

A comparison of two pasture growth models with observed data from Central Waikato from 2000 to 2020

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Abstract

Pasture is essential to New Zealand farming, but its seasonal and annual variability complicates feed budgeting, farm management, and research predictions. This study evaluated the AgPasture and McCall-Romera pasture models for predicting monthly growth rates and annual herbage accumulation using observed data from Scott Farm, Newstead, New Zealand, from 2000 to 2020. Both models overestimated annual pasture yield, with AgPasture showing a slightly higher bias (Mean Bias Error (MBE) = 1256 vs. 1155 kg DM/ha/year). However, the difference was not statistically or practically significant. Adjusting for differences in annual nitrogen use between the observed and modelled data improved accuracy. McCall-Romera performed slightly better (MBE = 692 vs. 793 kg DM/ha/year), but again, not statistically significant. Both models showed seasonal biases underestimating pasture growth in late autumn and winter and overestimating it in late spring and summer. In May, the MBE was -11 kg DM/ha/day for AgPasture and -6 kg DM/ha/day for McCall-Romera, whereas in December, the MBE was 46 kg DM/ha/day and 23 kg DM/ha/day, respectively. Despite increased variability over two decades (coefficient of variation for AgPasture increased from 67% to 74%; McCall-Romera 46% to 58%), prediction accuracy remained stable, demonstrating robustness under changing climate conditions. While both models are suitable for predicting pasture growth, further calibration is recommended to improve seasonal accuracy and enhance research reliability.

Keywords: dairy systems, decision support tools, model validation, pasture simulation, perennial ryegrass

Introduction

Pasture is a low-cost, high-quality feed source for dairy cows and provides the majority of feed on New Zealand's dairy farms (Holmes et al. 2002; Clark et al. 2007). Depending on the farm system, perennial ryegrass and white clover pastures typically constitute 80-90% of cows' total feed intake in New Zealand (Thorrold and Doyle 2007; DairyNZ 2016). This offers the New Zealand dairy industry a crucial cost advantage and enables it to compete with more intensive farming systems, such as those in the United States (Neal 2021).

To achieve long-term profitability and business sustainability, farmers must optimise both the growth and utilisation of homegrown feeds (pastures and forage crops) while strategically supplementing with imported feed options (e.g., palm kernel extract) as needed. Pasture growth is affected by many factors, including climate, soil conditions, pasture species and previous grazing management (Chapman et al. 2009). This makes grazing management complex and a challenge for farmers to maintain a reliable feed supply for consistent herd productivity (Chapman et al. 2009; Chapman et al. 2013).

Various feed budgeting software tools have been developed in the New Zealand context to help farmers manage feed supply and demand. However, the effectiveness of these tools depends on external inputs such as reliable estimates of herbage accumulation (e.g., daily pasture growth rates or annual pasture yield). Often, such data is unavailable, as many farmers do not routinely measure pasture covers. Reasons for this include the time-consuming nature of pasture measurement, limited confidence in the value proposition of measurement tools and concerns regarding their accuracy (Romera et al. 2010; Anderson and McNaughton 2018; Leddin et al. 2023). For those farmers who do conduct pasture walks, this data is often used for short-term decision-making (e.g., determining which paddocks to graze and when) before being discarded once these decisions have been made (Stevens and Knowles 2011).

Several process-based pasture production models, such as APSIM (Agricultural Production System Simulator) AgPasture (Andreucci et al. 2022) and McCall-Romera (Romera et al. 2009) have been developed and refined over the past two decades. These models use various explanatory factors, including climate data, pasture species, soil type, soil fertility, and fertiliser application, to predict daily growth rates or annual herbage accumulation (Peters et al. 2022). Both models vary in complexity; for example, AgPasture simulates detailed physiological processes in mixed-species swards, while the McCall-Romera model uses a simpler empirical approach typically focused on a single pasture species such as ryegrass (Romera et al. 2009; Li et al. 2011; Andreucci et al. 2022). These research-focused pasture models have been developed

to help researchers explore different farming options while accounting for climate conditions and associated variability in pasture growth. They also allow on-farm management practices (e.g., grazing practices and supplement conservation) to be included for improved farm system simulation. Thus, they present an additional tool to provide the necessary forage supply input to feed budgeting tools and support systems analysis tools.

