

## Improving the McCall herbage growth model

A. J. ROMERA\*

D. G. McCALL

J. M. LEE

DairyNZ

Private Bag 3221

Hamilton 3240, New Zealand

M. G. AGNUSDEI

EEA INTA-Balcarce

POB 276

Balcarce 7620, Argentina

\*Corresponding author:

alvaro.romera@dairynz.co.nz

**Abstract** The objective of this study was to improve the McCall herbage growth model. A more mechanistic senescence function was incorporated, replacing an empirical senescence function. The new function is based on leaf lifespan (LLS), measured in thermal time, which is characteristic of a given grass species, and can be measured independently or sourced from the literature. Other complementary changes were also incorporated, the major ones being to incorporate soil water infiltration constraints and to improve seasonal predictions in winter based on greater photosynthetic efficiency of leaves at low light intensity. The existing and new versions of the model were each calibrated against five time series of herbage growth data using the first half of each time series. The second half of each time series was used for validation, along with an independent dataset. A suite of goodness-of-fit indicators was used to evaluate and compare the existing and new versions of the model. The new version more accurately predicted herbage growth following calibration, showing higher concordance correlation coefficients ( $\rho_c$  = 0.59, 0.62, 0.81, 0.81 and 0.53 versus 0.85, 0.88, 0.81, 0.88 and 0.80, for existing and new versions

respectively). Most goodness-of-fit indicators also improved for the independent dataset (e.g.  $\rho_c$  = 0.708 versus 0.787, for existing and new versions, respectively). It is concluded that the new improved version of the model can be confidently used as a replacement for the existing version.

**Keywords** calibration; leaf lifespan; pasture; ryegrass; senescence; validation

## INTRODUCTION

The herbage growth model developed by McCall (1984), and later published in detail by McCall & Bishop-Hurley (2003), was designed to explain variation in the rates of dry matter (DM) accumulation of temperate grass pastures between years and sites, based on climatic and management variables affecting growth. The main purpose of the model, hereafter referred to as the McCall model, is to design grazing systems at the farm level that give optimal production responses and reduce risk (see for example Romera et al. 2005b). The model is used as part of three farm system models (Neil et al. 1997; Romera et al. 2004; Oltjen et al. 2008), and adapted for other research purposes (Snow et al. 2007). In addition, new applications are being investigated for the model, including combining it with interpolated weather data (Tait et al. 2006) to estimate herbage masses between intermittent assessments at the commercial farm level (Beukes et al. 2008). Its key attraction is its simplicity and ability to model temperate herbage production for a variety of conditions. In situations where more detailed representation of pasture and soil mechanisms are required, more comprehensive models are preferred, such as EcoMod (Johnson et al. 2008). The McCall model has been used mostly to simulate ryegrass dominant pastures, but can, in principle, be used for any other temperate grass species (Romera et al. 2005a). An additional attraction is that the inputs required to operate the model, mostly weather data, are readily available for many locations in New Zealand.

Certain components in the McCall model rely on empirical parameters, requiring site-specific calibration. In general, empirical components tend to restrict the portability of a model to other regions or situations (Håkanson 1995). This may be the case with the McCall model, as most of the calibration and validation has been conducted using datasets collected in the North Island of New Zealand. On the other hand, making models more complicated by describing the system in greater detail does not necessarily improve predictive precision at a particular site. According to Seligman (1993), the greater detail almost inevitably increases random divergence from the behaviour of the real system, putting a premium on reducing complexity to the essential minimum. The senescence rate calculation in the model is currently empirical, using constants derived from calibration to observed data. This can be made more mechanistic, in line with the available knowledge of the factors controlling the senescence process. Apart from making the model more mechanistic, it could potentially increase model portability and facilitate the representation of other grass species.

The main objective of this study was to improve the existing senescence function in the McCall model, but six other smaller complementary modifications were also incorporated and are described here.

## MATERIALS AND METHODS

### The McCall model

The McCall herbage growth model has been described in detail by McCall & Bishop-Hurley (2003). A brief account of the aspects of the model relevant to this study is presented here.

