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Dynamic algorithmic conversion of compressed sward height to dry matter yield by a rising plate meter

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ABSTRACT

The strategic allocation of pasture grazing area to dairy cows is essential for optimal management and increased outputs. Rising plate meters are frequently used to estimate pasture herbage mass, i.e. dry matter yield per hectare, by employing simple regression equations that relate compressed sward height to herbage mass. However, to improve the accuracy and precision of these equations, so that inherent variation of grasslands is captured, there is a need to incorporate differences in grass types and seasonal growth. Using a total of 308 grass plots, the variation of growth for both perennial ryegrass and hybrid ryegrass was recorded over the seven-month growing season, i.e. March–September. From these data three dynamic equations were derived. The models showed reduced levels of error in comparison to most other conventional equations. As such, the derived models represent a considerable advance for predictive assessment of herbage mass and will support more efficient grassland utilisation by farmers. Although all equations were found to be highly accurate and precise, only a single equation was considered the most effective (R^2 = 0.7; RMSE = 248.05), allowing herbage mass to be predicted reliably from compressed sward height data in relation to ryegrass type and calendar month. Although further research will be required, the results presented allow farm operators to calculate herbage mass, as well as support the development of decision support tools to improve on-farm grassland management, particularly at the local paddock rather than national level.

1. Introduction

There exists a substantial and growing demand for dairy products worldwide (Godfray et al. 2010), with global demand for milk expected to increase by 48% between 2005 and 2050 (Alexandratos & Bruinsma, 2012). In temperate climates, pasture-based ruminant production offers a competitive and sustainable alternative to intensive, high-input systems (Dillon et al. 2008; Lawrence et al. 2016; Delaby et al. 2020). In particular, the utilisation of grazed grass provides for a highly efficient, nutritious and inexpensive source of energy for ruminant production (Dillon et al. 2005; Finneran et al. 2012). Importantly, the quantity and quality of herbage offered to grazing animals has a substantial impact on their performance e.g. milk production (Patton et al. 2016). Accordingly, to meet the daily nutritional demands of animals, the strategic allocation of grazing area is an essential management practice (e.g., O'Donovan, 2000; Kennedy et al., 2009; Curran et al., 2010). However, determination of the appropriate allocation of grazing area can only be achieved when using reliably accurate and precise estimates of herbage mass (HM; kg DM ha^{-1}), i.e. dry matter yield per hectare.

Accurate measurement of HM can also be used to budget available forage in grazing systems, particularly as grass is an unstable resource (Sanderson et al. 2001; López-Díaz et al. 2011). For example, regular estimation can help ensure an adequate supply of herbage to meet demand throughout the grazing season and inform decisions on the removal of surplus herbage to balance its supply and demand, whist maintaining herbage quality. In addition, regular measurement of herbage can be used to identify poor performing grass swards, allowing the farmer to take corrective action such as reseeding, addressing soil

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fertility issues, and drainage (O'Donovan 2000; Hakl et al. 2012; Shalloo et al. 2011). Considerable potential exists to increase the accuracy and precision of pasture allocation, and subsequent farm productivity (Creighton et al. 2011; Dillon 2011). In essence, greater use of reliably collected on-farm data can improve management practices, through the provision of knowledge-based real-time decision support tools.

While accurate estimation of HM can be achieved through assessment of sward heights obtained from clipped quadrants, this is laborious and time intensive endeavour (Sanderson et al. 2001; López-Díaz et al. 2011). Although HM is most often estimated by visual observation, this method is highly subjective and prone to considerable inter-observer variability (Tucker, 1980; O'Donovan et al. 2002; López-Díaz et al. 2011). For optimal and informed management, grass needs to be measured quickly and reliably in relation to both accuracy and precision. The rising plate meter (RPM) can be used to estimate the HM of grasslands based on the compressed sward height (CSH) (Sanderson et al. 2001; Hakl et al. 2012). Overall, this device is considered to be an accurate, precise and labour efficient method for sampling HM (Sanderson et al. 2001; Soder et al. 2006). However, device reliability can be affected by the naturally large variation of dry matter (DM) within CSH, which is governed by numerous factors, such as plant growth state (Mosquera-Losada and Gonzalez-Rodriguez, 1998), season (Bransby et al., 1977; Rayburn 2020), species composition (Castle 1976; Rayburn 2020), and grassland management regime (Powell, 1974).