The DairyNZ Whole Farm Model (WFM) is one such example of a systems model, integrating various components of a farm system, including pasture growth predictions driven by pasture species, climate data, soil type and fertility, animal data (e.g., breed, genetic merit, production) with production driven by feed inputs, and farm management decisions to estimate physical performance, such as milk production and feeding, and farm profitability (Beukes et al. 2008; Neal et al. 2024). Pasture growth within the WFM is predicted using pasture models, specifically AgPasture and McCall-Romera, which draw on climate data, soil characteristics, pasture species, and fertiliser inputs. These components enable the WFM to support feed planning by estimating historical and seasonal pasture growth patterns, informing stocking rate decisions, and underpinning farm systems research (Macdonald et al. 2010). Given the role of the WFM in agriculture research, understanding the performance of its underlying pasture models remains essential, particularly under changing climate conditions in New Zealand (Ministry for the Environment & Stats NZ 2025).

With increasing climate variability observed in New Zealand over the past two decades (e.g., eight of the ten warmest years on record occurred between 2013 and 2022; Ministry for the Environment & Stats NZ (2025)), assessing how pasture models perform under a broader range of conditions is timely. This paper evaluates the predictive accuracy and seasonal patterns of herbage accumulation generated by the AgPasture and McCall-Romera models using historical data from a research farm in central Waikato from 2000 to 2020. Model performance was assessed by comparing simulated and observed herbage accumulation rates using Root Mean Squared Error (RMSE) and Mean Bias Error (MBE). Although both models are components of the WFM, this analysis focuses solely on their herbage accumulation predictions and does not extend to their impact on downstream outputs such as milk production or farm profitability.

Materials and Methods

Historical farm data, simulation modelling, and statistical analysis were used to evaluate pasture growth predictions. The following section outlines the data

sources, simulation settings, and analytical methods applied in this study.

Pasture dataset

The observed pasture growth dataset was collected from Scott Farm, a DairyNZ research farm located at Newstead, near Hamilton in the Central Waikato (- 37.7686°, 175.3664°). The dominant pasture type is a mix of perennial ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*) growing on a Horotiu loam soil (Lowe 2023). Data, including monthly pasture growth rates and annual herbage accumulation from farm systems trials using calibrated visual measurements, were gathered over 20 years (2000-2020). Each week, at least ten quadrats (0.2 m²) were selected to represent the range of pasture covers present. These were visually scored, then cut to ground level, with the herbage oven-dried at 95–100 °C for 48 hours to determine dry matter content. The resulting calibration equations were used to adjust the visual scores for all paddocks. Herbage accumulation was then calculated as the change in pasture cover between weeks in which no grazing or conservation occurred (Glassey et al. 2021). Annual nitrogen usage (as applied fertiliser, kg N/ha) was also recorded.

For both observed and modelled data, monthly herbage accumulation (kg DM/ha) was calculated by multiplying the monthly average daily pasture growth rate by the number of days in each month. Annual herbage accumulation was then calculated as the sum of monthly values from June 1st to May 31 the following year, aligning with the simulation year. This approach ensured consistent data processing for both datasets.

Simulation settings

Pasture simulations were conducted using the AgPasture (version 2.0.4.1) or McCall-Romera (version 1.35) pasture models within the DairyNZ WFM (version WFM – 8.2.h). These climate-driven, day-step models simulate the operations of a pasture-based New Zealand dairy farm and incorporate a wide range of user-defined management policies for pasture, feed, fertiliser, effluent, and animal management (Beukes et al. 2005; Neal et al. 2024).

The management module within the WFM was used to establish decision rules for the simulation, including fertiliser applications (i.e., nitrogen and maintenance fertiliser) and key farm management practices such as regrassing frequency, rotation length, and grazing residuals. These were based on the decision rules developed at the Dairying Research Corporation (DRC) No. 2 Dairy Unit (Macdonald and Penno 1998; Macdonald et al. 2010), later referred to as the ‘Macdonald rules’.

Simulations ran for 20 years, from 1 June 2000, to 31 May 2020, with an initial pasture cover of 2000 kg DM/ha for ryegrass-clover pasture on Horotiu soil. Weather data for Scott Farm was sourced via the Virtual Climate Station Network (VCSN), which provides daily estimates of climate variables through spatial interpolation of observations from physical climate stations. One such station is the Ruakura weather station (-37.7757° , 175.3051°), located approximately 5 km from the trial site. The VCSN covers approximately 11500 locations on a ~ 5 km grid and provides data on various factors, including rainfall, temperature, evapotranspiration, humidity, solar radiation, wind speed, and soil moisture (NIWA 2025).

