



Weather forecasts to enhance an Irish grass growth model

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ABSTRACT

Grass growth models have retrospectively predicted grass growth in Ireland using weather observations. However, to predict future grass growth to aid farm management, weather forecasts are necessary inputs. The Moorepark St. Gilles grass growth model (MoSt GGM) is mechanistic and was developed to predict perennial ryegrass growth on any Irish farm. To date, it has used local farm information, (retrospective) weather data and management factors to predict daily paddock-level grass growth. Here, we include weather forecasts in the MoSt GGM and assess its performance through two studies: daily grass growth predictions at four nitrogen fertiliser application levels using weather forecasts up to ten days in advance were compared with those using weather observations; and the GGM predictions for an Irish dairy farm using observed and forecast weather were compared with on-farm grass growth observations from 2013 to 2016. In the first study, all weather inputs captured the rise in grass growth predictions with higher fertiliser application. Based on the Root Mean Squared Error (RMSE), European Centre for Medium-Range Weather Forecasts (ECMWF) forecasts outperformed a forecast based on climatological averages as GGM inputs up to six days in advance, and up to ten days in advance after bias correction. In the second study, ECMWF forecasts were the best weather forecast to predict grass growth since they captured weather variability well and did not require the local weather observations necessary for bias corrections. Weather forecasts are useful inputs to the MoSt GGM, and yield accurate weekly predictions that could aid management decisions.

1. Introduction

The UN predicts worldwide population to grow from 6.9 billion people in 2010 to 9.7 billion in 2050 (United Nations, 2015). A 1.1% growth per annum in worldwide consumption of agricultural products is projected between 2005 and 2050, giving rise to an approximate food demand growth of 60% in this period (Alexandratos and Bruinsma, 2012). Food Wise 2025 (DAFM, 2015) anticipates an 85% increase in Irish agri-food exports between 2015 and 2025 to capitalise on this extra demand. To meet these targets, Irish farmers must ensure their foodstuffs can be produced sustainably. Maximising economic growth by expanding and making best use of available resources must be coupled with environmental protection (DAFM, 2015). Livestock convert grass into human food such as milk and meat, often on land that is less suitable for crop production (van Zanten et al., 2016; Wilkinson, 2011). It is imperative that Irish dairy and beef farmers make best use of their grassland resources as grazed grass is the cheapest feed source available to them (Dillon et al., 2005; Finneran et al., 2012).

Management of grasslands on a short-term basis is essential to

maximise grass growth and utilisation (Creighton et al., 2011; Dillon et al., 2005). However, some factors that strongly affect farm management decisions are outside the farmer's influence, for example weather conditions. Grass based milk production systems are predominantly based in temperate regions such as Ireland, other parts of North West Europe, New Zealand and parts of Australia. Grass based milk production systems are generally low input low cost systems as the temperate climate provides favourable conditions for high yields of grass dry matter (DM) from perennial ryegrass (*Lolium perenne* L.) over a long grazing season (O'Donovan et al., 2011). Perennial ryegrass growth begins at 5 °C and ceases around 20–25 °C (Frame, 1992; Hopkins, 2000), so the Irish growing season can last from early Spring to early Winter (Burke et al., 2004; Hopkins, 2000; Hurtado-Uria et al., 2013). Rainfall during the Irish growing season is often optimal for grass growth, although an excess of water can sometimes make grazing impossible or reduce grass growth (Burke et al., 2004). Solar radiation is essential for the conversion of carbon dioxide into biomass (Laidlaw and Frame, 2013); during a large part of the growing season, low solar radiation is more limiting than low temperature, and strongly affects

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growth in all seasons (Hurtado-Uria et al., 2013; Laidlaw and Frame, 2013).

A grass growth model (GGM) accounting for weather and local conditions, as well as factors that can be controlled by farmers, such as N fertiliser application, grazing rotation length and removal of excess herbage, would aid farm management decisions on feed supply and grassland management. GGMs accounting for some or all of these components have been developed for specific locations in countries such as England (Johnson and Thornley, 1983) and France (Jouven et al., 2006), as well as general models for multiple European sites in different countries (Schapendonk et al., 1998). These models can be mechanistic (for example Johnson and Thornley, 1983; Jouven et al., 2006; Schapendonk et al., 1998) or empirical (for example Breerton et al., 1996). Australian studies have assessed the potential usefulness of seasonal climate forecasts in agriculture (Ash et al., 2007), and included monthly to seasonal climatological hindcasts in a GGM (Harrison et al., 2017). Grass growth predictors such as the NZ Pasture Growth Forecaster (Dairy NZ, 2018) are being used in practice but do not use weather forecasts. The model used in this paper is the Moorepark St Gilles (MoSt) GGM (Ruelle et al., 2018), which is an Irish adaptation of the model developed by Jouven et al. (2006). Although Irish GGMs have been developed, none are being widely used in practice, and none have used weather forecasts. An operational GGM would allow the farmer to describe their location, soil type and management practices initially. It would then account for these parameters and local weather conditions to predict on-farm growth over the next seven to ten days. Based on these predictions, farmers could make informed management decisions. For example, they could plan to supplement feed if a grass shortage occurs or remove excess herbage from paddocks when there is a surplus of grass on-farm.