The model contains a major state variable, green pasture mass ( $G$ ; kg DM/ha), for which the rate of change (or net accumulation) is determined by the balance between new daily herbage growth ( $N$ ; kg DM/ha per day) and daily herbage senescence ( $HS$ ; kg DM/ha per day):

$$\frac{dG}{dt} = N - HS \quad \text{Eqn (1)}$$

The calculations involved in calculating  $N$  and  $HS$  are described below, followed by the proposed modifications to these calculations.

### Herbage growth rate

In the existing version of the model,  $N$  is calculated as:

$$N = (\alpha \times I \times g_t \times g_r \times g_w \times c(G) - r(G)) \times 10 \quad \text{Eqn (2)}$$

where:

$\alpha$  = relationship between daily radiation and net photosynthesis (g DM/MJ).

$I$  = incident solar radiation (MJ/m<sup>2</sup> per day)

$g_r$  = relative seasonal efficiency factor for above ground growth (0.75 or 1, for vegetative or reproductive sward, respectively)

$g_t$  = temperature growth factor (function of air temperature, values ranging from 0 to 1)

$g_w$  = soil water factor (actual evapotranspiration (AET)/potential evapotranspiration (PET), values ranging from 0 to 1)

$c(G)$  = green canopy light interception capability (values ranging from 0 to 1)

$r(G)$  = daily maintenance respiration (function of green mass and mean temperature, g DM/m<sup>2</sup> per day)

10: factor required to convert g DM/m<sup>2</sup> into kg DM/ha

The parameter  $\alpha$  represents the radiation-use efficiency (radiation in MJ) for above ground herbage growth when there are no other climatic or light interception constraints. The value of the parameter is related to the soil fertility and pasture species at a site. No attempt has yet been made to link  $\alpha$  to specific measurements of soil fertility or pasture species owing to the number of mechanisms that are implicated (McCall & Bishop-Hurley 2003). Therefore, this parameter must be determined by model calibration for site-specific data. For example, the DairyNZ farm system model (Whole Farm Model; Neil et al. 1997), which incorporates the McCall model to simulate herbage growth, uses the default value of 0.89 g DM/MJ for dairy pastures in the Waikato region of New Zealand.

### Senescence rate

In the existing version of the McCall model the proportion of the current green mass ( $G$ ) that senesces each day ( $\sigma$ , kg/kg per day) is assigned a specific value depending on the time of the year. The assumption is that  $\sigma$  needs to increase during the reproductive phase of growth to allow for increased senescence rates of the reproductive components of green mass. The reproductive phase is assumed to last from day 125 ( $t_r$ : 3 Nov) to day 160 ( $t_D$ : 8 Dec),

with time defined as days from 1 July. The values for  $\sigma$  are 0.0065 ( $\sigma_v$ ) and 0.0131 ( $\sigma_R$ ) for vegetative and reproductive swards, respectively. These four values were obtained by fitting the model to observed data from Korte et al. (1982).

Based on data from Cayley et al. (1980), a linear increase in senescence ( $S_w$ ) is assumed from the point when available soil water content as a proportion of field capacity ( $W$ ) falls below 0.2, to a maximum 3-fold increase above the base senescence rate, when available soil water content is zero:

$$S_w = \begin{cases} 3 - 10W, & \text{if } 0 \leq W \leq 0.2 \\ 1, & \text{if } 0.2 \leq W \leq 1 \end{cases} \quad \text{Eqn (3)}$$

The daily senescence rate is then calculated as:

$$HS = \sigma \times G \times S_w \quad \text{Eqn (4)}$$

McCall (1984) reported that the herbage senescence function in the model was limited, and may need to be reviewed with time. Such a function is entirely empirical, but the current understanding of the senescence process (Woodward 1998b) now justifies the use of a more elegant, mechanistic, and yet simple solution.