Up to 200 kg N/ha per milking season (July–May, five applications of 40 kg N/ha) was applied in the simulations, depending on the available soil moisture. While this rate exceeds the current recommendation of no more than 190 kg N/ha per annum for grazed pastures (DairyNZ 2024a), it reflects practices from farm trials conducted in the early 2000s, from which some of the observed data collected between 2000 and 2020 was sourced. The simulations were run without animals, with pasture harvesting occurring via cutting rather than grazing, following the Macdonald decision rules.

To align the simulated pasture growth with the observed nitrogen use on Scott Farm, a 10:1 kg DM/kg N response ratio was applied during post-processing based on typical annual nitrogen responses for the region (DairyNZ 2024b; Gray 2024). However, due to climate variability and pasture conditions, actual responses may vary during the season. Although the simulations assumed a constant 200 kg N/ha per year based on moisture availability, actual nitrogen applications on Scott Farm declined from the late 2000s. Applying this fixed growth response ratio after the simulations allowed the modelled pasture yields to better reflect historical changes in nitrogen use.

Data analysis

The accuracy of modelled monthly pasture growth rates and annual herbage accumulation was assessed by comparing model predictions to the observed values using RMSE and MBE. The RMSE quantifies the average magnitude of prediction errors, with lower values indicating better model performance (Hodson 2022). The MBE, calculated as Predicted minus Observed ($P - O$), was used to assess the direction and extent of bias. In this formulation, a positive MBE indicates overestimation, while a negative value indicates underestimation by the model (Gokken 2025).

To compare the performance of the two models' annual pasture yield predictions statistically, a paired

t-test was performed using 20 pairs of annual values, corresponding to each simulation year from June 1, 2000, to May 31, 2020. This test evaluated whether the mean differences in annual yields between the models were statistically significant. To assess whether prediction accuracy differed between decades, absolute monthly prediction errors were compared between 2000–2010 and 2011–2020 using two-sample t-tests assuming unequal variances. This analysis evaluated changes in model performance over time.

All analyses were conducted using R Statistical Software (v4.2.1; R Core Team 2022) and RStudio (v2024.4.0.735; Posit Team 2024).

Results

Annual yields

The comparison of observed and modelled monthly pasture growth rates and annual herbage accumulation assessed the accuracy of the AgPasture and McCall-Romera models. As shown in Figure 1, both models generally followed the seasonal pattern of herbage accumulation over the twenty-year study period. Across all years (Figure 2), the RMSE ranged from 17 to 34 kg DM/ha/day for AgPasture and 13 to 34 kg DM/ha/day for McCall-Romera. MBE ranged from -8 to 15 kg DM/ha/day for both models. These values indicate moderate variability in prediction accuracy and some directional bias across years. Seasonal analysis (Figure 3) showed higher errors in summer (RMSE: 34 kg DM/ha/day for AgPasture, 27 kg DM/ha/day for McCall-Romera) and autumn, with the greatest positive bias in summer (MBE: 19 kg DM/ha/day and 16 kg DM/ha/day, respectively), indicating a tendency to overpredict growth during these periods. In contrast, winter predictions were more accurate and less biased.

Both models overestimated the annual pasture yield, as indicated by the positive MBE shown in Figure 4 (Plot A). The AgPasture model exhibited a slightly higher bias (MBE = 1256 kg DM/ha/year) than the McCall-Romera model (MBE = 1155 kg DM/ha/year). The AgPasture model also had a higher RMSE than the McCall-Romera model at 2483 and 2219 kg DM/ha/year, respectively.

As illustrated in Figure 4 (Plot B), the nitrogen adjustment improved the RMSE and MBE for each pasture model. Specifically, the AgPasture model had a RMSE of 2202 kg DM/ha/year and an MBE of 793 kg DM/ha/year compared with a RMSE of 2021 kg DM/ha/year and an MBE of 692 kg DM/ha/year for the McCall-Romera model.