Weather forecasts are potentially highly influential inputs for a GGM to predict future grass growth. To date, only predictions from the MoSt GGM using retrospective weather observations have been verified (Ruelle et al., 2018). The inclusion of forecasts will introduce an extra level of uncertainty to the model. McDonnell et al. (2018) assessed the accuracy of European Centre for Medium-Range Weather Forecasts (ECMWF) forecasts at 25 Irish weather stations, and applied bias correction techniques to improve forecast accuracy. Air temperatures were forecast accurately up to ten days in advance, with improvements after bias correction, and rainfall forecasts generally performed well up to five days in advance. However, high rainfall observations were often poorly forecast. Inaccurate rainfall forecasts could decrease the accuracy of grass growth predictions from the MoSt GGM due to the strong influence of rainfall on grass growth.

The objective of this paper is to compare weather observations and forecasts as predictors in the MoSt GGM to ensure there is not a large decrease in accuracy when forecasts are used, and to assess model predictions against on-farm grass growth observations to determine the best weather forecast to use in the model. The practical benefits of the MoSt GGM as an on-farm management decision aid would be improved if weather forecasts can be identified as useful model inputs.

2. Materials and methods

2.1. Outline of weather forecast assessment studies

Two assessments of the inclusion of weather forecasts in the Moorepark St Gilles grass growth model (MoSt GGM) were performed:

1) **Fertiliser study:** The predictions from the GGM when weather observations were used as inputs were compared with those using weather forecasts. Predictions were performed using four different fertiliser application levels, assuming other conditions for a single farm.

2) **Observed grass growth study:** GGM predictions using i) weather observations and ii) weather forecasts were verified against on-farm grass growth observations.

The GGM predictions, the weather data (observed and forecast) and the observed grass growth data are described in the following sections.

The motivation for these two separate studies is as follows. The fertiliser study will compare grass growth predictions with weather observations versus weather forecasts at varying lead time as inputs in the MoSt GGM. If weather forecasts perform similarly to weather observations, it provides a first step in validating the use of forecasts. The observed grass growth study will compare grass growth predictions to real observed grass growth data with (i) weather observations and (ii) weather forecasts as inputs in the MoSt GGM. This second study will test the predictive ability of the MoSt GGM when using weather forecasts under more realistic settings than the first study, e.g., if predicting grass growth today for the coming seven days, the GGM will use observed weather up until today and will use weather forecast for the coming seven days. This study can identify how useful the MoSt GGM is at predicting grass growth (compared to observed real grass growth) when weather forecasts are employed as inputs, since in practice observed weather data is not available into the future, but is available up to the day on which the grass growth predictions are generated.

2.2. Grass growth model description

The MoSt GGM is a mechanistic grass growth prediction model developed in C++ (Ruelle et al., 2018). It describes perennial ryegrass (*Lolium perenne* L.) growth in dairy production systems and is an adaptation of the Jouven model (2006), which was customised for local conditions (Hurtado-Uria, 2013). The MoSt GGM incorporates N, and soil and water sub-models added by Ruelle et al. (2018), which describe the availability of N to the plants through immobilisation and mineralisation, and the movement of water through the soil. The sub-models also interact to describe N leaching. Senescence and abscission allow for the conversion of some green biomass to dead biomass, and subsequently to organic N. The MoSt model is designed to be able to predict grass growth for any location in Ireland. To do this, it requires inputs based on environmental factors (weather data (forecast or observed), N content, soil clay, sand and organic matter content) and management factors (N fertiliser application details, cutting data and grazing data including number of animals, paddock size, pre-grazing height, and post-grazing height). Based on all of these factors, it updates the state of the systems controlling grass growth on a daily basis, such as the amount of water and N available to the plant. The final output is a daily grass growth prediction at the paddock level, which can be summed over time. Predictions can be generated for multiple paddocks and aggregated to predict at farm level. The model is described in full detail in Ruelle et al. (2018).

2.3. Weather forecasts and observations

Six different weather inputs were examined in the GGM:

- 1) **Observed weather:** daily observations of rainfall, solar radiation and maximum, minimum and mean 2 m air temperature were collected between 2008 and 2016 inclusive at the Met Éireann synoptic weather station at Teagasc, AGRIC, Moorepark, Fermoy, Co. Cork, Ireland (52.16 N; 8.26 W). Missing weather observations were imputed by taking the mean of the observations from the days before and after the missing date. There was only a small number of missing observations: 14 across all weather variables, and only one (rainfall) from 2013 onwards.
- 2) **ECMWF forecasts:** for each daily observed weather value,

corresponding forecasts from one day to ten days in advance were taken from the ECMWF Atmospheric Model high resolution deterministic 10-day 0000 forecast. Forecasts generated at 0000 on the day of the observation are denoted day-1, and similar notation was used up to day-10 forecast.