#### Soil water

A standard soil water balance is used to determine actual soil water content. The water balance is conducted for two soil horizons. Water enters the top horizon (A) following rain until it is fully recharged. It then drains into the lower horizon (B). Water from rainfall enters the soil until it is fully recharged. Surplus rainwater is considered to drain through the profile or run off. Water is also lost from the soil through evapotranspiration, which is a function of PET (provided by the National Institute of Water and Atmospheric Research (NIWA) using the Priestly-Taylor equation), and available soil water (AW). Available soil water holding capacity (AWHC), daily rainfall and daily PET are all inputs to the model.

The AWHC is defined as the water that a soil can hold between field capacity (typically  $-0.01$  or  $-0.02$  MPa) and permanent wilting point (typically  $-1.5$  MPa) to a soil depth of 76 cm (Woodward et al. 2001). The AWHC can be measured in the laboratory and has been tabulated for many soils in New Zealand. In the McCall model, the default value, and the one normally used in the DairyNZ Whole Farm Model for AWHC is 90 mm (25 and 65 mm in horizons A and B, respectively). The AW is the current amount of available water in both horizons of the soil.

## Changes to the McCall model

### New senescence function

The maximum number of leaves on a grass tiller corresponds to the leaf lifespan (LLS) divided by the leaf appearance interval (phyllochron), all of which, when defined in terms of thermal time (in  $^{\circ}\text{C}\cdot\text{days}$ ), are relatively constant characteristics for a given grass species (Lemaire & Chapman 1996). The thermal time is measured as the product of daily mean air temperature ( $^{\circ}\text{C}$ ) and time in days. Perennial ryegrass (*Lolium perenne* L.), the focus of this research, generally has a maximum of three live leaves per tiller, with the oldest leaf (first to emerge) beginning to senesce as the fourth leaf emerges (Alberda & Sibma 1968).

The phyllochron of perennial ryegrass has been reported at  $110^{\circ}\text{C}\cdot\text{days}$  (Davies & Thomas 1983), but estimates range from 96 (Bahmani et al. 2000) to  $172^{\circ}\text{C}\cdot\text{days}$  (Fernandes Cauduro et al. 2006). Part of the variation can be explained by differences in the value of the base temperature used (typically  $0$ – $5^{\circ}\text{C}$ ), which is not always reported with the phyllochron estimates (Lemaire & Agnusdei 2000). Cultivar differences may also be responsible for some of the variation.

In Hamilton, New Zealand ( $37^{\circ}47'\text{S}$ ,  $175^{\circ}19'\text{E}$ ; elevation 40 m a.s.l.), perennial ryegrass leaf regrowth stage was determined on 10 randomly selected tillers per plot using the method outlined by Donaghy (1998). Measurements were made over three periods, between September and November 2004, between September 2005 and January 2006, and between April and August 2007. During each of the three periods, average daily air temperatures were recorded at a weather station  $<3$  km from the experimental site.

The accumulated temperature ( $^{\circ}\text{C}\cdot\text{days}$ ) between defoliation and when leaf regrowth stage was determined was calculated (Table 1). Phyllochron was calculated as the accumulated temperature divided by the number of new leaves that had regrown during the regrowth period (Table 1), resulting in an average phyllochron of  $169 \pm 32^{\circ}\text{C}\cdot\text{days}$  with a base temperature of  $0^{\circ}\text{C}$ . This value is used in calculations hereafter. Following the logic that any given portion of green tissue lives for a time span equivalent to the phyllochron times the maximum number of live (green) leaves (Lemaire & Chapman 1996), then the LLS for perennial ryegrass, based on the phyllochron of  $169^{\circ}\text{C}\cdot\text{days}$  measured locally, should be  $507^{\circ}\text{C}\cdot\text{days}$ .