A paired t-test was conducted to compare the performance of the two models, with the results showing no statistically significant difference in predictions either before or after the nitrogen adjustment ($t = 0.34$,

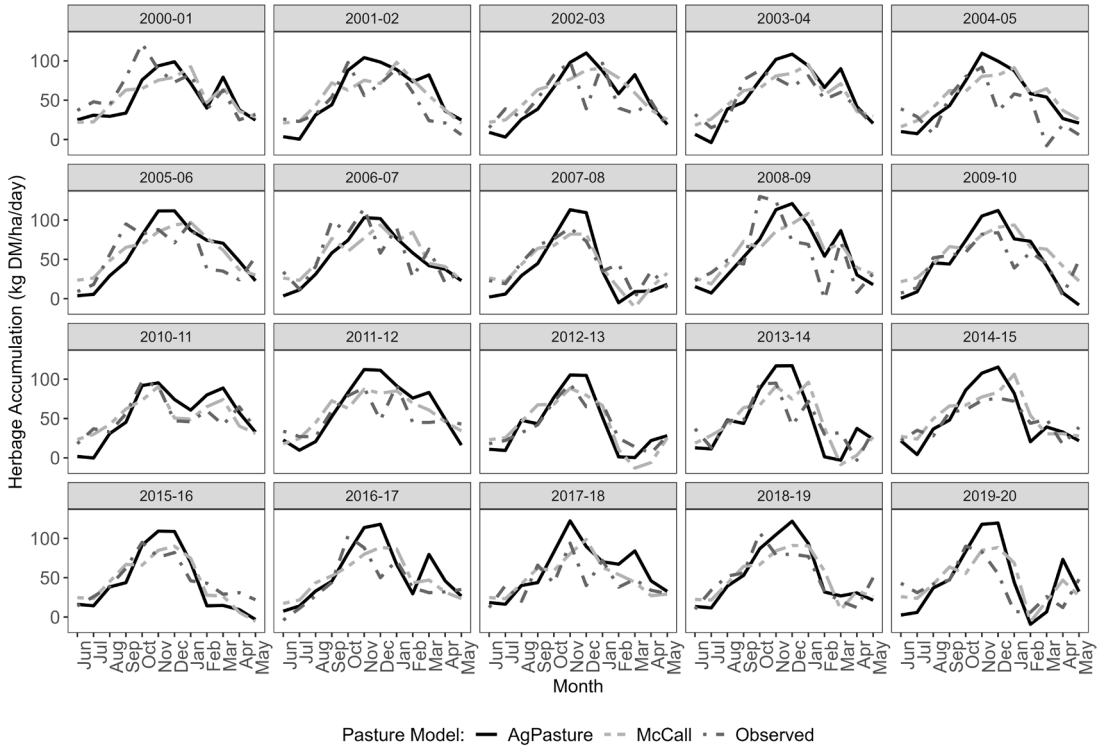


Figure 1 Daily herbage accumulation (kg DM/ha/day) by month for the tested pasture models and observed pasture data for the Horotiu soils on Scott Farm from 2000 - 2020.