In recent years, technological advances such as accurate sensors, Global Navigation Satellite Systems (GNSS), Bluetooth connectivity, and low-power portable user interfaces (i.e. smart-devices), have been used to improve farm management practices (Dillon 2011). Accordingly, these technologies can be used to improve in-field measurement and facilitate real-time decision support in relation to grassland management. In particular, an RPM utilising a micro-sonic sensor and digital data capture *via* a Bluetooth communications link to a smart-device application has been developed (i.e. Grasshopper, see McSweeney et al. 2019). This RPM device and its associated micro-sonic sensor were found to accurately measure sward height (McSweeney et al. 2019). Although the device can be programmed to calculate HM within its associated smart-device application using various formulas, a good reference population to act as baseline data that has realistically captured inherent variations of grassland is required for the development of effective, reliable and dynamic algorithms.

To optimize reliability, equations need to be developed across the growing season and for different grass species, ploidies and varieties. Previously, for example, a dynamic formula was developed for North West France on perennial ryegrass (*Lolium perenne L.*) monoculture swards and mixed swards of perennial ryegrass and white clover (Defrance et al. 2004). However, a significant effect of season was observed within this formula, i.e. calculated HM based upon CSH varied by month. Accordingly, optimal grassland management requires the use of a formula altered on a monthly basis. Here, therefore, we develop a dynamic formula to accurately determine HM for Irish temperate grasslands throughout the grass growing season, for both perennial and hybrid ryegrass.

2. Methods

2.1. Study site

The study was conducted upon perennial ryegrass and hybrid ryegrass plots ($n = 308$) sown on a free-draining acid brown earth soil of sandy loam texture at Teagasc, Animal & Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland (52°09′50″N, 08°15′50″W). Plots were managed under simulated ($n = 120$; 5 × 1.5 m) or actual grazing ($n = 188$: 10 × 1.5 m) regimes. Plots managed under simulated grazing conditions were mechanically harvested on eight to nine occasions annually. While animal grazed plots were managed equally on a 21–30 day grazing rotation resulting in eight to nine sampling occasions annually.

Before sowing, glyphosate was used to kill the previous sward, the entire area was then ploughed and tilled to provide a fine and firm seed bed which received 37 kg N ha^{-1}, 37 kg P ha^{-1} and 74 kg K ha^{-1}. All plots were sown using a plot seeder (WINTERSTEIGER Plotseed S; WINTERSTEIGER AG., Austria) in August. Once the newly sown plots had reached the two leaf growth stage they were sprayed with a post-emergence herbicide to control the establishment of broad-leaved weeds. With an equal number of diploids and tetraploids, simulated grazing plots were comprised of perennial ryegrass or hybrid ryegrass. Both ryegrass types were established as monocultures at a sowing rate of 37 kg ha^{-1}, and as polycultures totalling 37 kg ha^{-1}, for all possible combinations for sowing rates of: 9.25; 18.5; and 27.75 kg ha^{-1}. For example, sowing rates were combined for perennial ryegrass (9.25 kg ha^{-1}) and hybrid ryegrass (27.5 kg ha^{-1}), and again for the corresponding mix of perennial ryegrass (27.5 kg ha^{-1}) and hybrid ryegrass (9.25 kg ha^{-1}). Plots designated for actual grazing were likewise constructed using an equal number of diploid and tetraploid perennial ryegrass types, with sowing rates of 34 and 37 kg ha^{-1}, respectively. All actual grazing plots were sown as ryegrass monocultures.

All plots were constructed using a randomised complete block design, consisting of four replicates. For a simulated grazing protocol, plots were harvested using a rotary blade mower to a cutting height of 4 cm (Etesia Hydro 124D; Etesia Ltd., UK), when HM was visually estimated as ~ 1500 kg DM ha^{-1}. Animal grazed plots were likewise allowed to reach a visually estimated pre-grazing HM of ~ 1500 kg DM ha^{-1}. The grazed area was offered on a replicate basis to dairy cows for 24–36 h, dependant on animal intake, to reach a target residual grass height of ~ 4 cm. Before grazing, a 1 m^2 sub-sample was cut from actual grazing plots following the procedure outlined for simulated plots.

2.2. Dry matter yield

Dry matter (DM) yield was determined by weighing all herbage cut from simulated and actual grazing plots. Material from grazed plots was then returned to the source plot to allow consumption by grazing cows. In all cases, a 0.1 kg subsample was retained and dried at 60 °C for 48 h to determine percentage DM content (% DM) in relation to original wet weight. The HM was then derived with respect to the area cut, the wet weight and the percentage DM content.

2.3. Grass height measurement

Ten CSH measurements were collected from each plot both immediately before and post herbage removal. These measurements were captured with a micro-sonic sensor unit (Grasshopper II; True North Technologies, Ireland), mounted perpendicular to the shaft of a hand-held, commercially available RPM (Jenquip; Filip's Manual Folding Plate Meter, New Zealand). The Grasshopper micro-sonic sensor is designed to measure the distance between the sensor and the top of the rising plate, to determine height displacement of an object underneath the plate. Instantaneous capture of height data, together with a geo-tag describing the location, was facilitated via a Bluetooth communications link between the sensor unit and an accompanying smart-device application (Android operating system). All captured data was saved to the smart-device in a comma separated (.CSV) format. Before data capture, the micro-sonic sensor was normalised to ensure a baseline of height zero is established while the plate was at its resting position.