**Table 1** Average leaf regrowth stages, accumulated temperature over the regrowth period, and calculated phyllochron.

Date plot last defoliated	Date leaf regrowth stage measured	No. of days of regrowth	Average leaf regrowth stage (new leaves/tiller)	Accumulated temperature over regrowth period (°C-days)	Phyllochron (°C-days)
18 Jul 2004	7 Sep 2004	51	3.1	440	143
19 Jul 2004	7 Sep 2004	50	3.1	430	138
20 Jul 2004	7 Sep 2004	49	3.1	422	135
21 Jul 2004	7 Sep 2004	48	3.1	415	134
22 Jul 2004	7 Sep 2004	47	3.1	407	131
18 Aug 2004	27 Sep 2004	40	2.9	389	136
25 Aug 2004	4 Oct 2004	40	2.8	400	144
29 Sep 2004	22 Oct 2004	23	2.5	303	119
6 Oct 2004	26 Oct 2004	20	2.5	289	118
13 Oct 2004	1 Nov 2004	19	2.4	283	118
22 Oct 2004	16 Nov 2004	25	2.6	401	154
3 Nov 2004	29 Nov 2004	26	2.3	403	176
29 Jul 2005	12 Sep 2005	45	2.5	433	174
31 Aug 2005	5 Oct 2005	35	2.6	413	161
7 Sep 2005	12 Oct 2005	35	2.5	425	167
19 Oct 2005	8 Nov 2005	20	2.1	308	149
4 Nov 2005	28 Nov 2005	24	2.1	360	169
9 Nov 2005	5 Dec 2005	26	2.1	391	185
23 Nov 2005	13 Dec 2005	20	2.0	341	167
30 Nov 2005	19 Dec 2005	19	2.0	359	178
7 Dec 2005	26 Dec 2005	19	2.0	369	183
14 Dec 2005	2 Jan 2006	19	2.0	361	179
2 Apr 2007	18 Apr 2007	16	1.4	244	181
19 Apr 2007	15 May 2007	26	2.0	354	178
18 May 2007	20 Jun 2007	33	1.8	369	211
24 May 2007	20 Jun 2007	27	1.3	283	220
25 Jun 2007	19 Jul 2007	24	1.0	238	235
28 Jun 2007	22 Jul 2007	24	1.1	248	236
2 Jul 2007	26 Jul 2007	24	1.0	242	237
19 Jul 2007	3 Aug 2007	15	1.0	168	169
22 Jul 2007	6 Aug 2007	15	1.0	166	168
26 Jul 2007	10 Aug 2007	15	1.0	173	170
3 Aug 2007	20 Aug 2007	17	1.0	193	189
6 Aug 2007	23 Aug 2007	17	1.0	186	183
10 Aug 2007	27 Aug 2007	17	1.1	189	178

The physiological age varies within a leaf (the leaf tip is generally up to a phyllochron older than the base of the leaf; Robson & Deacon 1978), between different leaves on a tiller and between tillers in a canopy. Therefore, an established canopy is composed of a mixture of leaves at different stages of growth. Thus, on average for the whole canopy,  $\sigma$  depends on the LLS (in °C-days) and mean daily temperature. For example,  $\sigma$  will be greater during periods of higher temperatures because the LLS will be attained in a shorter time.

As leaves senesce, their weight declines due to respiration, and carbohydrate and protein remobilisation

(Robson & Deacon 1978). The amount of carbohydrate and protein remobilised varies (Cros et al. 2003), but has previously been estimated at 30% (from fully expanded to completely dead leaf; Robson & Deacon 1978).

A new senescence calculation, based on mean daily air temperature (in °C;  $T_m$ ), was implemented in the model (Eqn 5), considering a LLS of 507°C-days, with a base temperature of 0°C and a remobilisation coefficient (*rem*) of 0.3 (Cros et al. 2003).

$$\sigma = \frac{T_m}{LLS} \times (1 - rem) \quad \text{Eqn (5)}$$



The same approach was followed before by Cros et al. (2003). However, those authors imposed an upper limit on  $T_m$  of 18°C, which was not used here, as no justification was found in the literature.

The proposed advantage of using an approach based on LLS (in turn a sole function of maximum number of green leaves and phyllochron) is that senescence will be based on biological parameters, and it will be controlled by climate instead of calendar date. This should make the model more portable between regions. Furthermore, given that LLS is characteristic of a species/cultivar, this representation of the senescence flow could help in the simulation of different species/cultivar. For example, Cros et al. (2003) reported LLS of 500°C-days for perennial ryegrass, 600°C-days for cocksfoot (*Dactylis glomerata* L.), or 700°C-days for tall fescue (*Festuca arundinacea* Schreb). This is consistent with the recommended increase in the inter-defoliation interval for these species when the interval is based on leaf-stage (Rawnsley et al. 2002; Turner et al. 2006; Donaghy et al. 2008).