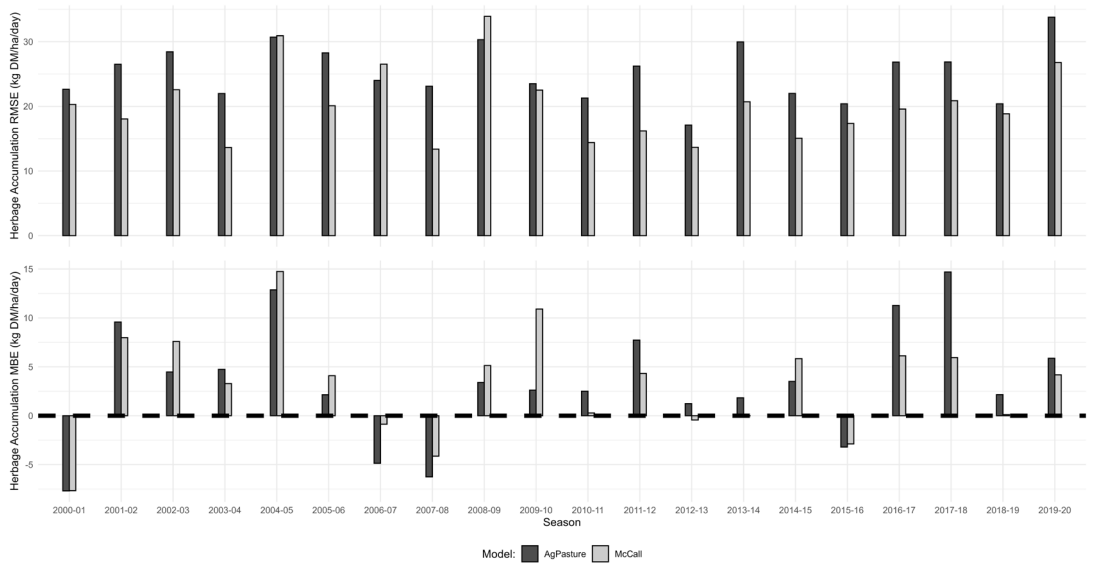


Figure 2 Herbage accumulation annual Root Mean Squared Error (RMSE; top) and Mean Bias Error (MBE; bottom) for the AgPasture and McCall-Romera models over the 2000 to 2020 period. The dashed line in the MBE plot indicates zero bias, indicating no over- or under-prediction.

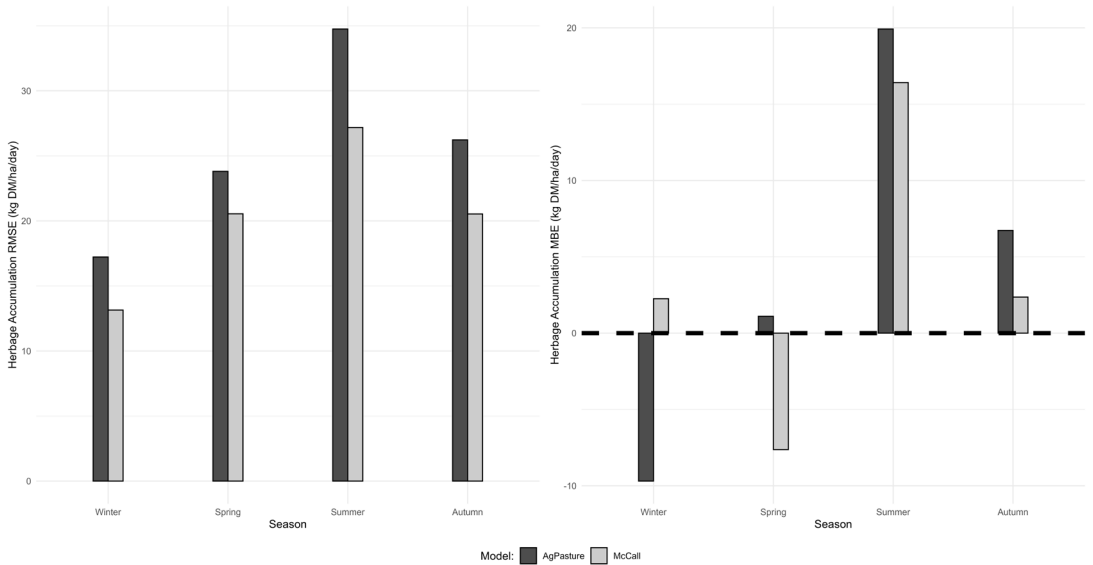


Figure 3 Herbage accumulation seasonal Root Mean Squared Error (RMSE; left) and Mean Bias Error (MBE; right) for the AgPasture and McCall-Romera models across winter, spring, summer, and autumn, based on data from 2000 to 2020. The dashed line in the MBE plot represents zero bias, indicating no over- or under-prediction.