- 3) *Forecasts bias corrected monthly*: this correction used a leave one out method: the training set contained all data from the month for which the forecasts were being bias corrected, except the data from the particular year being bias corrected. For example, to obtain bias corrections in June 2013, the training set contained the values from June in all available years except 2013. The monthly mean difference between ECMWF forecasts and observed weather in the training set was calculated, and subtracted from each of the daily ECMWF forecasts in the month being corrected to obtain the bias corrected forecasts.
- 4) *Forecasts bias corrected yearly*: as per the monthly bias correction, except the differences was computed annually (rather than monthly).
- 5) *Forecasts bias corrected by a model*: the following regression model with the month and daily weather forecast as predictors of the observed weather was estimated:

$$E[y] = \beta_0 + \beta_1 f + \delta_j$$

where y is the observation, f is the ECMWF forecast, δ_j is a categorical month specific term, $j = 1, \dots, 12$. For each year of daily data, the regression model was calibrated using a leave one out method (i.e. current year excluded, all other years of data included), and the resulting model was used to predict the observations. These regression model predictions were then used as the bias corrected forecasts.

- 6) *Mean climatological forecasts*: Mean climatological forecasts for rainfall and air temperature were created using the Met Éireann mean climatological data for Ireland which was generated from historical data by Walsh (2012). The mean climatological value for each month was used as the forecast for every day in that month. Mean climatological forecasts predict the same value for every day in the same month, giving a ‘low-skill’ forecast to compare the other forecasts against. Since mean climatological data for solar radiation is not available at a national level in Ireland, solar radiation observations recorded locally at the research station at Moorepark from between 2001 and 2016 were obtained, and monthly mean climatological forecasts were calculated using them: for example, the average of all values from January over the 16 years provides the forecast for every January day.

Further details on these bias correction techniques are available in McDonnell et al. (2018) and Joliffe and Stephenson (2011).

2.4. Grass growth observations

A grazing experiment investigating the effect of calving date and stocking rate on animal performance was conducted at Teagasc Moorepark Curtins Research Farm, AGRIC, Moorepark, Fermoy, Co. Cork, Ireland (Coffey et al., 2018). Visual cover assessments of grass growth (Hanrahan, 2017) recorded for the 54 perennial ryegrass paddocks from 2013 to 2016 inclusive are used in this paper. The grazing season lasted from early February until late November each year and three stocking rates were studied in a randomised block design: 3.28, 2.91 and 2.51 cows/ha. Nitrogen fertiliser application rates were 250 kg N/ha per year for every paddock on every treatment. Full details of the experiment are described by Coffey et al. (2018). The visual assessments were regularly calibrated by cut and weigh measurements as described by O’Donovan et al. (2002a). Visual assessment was undertaken by a team of at least two trained observers each week. The same

persons undertook the assessment weekly. The daily growth observations for each paddock were calculated using the visual cover estimates, previous growth rate, the number of days pre-grazing, the grazing residuals and the number of days since the last growth figure was obtained (Hanrahan, 2017). Although it is the most accurate method of pasture cover estimation (O’Donovan et al., 2002b), there are errors associated with visual assessment (Hanrahan, 2017). O’Donovan et al. (2002b) reported that visual assessment was the most accurate of four non-destructive methods evaluated and had a R^2 of 0.95 compared with harvesting. Hanrahan (2017) reported an R^2 of 0.84 when visual assessment was compared to mechanical harvesting.

2.5. Assessment of weather forecasts in MoSt GGM

2.5.1. Fertiliser study

Weather observations of rainfall, solar radiation and minimum, maximum and mean 2 m air temperature were employed as model inputs to give paddock-level daily grass growth predictions from the MoSt GGM between 2008 and 2016. These were compared with daily predictions from the GGM using day-1 to day-10 ECMWF and bias-corrected forecasts of rainfall, solar radiation and minimum, maximum and mean 2 m air temperature as inputs. Low-skill mean climatological forecasts were also used as weather inputs to compare with the GGM predictions employing more skilful forecasts. All of these predictions (daily predictions over nine years for each set of weather inputs) were performed at four fertiliser application levels: 0, 100, 200 and 300 kg N/ha, with the first fertilisation for each year on day 65 of the year, and the day after the end of each of the first four grazing events of the year. For each fertiliser application level, the fertiliser events applied the same amount at all five stages of the year. The first yearly grazing event happened when the paddock height reached 9 cm, and at 8 cm thereafter. There were 40 animals per grazing event in all model runs. An example of the grazing dates for the predictions with 300 kg N/ha using day-1 ECMWF forecasts is provided in Table S1.