After a grazing event, or at the start of spring, there is a lag between new growth and senescence in a regrowing pasture, allowing greater net growth of green leaf. This senescence function (Eqn 5) does not take this delay into consideration. However, Woodward (1998a) analysed the effect of including such lag in a model and found that it is likely to be small; Woodward therefore suggested that treating senescence as being proportional to herbage mass is an adequate option for most applications.

#### Concomitant changes to the McCall model

In addition to the changes to the senescence function of the model, appropriate revisions were made to related parameters to fit with the fact that the senescence peak would be different from the existing version of the model. These revisions were:

(1) The seasonal factor ( $g_t$ ) was eliminated because it was an empirical factor, whose value was fitted for the Waikato climate, but would demand re-calibration for other climates. Also, preliminary runs indicated that the new version of the model could obviate this factor.

(2) A different temperature factor (TF), adapted from Cros et al. (2003), was implemented:

$$TF = 0.37 + 0.09 \times T_m - 0.0022 \times T_m^2 \quad \text{Eqn (6)}$$

In this function as well Cros et al. (2003) imposed an upper limit of 18°C on  $T_m$  which was also obviated here. The reason being that it would prevent capturing the detrimental effects of high temperatures

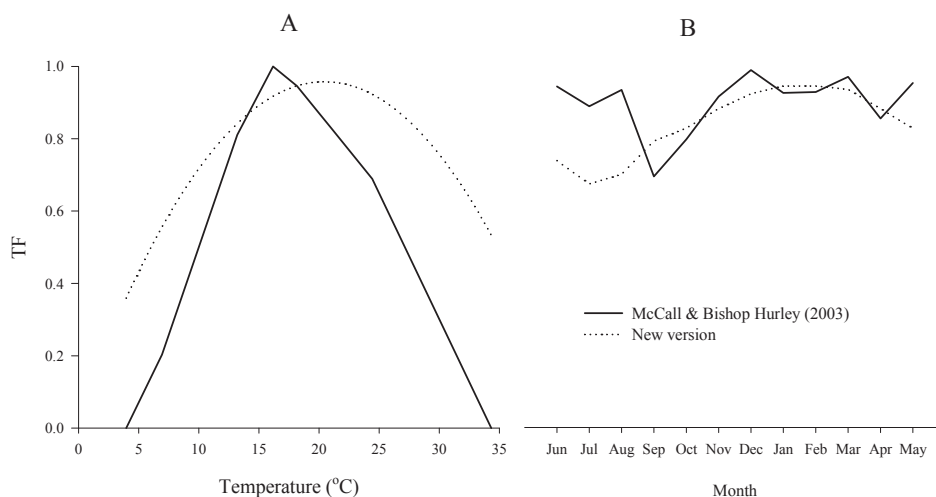
on growth. Notice that, for New Zealand conditions,  $T_m$  (daily mean air temperature) rarely goes too far above the optimum of Eqn 6. For example, there were only 17 days with  $T_m > 25^\circ\text{C}$  in the whole Winchmore weather dataset (1972–2009, one of the four used here for model testing). No records of  $T_m > 25^\circ\text{C}$  were found in the other three datasets (see below).

Equation 6 replaced the existing temperature factor ( $g_t$ ), which used maximum daily temperature in winter, and mean temperature during the rest of the year (Fig. 1). Evidence presented by Woledge & Dennis (1976) does not support the strong decrease in growth above 15°C, nor the low temperature effect, implied in the original function. However, the Woledge & Dennis (1976) data did not exceed 25°C, and data reviewed by McCall (1984) show growth rate of  $C_3$  plants slows down above 20–25°C. In the new function, the peak is reached at 20.45°C and growth slows down gradually below and above this value (Fig. 1). This trend line is also supported by the findings of Robson (1988) and others that the optimum temperature for leaf growth is in the region of 20–25°C for most temperate grasses. Also, the existing function generates an unjustified drop in TF between August and September (Fig. 1B), which was eliminated with the new function.