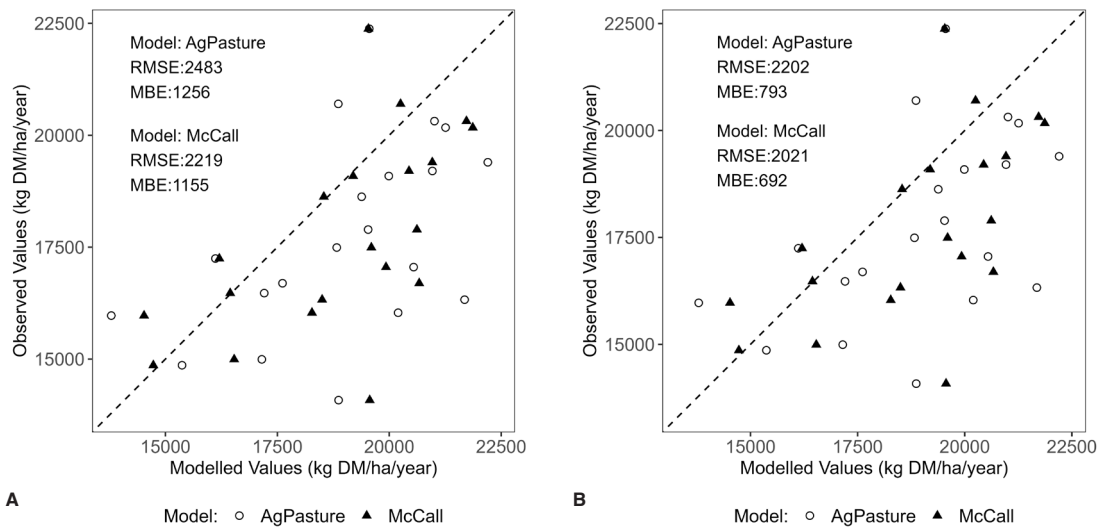


Figure 4 Comparison of observed versus modelled annual herbage accumulation (kg DM/ha/year) for the AgPasture and McCall-Romera pasture models. Plot A is before nitrogen adjustment, and Plot B is after nitrogen adjustment. The dashed line is the 1:1 line.

$p = 0.74$). The 95% confidence interval for the mean difference between the models remained consistent, ranging from -520 to 722 kg DM/ha/year, with a mean difference of 100 kg DM/ha/year. Therefore, regardless of any adjustments made, both models provide a similar estimate of annual pasture yield.

Monthly yields

The predictive performance of the pasture models was also evaluated monthly to identify any seasonal variations in accuracy. As shown in Figure 5, the AgPasture model underestimates growth during winter and early spring, with the most pronounced