2.5.2. Observed grass growth study

Predictions from the MoSt GGM were performed for Teagasc Moorepark Curtins Research Farm, AGRIC, Moorepark, Fermoy, Co. Cork, Ireland (52.17 N; 8.27 W) using all of the weather inputs described in Section 2.3, and were compared to the grass growth observations described in Section 2.4. To allow accurate comparisons between the experimental grass growth observations and predictions from the MoSt GGM, the farm management inputs in each of the 54 experimental paddocks were replicated in the model. For each grass growth observation, weather observations were the model inputs from the first day of the year in question until the day before the period of the grass growth observation to allow the updates of the MoSt GGM sub-models. Then the most recent weather forecasts available were used for the period of the grass growth observation. For example, the model run between March 4th and 10th 2013 used weather observations from January 1st to March 3rd, day-1 forecasts for March 4th, and day-7 forecasts for March 10th. The model predictions were also generated using realised weather observations for the period of the grass growth observation to allow comparisons. If the period of the grass growth observation was greater than ten days, forecasts were not available, and the period was not used for comparisons. This usually happened outside of the peak growing season (April to September). Thus, some periods at the beginning and end of the growing season (February to November) are not described in the study. The period of the grass growth observation is referred to as a ‘weekly’ observation but can be from four to ten days in length since it is the growth between pasture cover estimations. The grass growth was predicted for each paddock with available grass growth figures for the ‘week’, and the ‘weekly’ average paddock values were computed to describe average farm growth. The

‘weekly’ values were scaled to daily averages to ensure reasonable comparisons across weeks, and did not always contain the same number of paddocks.

2.6. Statistical methods for comparisons

The methods used to compare the MoSt model predictions with each other and with observed grass growth include Mean Systematic Bias (MSB = $\frac{\sum_{i=1}^n (p_i - o_i)}{n}$), Mean Squared Error (MSE = $\frac{\sum_{i=1}^n (p_i - o_i)^2}{n}$) and Root Mean Squared Error (RMSE = \sqrt{MSE}), where p_i and o_i are the i^{th} predicted and observed values respectively, and n is the number of predicted and observed values. Relative Prediction Error (RPE) is the RMSE divided by the mean of the observed values (Rook et al., 1990). The MSE can be partitioned into errors in central tendency (mean bias = $(\bar{p} - \bar{o})^2$), errors due to regression (slope bias = $\sigma_p^2(1 - b)^2$) and errors due to unexplained random variation ($\sigma_o^2(1 - R^2)$), i.e.:

$$MSE = \frac{\sum_{i=1}^n (p_i - o_i)^2}{n} = (\bar{p} - \bar{o})^2 + \sigma_p^2(1 - b)^2 + \sigma_o^2(1 - R^2)$$

Where, σ_p^2 and σ_o^2 are the variances of the predictions and observations respectively, b is the slope of the regression line of observed on predicted and R^2 is the coefficient of determination from this regression. Ideally, the MSE (and therefore each of the three components) is close to zero, meaning the predictions and observations agree closely. A high mean bias component means the predictions are consistently over or under predicting the observed values. A high slope bias means the best fit regression line is not similar to the line of equality, meaning equality of predictions and observations does not describe the relationship. Errors due to unexplained random variation cannot be bias corrected by linear correction methods. A high value indicates that the points are scattered widely about the best-fit regression line. These comparison methods were also sometimes used to compare two sets of predictions from the MoSt GGM, those using weather forecasts with those using weather observations.

3. Results

3.1. Fertiliser study

Yearly total grass growth predictions increased as the amount of N fertiliser increased. For example, the predicted grass growth yearly totals in 2016 from model runs using weather observations with 0, 100, 200 and 300 kg N/ha were 10100, 12800, 14,800 and 16,200 kg DM/ha, respectively. However, across N application levels for each forecast period, the RPE of the predicted grass growth using ECMWF forecasts versus observed weather was similar, so the accuracy of the predictions did not change with N application levels (Table S2).

The MoSt GGM predictions using forecasts generally followed those using weather observations closely for 200 kg N/ha of fertiliser (Fig. 1, S1). This shows that forecasts can be interchanged with observed weather with no serious change to the grass growth predictions, but the interchangeability decreases as the forecast period increases (Fig. S2). Of the weather forecast types examined, grass growth predictions using forecasts bias corrected by model gave the lowest RMSE values at all forecast periods up to eight days in advance (Table 1). It was also the most effective forecast in predicting grass growth in the short term (Fig. 1, S1), but did not capture the variations in daily growth as well for forecast periods over five days (Fig. S2). The ECMWF forecasts yielded better grass growth

predictions than the low-skill mean climatological forecasts up to six days in advance, but not for any longer forecast periods (Table 1).

For each forecast period in each year, most of the MSE from the GGM predictions using ECMWF forecasts was attributable to unexplained random variation (always above 67% for all N application levels). The remainder was predominantly due to slope bias. The

error due to unexplained random variation was only 63.6% of the total MSE at forecast period nine in 2012 with 300 kg N/ha. In 2012, the errors due to regression from the GGM

predictions using ECMWF forecasts were higher at forecast periods of over five days than in the other years examined. This was due to ECMWF forecasts of solar radiation and rainfall over-predicting and under-predicting, respectively, the observations for many days in June