2.4. Algorithm establishment

To establish an algorithm for the conversion of CSH to predicted HM, a variety of variables were examined, including: type of ryegrass (TRG; 2 levels: perennial ryegrass and hybrid ryegrass); Month (7 levels: March – September, inclusive); the percentage DM content (% DM); actual HM (kg DM ha^{-1}); pre-cut CSH of grass (cm); height cut (cm), i.e. pre-cut

CSH minus the post-cut CSH; and DM per centimetre of grass cut, i.e. HM divided by height cut (kg DM cm^{-1}). Pre-cut CSH of < 5 cm were discarded, as were unrealistic values of > 550 kg DM cm^{-1}. Correlation coefficients were calculated for the examined variables to determine effect statistics (see Table 1). These coefficients were used to derive and validate values for the prediction of HM, in relation to actual values recorded for each plot. To assess model performance, Root Mean Square Error (RMSE) values were calculated for each equation, as well as the coefficient of determination (Pearson's R^2) and relative prediction error (RPE). Model bias was calculated in relation to mean percentage error (MPE). These assessment criteria have been employed by similar prediction modelling studies (see Murphy et al. 2021, and citations therein), and will facilitate a comparative assessment of the results with those of other studies.

3. Results

In total, the constructed dataset was comprised of 1640 usable plot assessments, with each of these including values for all the required variables. First, a value for predicted HM was derived in relation to actual pre-cut CSH (h) values, and the pre-cut CSH square expression (h^2). Within the equation, the corresponding coefficients were each multiplied by these selected parameters (Eq. (1): $R^2 = 0.59$; $P < 0.001$). All coefficients were highly significant at $P < 0.001$ (Table 1). RMSE of 291.21, RPE of 19.8% and MPE of −3.5% were calculated for Eq. (1):

$$\text{Predicted herbage mass} = \left(-227.6 + (233.3 \times \text{h}) + \left(-5.35 \times \text{h}^2\right)\right) \quad (1)$$

Second, building on this approach, a predicted value for HM was derived using coefficients for TRG (t) and month (m), with inclusion of the actual pre-cut CSH (h) and the pre-cut CSH square expression (h^2). Once again, the coefficients for both pre-cut CSH and the pre-cut CSH square expression were each multiplied by these model parameters (Eq. (2); $R^2 = 0.7$; $P < 0.001$). All coefficients were highly significant at $P < 0.001$ (Table 1). RMSE of 248.05, RPE of 17.9% and MPE of −3.3% were calculated for Eq. (2):

$$\text{Predicted herbage mass} = \left(-446.5 + \text{t} + \text{m} + (263.9 \times \text{h}) + \left(-6.6 \times \text{h}^2\right)\right) \quad (2)$$

Table 1
Derived coefficients and associated F values ($n = 1640$). All $P < 0.001$, excepting the effect of percentage dry matter content (% DM) at $P < 0.05$.

	Eq. (1)	F	Eq. (2)	F	Eq. (3)	F
Intercept	−227.6		−446.5		111.8	
TRG		–		83.58		86.89
PRG	–		72.3		78.2	
HRG	–		−72.3		−78.2	
Month		–		76.2		64.11
March			90		−0.3	
April	–		22.5		5.4	
May	–		75.1		75.1	
June	–		64.3		33.6	
July	–		−275.9		−209.7	
August	–		−160		−154.2	
September	–		184		250.1	
Pre-cut CSH	233.3	279.34	263.9	388.9	118.7	2133.01
Sq. Pre-cut CSH	−5.35	70.49	−6.6	120.67	–	–
% DM	–	–	–	–	8.9	6.48
R^2	0.59	1170.54	0.7	428.09	0.68	388.35
Root Mean Square Error	291		248		256	
RPE (%)	19.8		17.9		19.2	
MPE (%)	−3.5		−3.3		−4.3	

A third model for predicted HM was then developed using coefficients for TRG (t) and month (m), with inclusion of the percentage DM content (d) and the corresponding value for pre-cutting CSH (h). As before, the coefficients for the effects were each multiplied by their dependent model parameter (Eq. (3); $R^2 = 0.68$; $P < 0.001$). All coefficients were significant at $P < 0.001$, other than calculated percentage DM at $P < 0.05$ (Table 1). RMSE of 256.56, RPE of 19.2% and MPE of −4.3% were calculated for Eq. (3):

$$\text{Predicted herbage mass} = (111.8 + \text{t} + \text{m} + (8.9 \times \text{d}) + (118.7 \times \text{h})) \quad (3)$$