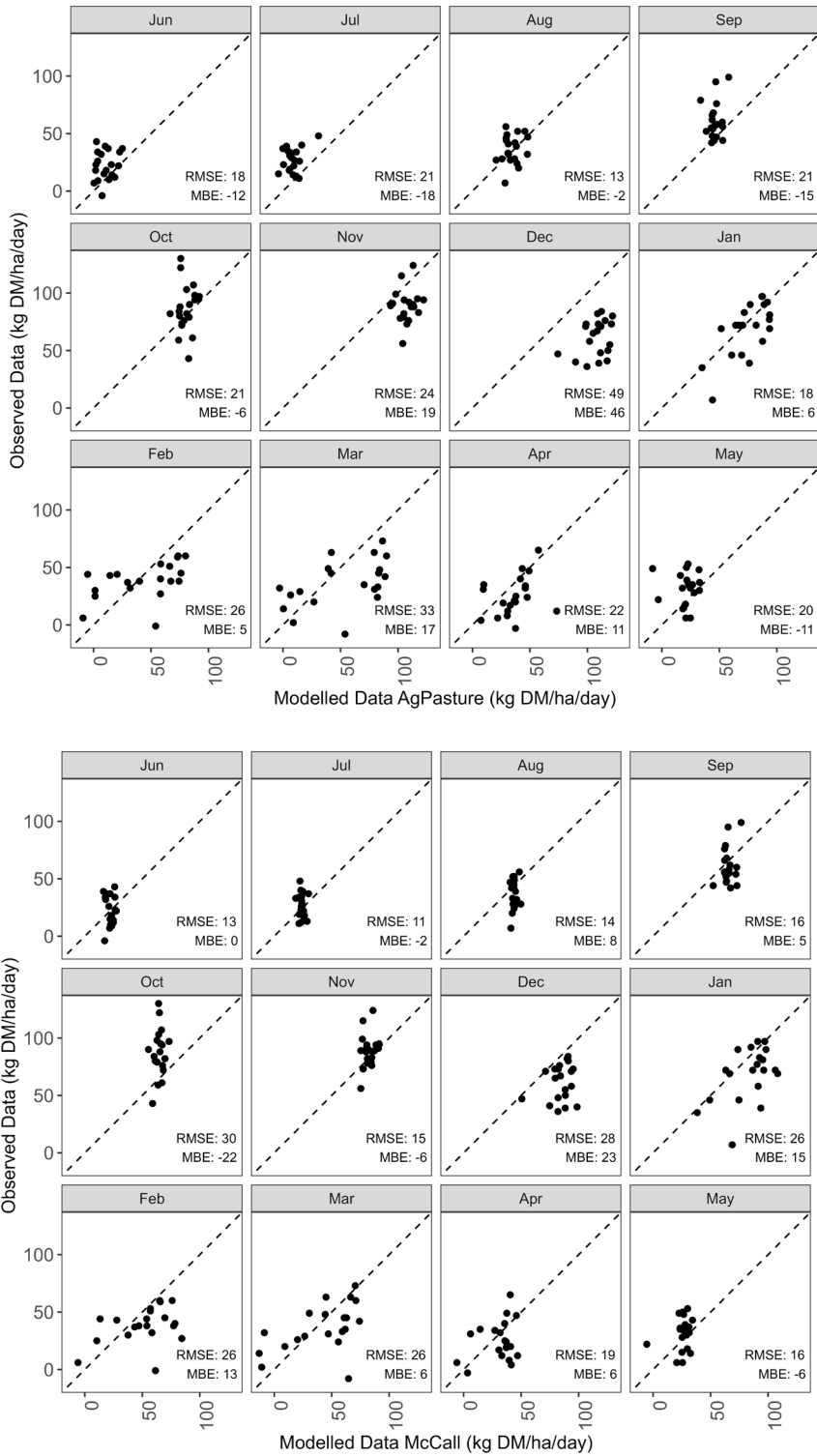


Figure 5 Comparison of observed and modelled monthly pasture growth rates (kg DM/ha/day) for the AgPasture (top plot) and McCall-Romera (bottom plot) pasture growth models for Horotiu soils on Scott Farm. The dashed line represents the 1:1 line.

negative biases occurring in July (MBE = -18 kg DM/ha/day) and September (MBE = -15 kg DM/ha/day). Conversely, the AgPasture model overpredicted growth in late spring and early summer, particularly in November (MBE = 19 kg DM/ha/day) and December (MBE = 46 kg DM/ha/day). December had the highest prediction error, with an RMSE of 49 kg DM/ha/day. Similarly, the McCall-Romera model (Figure 5) underestimated pasture growth in late spring, with the most substantial negative biases being recorded in October (MBE = -22 kg DM/ha/day). In contrast, it overestimated growth during summer, most notably in December (MBE = 23 kg DM/ha/day) and January (MBE = 15 kg DM/ha/day), with October having the highest overall error (RMSE = 30 kg DM/ha/day).

Model error and variability by decade

The coefficient of variation in monthly daily pasture growth rates increased for both the AgPasture (from 67% to 74%) and McCall (from 46% to 58%) models between 2000–2010 and 2011–2020, indicating greater relative variability. The variability in the observed data remained relatively stable. Despite increased climate variability in the later decade, as discussed by Glassey et al. (2021), the models maintained stable predictive accuracy. RMSE values declined slightly over time for both the AgPasture (25.7 to 25.3 kg DM/ha/day) and McCall (22.4 to 19.1 kg DM/ha/day) models, indicating marginal improvements in average accuracy. Consistent with the methods, a t-test assuming unequal variances found no statistically significant differences in absolute prediction error between the two decades for either model (AgPasture: $p = 0.70$; McCall: $p = 0.26$). These results suggest that increased variability in modelled growth did not lead to a decline in prediction accuracy.

Discussion

The results show that both the AgPasture and McCall-Romera pasture models can estimate monthly herbage accumulation rates and the annual yield of perennial ryegrass-based pastures. This aligns with Li et al. (2011), who found that the AgPasture model closely matched observed values using a dataset from 32 sites across New Zealand with varying soil types and climates. Similarly, using data from Scott Farm, Romera et al. (2009) found that the McCall-Romera pasture model could reliably simulate ryegrass-dominant pastures. The consistent predictive accuracy observed in this study supports the continued relevance of these pasture models, even under the more variable climate conditions observed during the 2011–2020 period at the site supplying the observed data (Glassey et al. 2021).

However, the agreement between modelled and observed values shows notable month-to-month variation. Seasonal discrepancies between the predicted

and observed values for herbage accumulation were consistent with findings from previous modelling studies using a range of pasture models and software (Cullen et al. 2008; Romera et al. 2009; Li et al. 2011). These differences may result from the models' ability to represent key plant growth processes under farm management conditions. For example, Cullen et al. (2008) suggested that the models simplify plant development and do not account for persistence or carbohydrate reserves. Li et al. (2011), using AgPasture, suggested that other possible model improvements, including the more accurate representations of grazing effects, soil temperature responses, and soil moisture dynamics, were required. Importantly, weather events like droughts or floods, and their delayed effects on pasture regrowth, may not be well captured by models, which may lead to overestimation of yields.