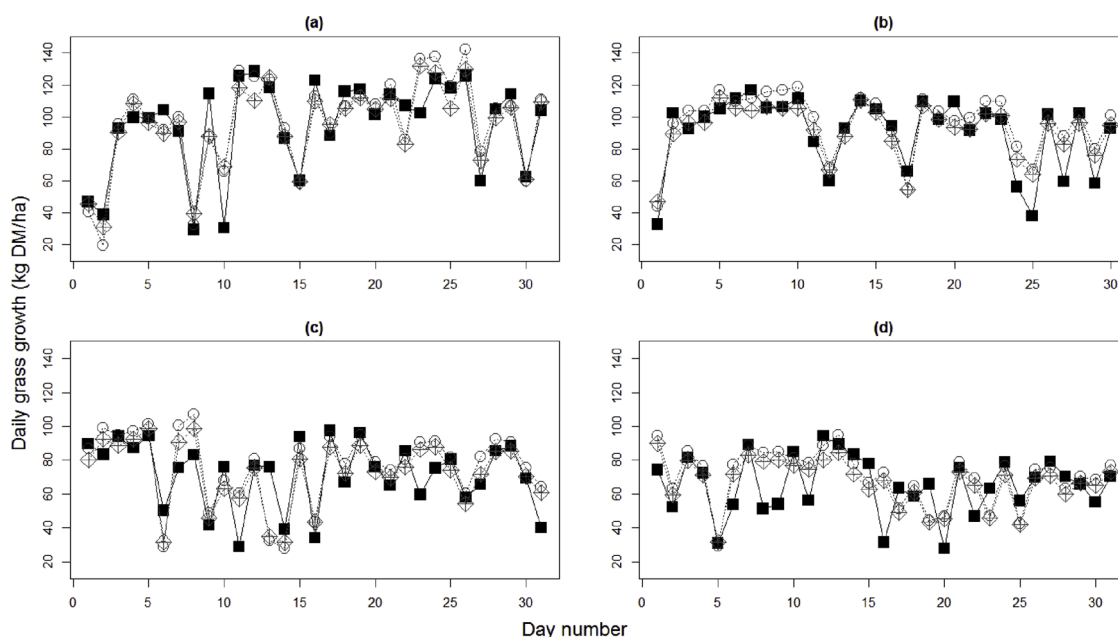


Fig. 1. Predicted daily grass growth in 2015 for (a) May, (b) June, (c) July and (d) August from the MoSt GGM using weather observations (filled squares), day-2 ECMWF forecasts (empty circles, dotted line) and day-2 forecasts biased corrected by model (crossed diamonds, dotted line) with 200 kg N/ha.

Table 1
RMSE values (kg DM/ha) comparing daily grass growth predictions for 2008 to 2016 from the MoSt grass growth model using observed weather, with grass growth predictions from the model using five weather forecasts (weather forecast type) from 1 to 10 days in advance (forecast period). The fertiliser application level for these predictions is 200 kg N/ha. The most accurate predictions for each forecast period are shaded in grey.

Forecast period	Weather forecast type				Mean climatology
	Bias correction method				
	ECMWF	Monthly	Yearly	Model	
1	10.7	10.7	10.7	10.0	17.7
2	11.8	11.9	11.9	10.9	17.8
3	13.5	13.8	13.7	12.3	17.7
4	15.4	15.9	15.7	14.1	17.7
5	17.5	18.2	17.9	15.2	17.7
6	19.0	19.8	19.4	16.2	17.7
7	20.6	21.7	21.3	17.0	17.8
8	20.9	21.9	21.6	17.2	17.7
9	22.5	23.5	23.2	17.8	17.7
10	22.5	23.4	23.1	17.8	17.7