4. Discussion

This current study confirms the relationship between CSH and HM. Basically, the height of grass can be used as a reliable indicator of HM. Although Eq. (1) provides a simple straightforward estimate based on pre-cut CSH values alone, this equation cannot facilitate a dynamic assessment for type of ryegrass measured and time of year. Eq. (1) is also the least reliable given the associated Pearson's R^2, RMSE and RPE values. Both Eqs. (2) and (3) are especially beneficial as both can account for perennial ryegrass type and variation in relation to time of year. These equations will allow for the construction of dynamic formula within the smart-device application and associated novel micro-sonic RPM linked technology. The most applicable formula can be selected by an on-farm operator, based on the readily available information concerning the type of ryegrass and sampling month, to reliably predict HM. However, Eq. (2) is marginally more accurate and precise than Eq. (3), with respect to Pearson's R^2, RMSE, RPE and MPE values. Importantly, Eq. (2) is also a more advantageous formula, as it is derived from pre-cut CSH values rather than actual percentage DM content, which is not necessarily readily measurable on-farm because of impracticalities.

As demonstrated by many previous studies, it has been difficult to achieve RMSE values of below 250 kg DM ha^{-1}, with most studies achieving values closer to 300 kg DM ha^{-1} (López-Díaz et al. 2011; Murphy et al. 2021). Although imprecise, RMSE values ranging from 250 to 300 kg DM ha^{-1} represent the best available predictive equations for HM assessment based on measurements obtained from RPMs. Accordingly, the RMSE values obtained for all equations in this study are within an acceptable range, while both Eqs. (2) and (3) have especially favourable RMSE statistics. Interestingly, the inclusion of meteorological data in model calculations derived from machine learning techniques can provide for an improved RMSE value (243 kg DM ha^{-1}: Murphy et al. 2021). However, this is not considered to be a practical approach given the expense of on-farm meteorological sensors (see Murphy et al. 2021).

To date, most regression formulas used to calculate HM from CSH have been linear in nature, as this allows for easier calculations. However, smart polynomial regression formula, such as the equations derived by this study, are a far more accurate estimation of HM. For example, Michell and Large (1983) achieved strong correlations between CSH and HM ($R^2 = 0.98$) for specific time points across the grass growing season. However, when Sanderson et al. (2001) applied one of these time specific formulas consistently over a full grazing season, the correlation was significantly reduced ($R^2 = 0.31$). The additional model parameters required by Eq. (2), i.e. type of ryegrass and month, will be known to farm operators in the field and can, therefore, be selected as required. In general, all three derived equations displayed reduced error parameters (<20 % RPE, <5 % MPE) in comparison to most other models (≥24 % RPE, ≥9% MPE; see Murphy et al. 2021, and citations therein). In particular, Eq. (2) considerably improves upon conventional models through reduced RPE and lower MPE values, and will advance the prediction of HM for pasture-based grazing systems in temperate zones.

Despite statistical indications of high accuracy and precision, further research will be required to better understand elements of formula

inaccuracy and imprecision. Therefore, an improved knowledge of on-farm variability is needed. To achieve this, additional model parameters could be included and validated, with a view to produce regional if not paddock specific formula, rather than national level equations. These equations could then be used to produce dynamic algorithms capable of calculating reliable HM estimates, based on operator selected criteria. With the advent of automated grass height data capture tools, such as micro-sonic RPMs and associated smart-device web-applications, dynamic and reliable calculation of HM can be achieved in a practical user-friendly manner. In addition, these tools can potentially be linked to other grassland technologies, to provide 'smart-farm' solutions through highly automated systems, including the deployment of virtual fences (see McSweeney et al. 2020). For example, upon collection of CSH data with a smart-device linked to an RPM with an on-board link to satellite navigation, a web based geolocation application can be used to define the optimal grazing area for the herd within a pasture. Here, we have produced a series of formulae that can be used within smart-device linked RPMs, for reliable algorithmic conversion of CSH to HM. Although further research is required to develop the equations to encompass more site-specific effects, our results represent a promising starting-point for the further advancement of decisions support tools, to improve on-farm grassland management.

CRediT authorship contribution statement

Diarmuid McSweeney: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Luc Delaby:** Conceptualization, Formal analysis, Methodology, Validation, Writing – review & editing. **Bernadette O'Brien:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Alexis Ferard:** Data curation, Formal analysis, Investigation, Methodology, Writing – review & editing. **Nicky Byrne:** Data curation, Investigation, Resources, Writing – review & editing. **Justin McDonagh:** Data curation, Investigation, Resources, Writing – review & editing. **Stepan Ivanov:** Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing. **Neil E. Coughlan:** Data curation, Formal analysis, Investigation, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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