(3) The effect of water deficit on senescence ( $S_w$ ) has been eliminated. This change was based on the results of preliminary model runs in this study, and is supported by findings of Woodward (1998b), who referred to evidence (Cayley et al. 1980; Barker 1983) that leaf senescence rate (per thermal time unit) is insensitive to water availability.

(4) Using soil moisture data from many soil types, Woodward et al. (2001) fitted values for AWHC for different soils in the field and observed that those values were much greater (typically double) than those obtained in the laboratory for the same soil. This indicates, the authors argue, that the plants are able to extract a greater proportion of the soil water than usually assumed in laboratory measurements, and that a significant amount of water is extracted from matric potential below –1.5MPa in the field. As a result, in the new version of the model AWHC was fitted during calibration, rather than using the default value of 90 mm.

(5) A rewetting function was incorporated in the soil model, adapted from the concept developed by Bircham & Gillingham (1986). According to these authors, the rate of rewetting of the soil depends on its moisture content ( $SM$ , mm =  $AW + WP$ , where



**Fig. 1** **A**, Temperature effect (TF) on herbage growth according to McCall & Bishop-Hurley (2003) and the new version of the model. **B**, Evolution of TF through the months (using average temperatures from the Ruakura climatological station).

WP is soil water content at permanent wilting point). This is most important and evident when soils are dry and become hydrophobic (Schijf et al. 2008). They empirically derived an exponential relationship, which defined that the minimum period of time (RWt, days) for soil to rewet following complete drying of the surface horizon is 3.3 days. This determines the maximum amount of water that can infiltrate the soil in one day ( $WI_{max}$ ):

$$WI_{max} = SM \times (e^k - 1) \quad \text{Eqn (7)}$$

The value for  $k$  can be derived from

$$\frac{dSM}{dt} = k \times SM,$$

then integrating and assuming that the relationship between soil water content at maximum plant available water is three times the soil water content at minimum plant available water (from table 1 in Bircham & Gilligham 1986) gives  $3 = e^{(k \times RWt)}$ . Solving for  $k$  gives:

$$k = \frac{\ln(3)}{RWt} \quad \text{Eqn (8)}$$

The 3.3 days time lag may vary with soil characteristics, the point here was to capture this effect, at least in principle, by using this value. A future enhancement would be to determine the lag for other soils, or make the lag a function of soil properties which could be easily modified in the model.

(6) A simple non-linear response function to incident radiation was introduced (Eqn 9). This modification was introduced to address issues with the model underpredicting winter herbage growth rates because it did not allow efficiency of radiation use to vary with light intensity. Grass leaves are able to convert radiation into growth more efficiently at low light intensities (e.g., in winter), as previous research clearly shows (Cooper 1970; Peri et al. 2003b). Non-linear functions have been used to model radiation conversion efficiency in the past (Johnson & Thornley 1983; Johnson et al. 1995; Peri et al. 2003a). In the new version, the parameter  $\alpha$  (see Eqn 2) increases at low radiation levels:

$$\alpha = \frac{b}{1 - e^{(-a \times I)}} \quad \text{Eqn (9)}$$

where:

$I$  = incident solar radiation (MJ/m<sup>2</sup> per day)

$a$  = constant determining the shape of the function (0.007)

$b$  = asymptotic value of  $\alpha$  when the growth response to  $I$  reaches saturation (g DM/MJ)

## Datasets

Six datasets from New Zealand were used to test the proposed changes to the model, four from flat sites (two in the North Island (Waikato) and two in the South Island (Canterbury and Southland)) and two from hill country in the Waikato.

The first flat site dataset was collected between 1982 and 1992 from perennial ryegrass dominant pasture at No. 2 Dairy (Hamilton, New Zealand; 37°46'S, 175°18'E). Herbage growth was estimated using the trimmed cage technique (Piggot 1997), in which pasture was harvested from three cages every 28 days. A detailed description of this dataset was provided by McCall & Bishop-Hurley (2003).