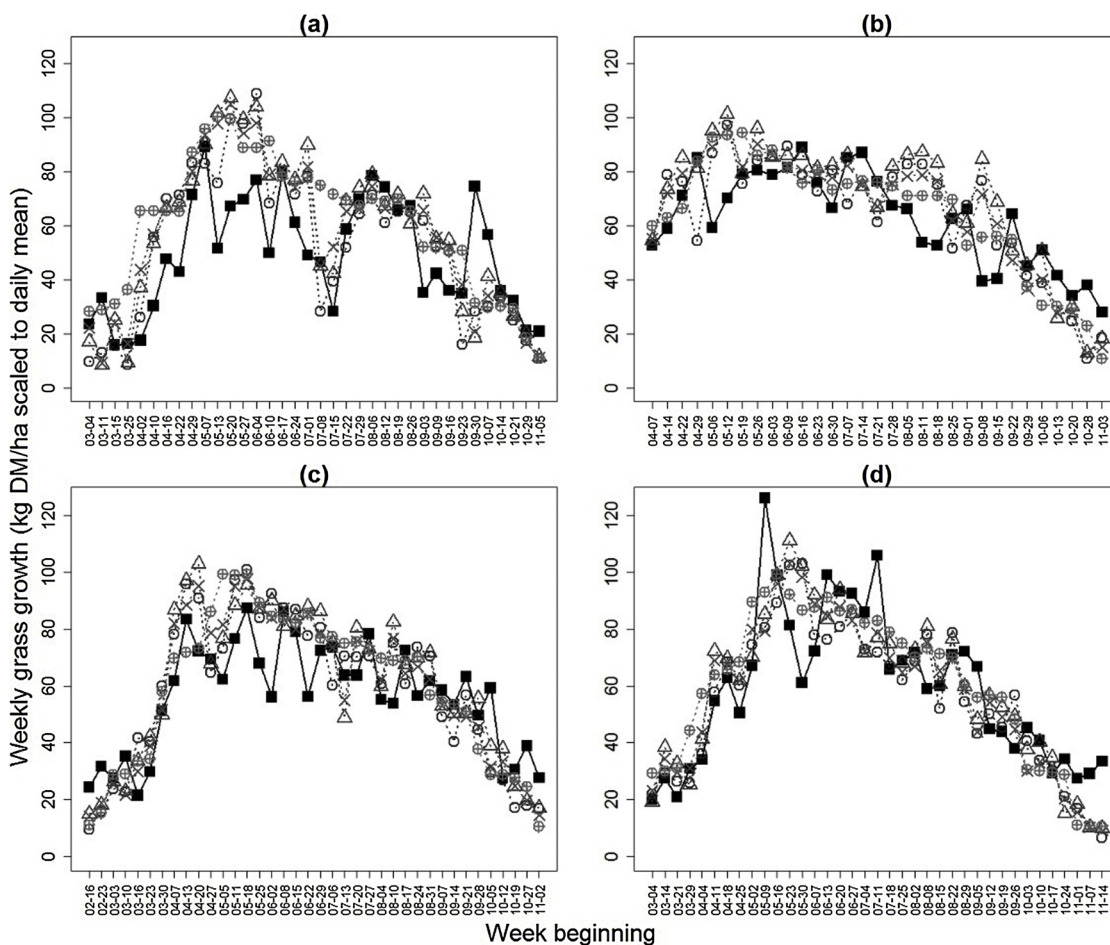


Fig. 2. Weekly grass growth (kg DM/ha scaled to daily mean) across all 54 paddocks (filled squares), and corresponding predicted yearly grass growth from the MoSt GGM using observed weather (empty circles), ECMWF forecasts (empty triangles), forecasts bias corrected by model (crosses), and mean climatology forecasts (crossed circles) in (a) 2013, (b) 2014, (c) 2015, and (d) 2016. Grass growth is only shown for weeks in which it was recorded.

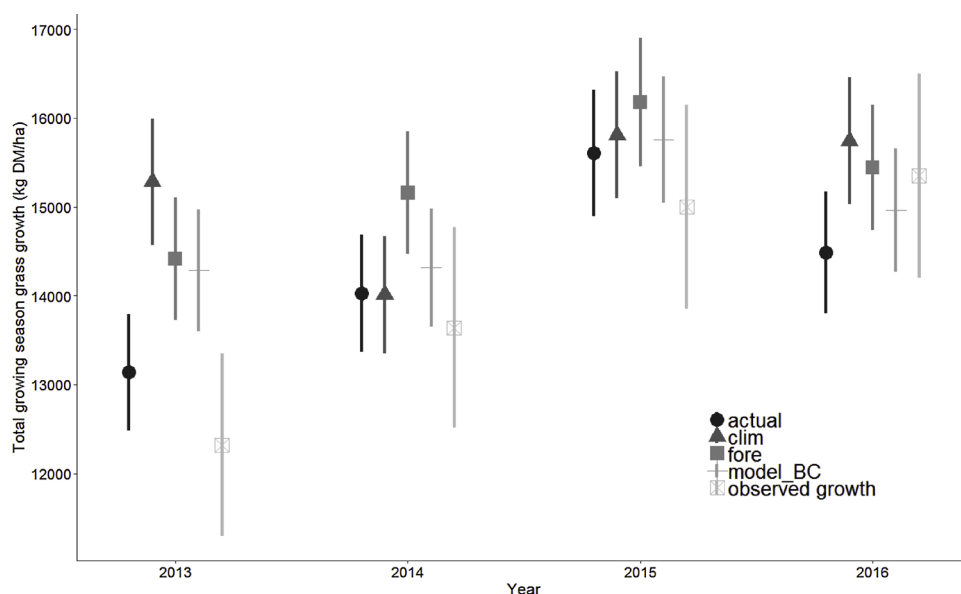


Fig. 3. Total grass growth during the growing season, averaged across all 54 paddocks from 2013 to 2016 (observed growth), and corresponding predicted grass growth from the MoSt GGM using actual weather (actual), mean climatology forecasts (clim), ECMWF forecasts (fore), and forecasts bias corrected by model (model_BC). The standard errors of the observations and predictions are shown in the error bars.

2012, leading to over-predictions of grass growth in the month. Bias correction by model of the day-9 forecasts reduced the RMSE of the grass growth predictions in June 2012 from 37.8 kg DM/ha when ECMWF forecasts were used to 29.2 kg DM/ha.