Differences between the models themselves may also explain variation in performance. For example, AgPasture is a process-based model that simulates detailed physiological responses to nitrogen, water, temperature, and defoliation in mixed swards comprising either C_3 (e.g., ryegrass, white clover) or C_4 (e.g., kikuyu) grass species (Li et al. 2011; Andreucci et al. 2022). In contrast, the McCall-Romera model uses a simpler empirical approach, typically representing a single pasture type such as ryegrass, with fixed radiation use efficiency (Romera et al. 2009). These structural differences influence how each model responds to seasonal and management variability.

Observational uncertainty is another important source of error. Measurement errors, particularly in relation to measuring herbage mass, could contribute to the discrepancies identified between the simulated and observed pasture growth for Scott Farm. These errors may be seasonally influenced due to changes in the botanical and morphological composition of ryegrass and white clover pastures. For example, variations in tiller density, leaf-to-stem ratio, and clover content throughout the year affect the accuracy of herbage mass estimation (Murphy et al. 2021). Wet conditions in winter and spring can also cause pugging, further reducing accuracy. Additionally, over the 20 years of this study, changes in personnel involved in data collection and the evolution of measurement techniques may also account for some variation. Likewise, methodological differences, such as grazing in the observed datasets versus cut-and-carry assumptions in the simulated data. Together, these factors contribute to challenges in accurately validating pasture growth models.

The AgPasture model has demonstrated reasonable accuracy in simulating pasture growth in New Zealand dairy systems. Using a 10-year dataset (1982–1992) from the No. 2 Dairy in Hamilton, New Zealand, to evaluate the AgPasture model, Li et al. (2011) reported simulated

and measured mean annual herbage accumulation of 16209 and 16725 kg DM/ha, respectively, with a Root Mean Squared Deviation (RMSD) of 14%. Similarly, the current study, using an extended dataset from a nearby site (Scott Farm), applied the AgPasture model. Simulated mean annual herbage accumulation was 18543 kg DM/ha, compared to the measured value of 17750 kg DM/ha, yielding a RMSD of 12.4%. Using the McCall-Romera pasture model, the 20-year average simulated herbage production at Scott Farm was 18442 kg DM/ha (RMSD = 11.4%).

Seasonal discrepancies in model accuracy were also consistent across studies. Li et al. (2011) reported that the AgPasture model tended to underestimate pasture growth during spring (October - November) and overestimate in summer (December - February), which aligns with the results of this study where pasture was underestimated in the late winter-spring period (September - October) before being overestimated over the summer months (December - March). A similar trend was observed when using the McCall-Romera model.

These seasonal discrepancies are not unique to the AgPasture or McCall-Romera pasture models. A broader evaluation of a range of pasture models across various environments and pasture management systems in both Australia and New Zealand by Cullen et al. (2008) reported a greater accuracy between modelled and observed growth rates in winter and summer than in autumn and spring, with better agreement in temperate climates than sub-tropical climates. They attributed these differences to model limitations such as the lack of plant phenological development and persistence, which are especially important in subtropical regions.

While the models are valuable as inputs to decision support tools, they are also useful for agricultural research where long-term pasture growth data is lacking. However, they should be used only as a guide and in combination with field observations and expert knowledge to help mitigate some model limitations and account for on-farm factors (Chapman et al. 2009).

Future research could incorporate real-time data, such as pasture growth measurements or climate forecasts, using data assimilation approaches (e.g., Kalman filtering or similar methods) to improve model responsiveness and accuracy. Enhancing the models' ability to capture seasonal changes, particularly during transitions such as late winter to spring, could also improve accuracy and make the models more dependable and adaptable to the diverse farming systems, regions, and climates found across New Zealand.

Conclusions

Both the AgPasture and McCall-Romera models produced similar estimates of monthly herbage accumulation and annual dry matter yield in perennial ryegrass- white clover-based pastures. While the models tended to overestimate annual production and performance varied by month and season, our analysis showed no consistent or statistically significant difference in overall model accuracy. This suggests that either model can be used for simulating pasture growth, but seasonal biases remain a consideration. The residual errors indicate that additional factors beyond nitrogen application differences contribute to the prediction discrepancies. Although the evaluation included data from the recent decade (2011-2020), further testing is required to assess model accuracy under highly variable climate conditions.

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