At the second flat site (Scott Farm, Dexcel, Hamilton, New Zealand; 37°47'S, 175°19'E), between September 2004 and May 2006, perennial ryegrass dominant plots were mown using a rotary lawnmower at the 3-leaf stage of regrowth. Pasture harvested from the plots was weighed and subsamples oven-dried at 95°C for 48 h to estimate herbage growth (Lee et al. 2008). Only data from unfertilised (control) plots were used to validate the proposed changes to the model.

Hill country data (Gillingham et al. 1990) were obtained from two paddocks in a fertiliser experiment at Whatawhata Research Centre (37°49'S, 175°05'E) between September 1996 and September 1998. Paddock 4 (P4) had a history of high fertiliser applications (1000 kg superphosphate per year), while Paddock 14 (P14) had no fertiliser applied over the previous 8 years. Green herbage mass was estimated once each week at 40 fixed locations arranged in four transects in each paddock. A non-disruptive method of herbage growth measurement described by Hanna et al. (1999) was used, based on measuring herbage reflectance from different wavelengths. While herbage mass estimates were recorded weekly, the green mass accumulation between grazing events was used for testing the model.

Two datasets from the South Island of New Zealand were provided by AgResearch. One set was from Woodlands, Southland (46°21'S, 168°29'E), on a Waikiwi silt loam soil (Typic Firm Brown), spanning from July 2000 to December 2003. Herbage growth was estimated using the trimmed cage technique, cutting every 28 days approximately. The second site was from Winchmore, Canterbury (43°47'S, 171°47'E), on a non-irrigated Lismore Stony Silt Loam Soil (Pallic Firm Brown), from July 1966 to June 2004 (climate data available since 1972). Unfortunately, information regarding cutting dates was not available for this last site, therefore only monthly averages were considered.

To assess the intrinsic variability within the datasets, the standard deviation between samples (i.e., representing spatial variability between cages, plots or transects) was calculated at each sampling

date and then averaged for each month of the year. Weather data from the closest climatological station to each site (provided by NIWA, Hamilton, New Zealand) were used to run the model.

### Model calibration and validation

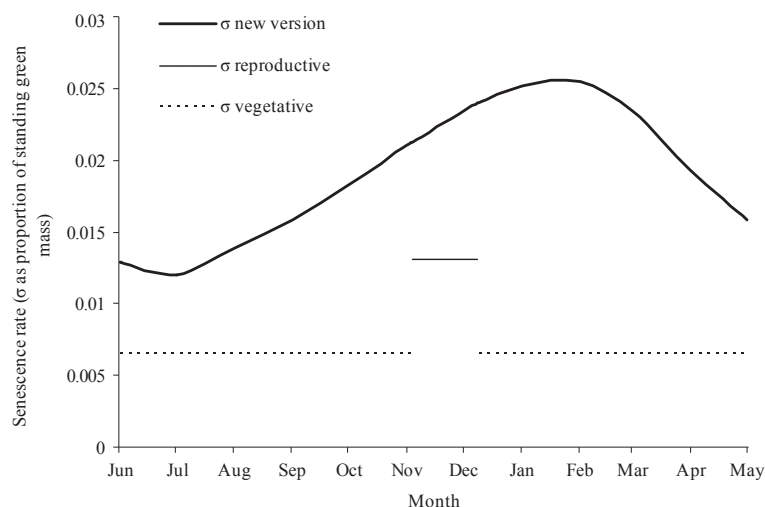
Both versions of the model were implemented in the Java programming language, which will facilitate code reuse in future applications. The model reads the required input from a series of text files, including (a) weather data, (b) defoliation events (dates and grazing-residuals) and (c) observed data (for comparison with simulated results for calibration or validation).

