weather data, soil condition, field and farm data and combining these into models of grassland nutrition and biomass predictions. PastureBase Ireland (Hanrahan et al., 2017) is a web-based grassland management application incorporating a dual function of grassland decision support with a centralised national database to collate commercial farm grassland data. This database facilitates the collection and storage of vast quantities of grassland data from grassland farmers and spans across dairy, beef and sheep. It is a data informed decision support tool to function at the field level. Farmers enter their own data through the completion of regular pasture cover estimations, allowing the performance of fields to be evaluated within and across years. PastureBase Ireland works in real time, providing decision support while capturing farm grassland data in the background for benchmarking and research purposes. Using tools such as budgeting, spring and autumn rotation planners work simultaneously to aid an optimum quantity of pasture at critical times in the grazing calendar. Rotation planners specify an area of grass that a farmer can afford to allocate to livestock on a daily basis in order to maximise the amount of pasture in the diet.

By introducing complex technology onto farms before it is fully user-friendly and reliable presents a large amount of risk. Where a farmers’ livelihood is at stake, this risk cannot be taken lightly. A farmer investing in any new technology would require considerable guidance and backup by trained individuals, and it would also depend on the farmer having a degree of resilience and desire to adapt and to make any management changes a success. Social factors have a huge influence on the success of PA (Kutter et al., 2011). Employing the services of contractors may be necessary, particularly those with specialist knowledge of a technique (Kutter et al., 2011). There should be clear farmer benefits economically in terms of their financial investment and also the time involved in learning and adopting new management strategies. Farmers should be actively involved in creating appropriate PA solutions, as specific needs will vary depending on location and local farming practices. PA is likely to be more appealing to intensive more profit-driven farmers where the land area is larger and where they have capital money to invest (Edwards-Jones, 2006). For the smaller, less intensive and possibly part-time farmer who does not make much profit and indeed where farming may not be the primary income, investment in expensive PA technology may both be undesirable and possibly less beneficial than to a larger farmer who is open-minded, forward thinking a willing to take risks and accept new challenges. Smaller, less intensive farms with an aging farmer profile, and also those farms in uplands and harsher landscapes may not have the same desire or outcome when adopting new technology. However, adopting more precise management strategies, including small changes such as maintaining regular soil sampling and grass growth monitoring, can all provide benefit.

2. Reflections and future research

The objective of this review was to assess whether productivity and soil nutrient management on grassland farms in the UK and Ireland could be improved by adopting a PA approach to management. Although the current research base behind grassland PA technology is lower, there is promising potential for huge strides to be made in this sector. Technology is developing rapidly and there are a range of sensors now available for monitoring soil properties, grass yields and animal health. For example, many farmers are beginning to recognise the benefits of regularly measuring grass growth using rising plate meters. Controlled Traffic Farming and Variable-rate fertiliser application has potential economic as well as environmental benefit, however there is currently not enough research, including economic research, into the merits of this technology. Remote Sensing is advancing rapidly in terms of resolution and frequency of re-visit times. In recent years the unavailability of suitable images at times that were appropriate for decision making was a huge problem. However the advancement of SAR and UAV technology are slowly overcoming the issues of cloud cover and facilitating the sub-field scale monitoring that is crucial in order for PA to make a worthwhile contribution to on-farm management.

The sustainability of many grassland enterprises is challenging in an increasingly competitive global market. Farmers in future will need to embrace innovation. PA has its place within grassland farming and it will likely be a very gradual transition and change within this group in order to fully implement new concepts. Grassland farmers require the support of government, researchers, technology providers and many other rural stakeholders to implement change where necessary and promote sustainability. While there are a large number of new and developing technologies available, future research should focus on fully testing these technologies so that the data they collect is robust, interpretable and fits meaningfully within the farm matrix.

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