3.2. Observed grass growth study

Weekly predictions from the MoSt GGM generally followed the grass growth observations closely for all weather inputs (Fig. 2). However, in many cases the predictions did not capture the weekly variability well (for example in May and June 2015, Fig. 2c). The grass growth observations suitable for comparisons in 2015 went from February 16th to November 2nd, the longest of the four years in the study (Fig. 2c). The weekly MoSt GGM predictions at the end of the growing season were often lower than observed grass growth, suggesting that there are physical processes sustaining grass growth at the end of the year that are not being captured by the MoSt GGM (Fig. 2). Although mean climatology forecasts yielded good predictions in many weeks, they do not capture variability in weather and therefore did not capture weekly variability in grass growth as well as other weather inputs, for example in July 2013 (Fig. 2a). However, in some years, the weekly variability of the grass growth observations was not predicted well by the MoSt GGM regardless of the weather input used, for example in August 2014, and in May and June 2015. This was likely due to the fact that the MoSt GGM must describe a number of physical processes to predict grass growth such as N leaching and the water content in the soil. These physical processes cannot be checked for accuracy using actual observations, and if they become inaccurate the grass growth predictions will be less accurate. The total grass growth during the growing

season was predicted accurately in most years from 2013 to 2016, inclusive, by MoSt GGM predictions using actual weather, ECMWF forecasts, forecasts bias corrected by model and mean climatology forecasts as weather inputs (Fig. 3). However, all weather inputs over-predicted the observed total grass growth in 2013, 2014 and 2015 (Fig. 3). As expected, the predictions using actual weather generally gave the best estimates of the yearly total. The paddock variability of the yearly totals was similar for all predictions from the MoSt GGM regardless of the weather input. The paddock to paddock variability of the observed grass growth (obs) was slightly higher than predicted in all years (Fig. 3). This was also the case for the weekly grass growth values, for example in 2014 (Fig. S3). The monthly observed grass growth totals were followed closely by monthly grass growth predictions for each of the weather inputs (Table 2). The MoSt model run

Table 2

Monthly grass growth observations and predictions (kg DM/ha) for 2013–2016.

Weather input						
Month	Year	Observed grass growth	Actual weather	ECMWF	BC by model	Mean climatology
4	2013	1481	2129	2110	2164	2465
5	2013	1924	2506	2798	2707	2684
6	2013	1798	2196	2298	2199	2256
7	2013	1837	1900	2316	2364	2594
8	2013	1991	1832	1932	1689	1916
9	2013	1525	1405	1524	877	1604
4	2014	1937	1916	2134	2099	1974
5	2014	2044	2404	2603	2504	2561
6	2014	2665	2766	2864	2751	2704
7	2014	2280	2064	2247	2177	2194
8	2014	1581	1960	2161	1989	1909
9	2014	1788	2043	2171	1916	1797
4	2015	2016	2295	2463	2408	2124
5	2015	2065	2495	2442	2540	2701
6	2015	2393	2882	2918	2824	2802
7	2015	2034	1970	2014	2010	2176
8	2015	2043	2324	2401	2266	2274
9	2015	1574	1336	1466	1382	1378
4	2016	1416	1558	1714	1701	1787
5	2016	3103	3253	3376	3294	3312
6	2016	2427	2165	2390	2323	2377
7	2016	2355	1977	2107	2063	2309
8	2016	2265	2253	2381	2284	2347
9	2016	1356	1371	1445	1342	1519

using forecasts bias corrected by model gave a lower RMSE value in 2015 than the runs using actual weather, and ECMWF and mean climatology forecasts (Table 3). In some of the years, and in some seasons within the years, actual weather had higher RMSE values than BC by model and mean climatology forecasts.

4. Discussion

4.1. Fertiliser study

The results suggest that weather forecasts can be useful predictors in a GGM, with varying accuracy for the different methods. The fertiliser study showed that grass growth predictions from the MoSt GGM using

Table 3
RMSE values (kg DM/ha) comparing daily average of ‘weekly’ grass growth observations for 2013 to 2016 with grass growth predictions from the model using the weather observations and various weather forecasts.

Year	Weather input			
	Actual weather	ECMWF	BC by model	Mean climatology
2013	18.8	21.8	24.4	22.7
2014	16.7	18.2	14.9	13.0
2015	14.7	15.1	13.8	14.6
2016	16.4	16.2	15.7	14.0

weather forecasts can give similar predictions to those using weather observations, particularly after bias corrections, although decrease in accuracy as forecast period increases (Fig. 1, Table 1). This is because weather forecasts predict weather observations less accurately as forecast period increases. The example in which poor ECMWF forecasts in June 2012 resulted in poor predictions from the MoSt GGM illustrates the influence that inaccurate weather forecasts can have on predictions from the MoSt GGM, and how bias corrections can improve prediction accuracy.

The predictions using forecasts bias corrected by model failing to capture variability was linked to the problem identified in McDonnell et al. (2018): ECMWF forecasts (particularly of rainfall) were not accurate at longer forecast lead times, so forecasts bias corrected by model were close to the mean rainfall. This resulted in similarly conservative grass growth estimates from the MoSt GGM. When using the MoSt GGM in practice, if the intention is to get accurate daily grass growth predictions between 1 and 6 days in advance, it is generally best to use forecasts bias corrected by model (Fig. 1, S1). However, if the priority is to predict the daily fluctuations in grass growth for 7–10 days in advance, it would be recommendable not to use forecasts bias corrected by model or mean climatological forecasts, but to use ECMWF forecasts instead (Fig. S2).

4.2. Observed grass growth study

The observed grass growth simulations showed that grass growth could be modelled accurately during the growing season using weather observations, and predicted a week in advance by weather forecasts. Bias corrected by model and mean climatological forecasts often gave the most accurate grass growth predictions, according to the RMSE values (Table 3). RMSE gives a high weight to high errors, and the more conservative bias corrected by model and mean climatological weather forecasts yield grass growth predictions with lower RMSE values, suggesting that the MoSt GGM does not capture some extreme grass growth observations. Mean climatology can be a useful weather input, as it gives the expected grass growth performance of the farm based on the usual weather for the month in question. It does not capture grass growth variability, but it is a good prediction to compare with predictions using other weather inputs which should describe the fluctuations in grass growth more accurately.

The grass growth predictions at the end of the growing season were generally lower than the observed grass growth for all weather inputs to the MoSt model. This could be due to the method of estimation for the grass growth observations. Visual observation may result in the estimation of higher covers on pastures than the actual values. In many weeks, forecasts bias corrected by model gave similar grass growth predictions to the mean climatological forecast grass growth predictions. This was due to the poor forecasting ability of rainfall and solar radiation at long forecast periods causing bias correcting by model to give forecasts close to the mean climatology for these weather variables. Thus, grass growth predictions using forecasts bias corrected by model often under-predicted weekly grass growth fluctuations. Some of

the large changes in weekly grass growth were not predicted well by the MoSt GGM regardless of the weather used, including weather observations. This suggests that the MoSt GGM is not always describing the physical processes required in the model sufficiently to allow the weather to predict the change in grass growth accurately. However, this is a first step towards the inclusion of weather forecasts in a GGM which shows promise. As more data is acquired over longer time scales and at more locations, it will be possible to adapt the MoSt GGM to better describe these processes such as N leaching.

These predictions were conducted at one site which is a well-managed dairy research farm with free-draining soils and high grass growth, and easily accessible weather observations. However, if this GGM tool was to be used in practice by farmers as part of the Pasture Base Ireland framework (Hanrahan, 2017), it would have to give accurate predictions in many different locations on different soil types with varying levels of farm management (Ruelle et al., 2017). Although an increasing number of Irish farmers record daily on-farm weather observations, they will not be available at most sites, and the bias-correction methods may not give improvements as the nearest available weather stations may not describe the farm accurately enough. In these cases, it would make sense to use the ECMWF forecasts in the MoSt GGM.

4.3. Future work

The predictions presented in this paper are from the MoSt GGM described in Ruelle et al. (2018). The MoSt GGM will be incorporated into the Pasture Base Ireland framework, and use weather forecasts to give farmers grass growth predictions for their farm. As with any predictive model, it can be updated to improve the accuracy of the predictions. The MoSt GGM currently predicts for perennial ryegrass systems (Ruelle et al., 2018). However, it could be adapted to include mixed-species swards, including those with white clover. White clover is being included in increasing numbers of grassland systems in Ireland because of its N fixation traits, and the resultant increase in dry matter yield (Guy et al., 2018), as well as increased animal performance associated with mixed perennial ryegrass white clover swards (Egan et al., 2018). Sowing species mixtures that include legumes such as white clover can help to stabilise yield output at different levels of N application (Suter et al., 2005). For example, in the fertiliser study, the dry matter yields would probably have been more similar across the N fertiliser levels if white clover was included in the system.

The MoSt GGM under-predicted grass growth in the early and late growing season. Also, many of the extreme grass growth observations were not detected by the model for any of the weather inputs. It should be investigated whether these poor predictions happen at other locations, and if so, the causes of the problems identified and fixed. Weather forecasts are not usually good at predicting extremes accurately at a weekly scale but, using weather and grass growth observations, the GGM model runs could be updated to capture the extreme grass growth values. It is important for farmers to be able to prepare for extreme weather and grass growth conditions.

5. Conclusions

The MoSt GGM can utilise weather forecasts to predict short-term grass growth, and aid farmers with their daily management decisions. It has been shown to capture the variability in systems using different amounts of N fertiliser, and to accurately describe weekly on-farm grass growth observations. We have demonstrated that weather forecasts can be a useful input to a grass growth model and have the potential to enhance on-farm resource use efficiency, as pressure mounts on farms to increase outputs to meet extra food demands. As the MoSt GGM uses weather forecasts to predict grass growth at more farms, and over longer time periods, it can be adapted to describe physical processes that influence grass growth more accurately, improving the accuracy of the predictions. ECMWF forecasts are the best overall input to predict

future grass growth. Forecasts bias corrected by model require local weather observations which are not always available, and they often give conservative forecasts close to the mean climatological value for rainfall and solar radiation. This means the MoSt GGM cannot predict the more extreme grass growth changes using forecasts bias corrected by model. Similarly, because they do not capture daily changes in weather, mean climatological values are not as useful as ECMWF forecasts as inputs for the MoSt GGM. However, they are easily obtained in comparison to the other weather inputs since they are the same for each year. ECMWF forecasts predict the weekly variation in grass growth best, which is what farmers using the MoSt GGM in practice would be most interested in.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.eja.2019.02.013>.

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