Calibration and testing were done on average daily DM accumulation between defoliation events. The objective of the calibration was to minimise the sum of squares of difference between actual and predicted herbage accumulation (SSQ). An open source genetic algorithm package (JGAP; Meffert & Rotstan 2008) was incorporated into the model (with permission from the authors) and used for the calibrations. The JGAP is a versatile Genetic Algorithm and Genetic Programming component provided as a Java framework. Initially, the calibration was performed by changing the parameter  $\alpha$  alone (Eqn 2), but much better fits were obtained when both  $\alpha$  and AWHC were included in the calibration procedure, and is the basis of results reported here. The asymptotic value of  $\alpha$  (parameter  $b$  in Eqn 9) was calibrated in the “changed McCall” model, leaving  $a$  constant (at 0.007).

For site-specific calibrations of  $\alpha$  and AWHC, each time series dataset (except for the Scott Farm site) was split in half. The first half was used to calibrate the parameters in the model, and the second half was used for the validation. During the simulations, the two state variables in the model, green and dead mass (kg DM/ha) were set to the observed values after each harvesting event to account for the utilisation regime to which the pastures were subjected.

A series of indicators was used to test goodness-of-fit of the model to the validation data. Measures describing the strength of the linear regression relationship between actual and simulated data included the Pearson's correlation coefficient ( $r$ ) and the coefficient of determination ( $R^2$ ), which represents the proportion of the total variance in the observed data that can be explained by the model (Legates & McCabe 1998).

While useful, indicators like  $r$  and  $R^2$  fail to detect inaccuracies associated with the departure of the best



**Fig. 2** Relative senescence rate (proportion of the standing green material) as function of mean daily temperature (new version) compared with the values currently used in the McCall model for vegetative and reproductive states.

fit regression line (i.e., linear regression line between observed and modelled data) from the desired  $Y = X$  line (i.e., the concordance line). Accuracy can be measured by the bias correction factor ( $C_b$ , see Appendix) proposed by I-Kuei Lin (1989), which indicates how far the regression line deviates from the concordance ( $Y = X$ ) line. The concordance correlation coefficient ( $\rho_c$ ) integrates both, precision ( $r$ ) and accuracy ( $C_b$ ) (see Appendix; I-Kuei Lin 1989). It assesses agreement between observed and predicted results by measuring the deviation from the concordance line. Any departure from the concordance line (i.e., bias) would produce  $\rho_c$  lower than 1 even if  $r$  is 1. A bias from the concordance line could consist of a scale shift ( $v$ , assessed by the ratio of observed to predicted standard deviations) and a location shift ( $\mu$ , which is the squared difference between observed and predicted means relative to the product of the two standard deviations). As explained by Pell et al. (2003), a systematic divergence from the line of concordance corresponds to bias in the model and can be characterised in terms of the slope (scale shift) and intercept (location shift). In the absence of bias, slope and intercept of the regression relationship between observed and predicted data correspond to values of 1 and 0, respectively (see Appendix).

Legates & McCabe (1998) compared different goodness-of-fit measures in model validation, and recommend the use of the Coefficient of Efficiency ( $E$ ) or the Modified Index of Agreement ( $d_i$ ) to evaluate simulation models. A value of the coefficient  $E$  ranges from minus infinity to 1, and is the ratio of the mean square error to the variance of the

observed data, subtracted from the unity. A value of 1 indicates perfect agreement. The Modified Index of Agreement ranges from 0 to 1 and specifies the degree to which observed deviations about the observed mean ( $\bar{Y}_o$ ) correspond, both in magnitude and sign, to the predicted deviations about  $\bar{Y}_o$  (Willmott 1981).

Other parameters used to compare the alternative models were the total sum of squared errors (SSQ), root mean squared error ( $RMSE = \sqrt{SS/n}$ ), and the mean absolute error (MAE).

The approach in this study was to look at a series of indicators, including pictorial representations, as each of them focuses on different aspects of the data and none is totally comprehensive. This provided a better picture of the prediction quality achieved by the model. The calculation of all the indicators described above is inbuilt into the model code, and a full report is automatically generated after each validation simulation.

## RESULTS AND DISCUSSION

### Senescence function

Using the monthly average for  $T_{\text{mean}}$  for the Rukura Climatological Station for illustration (37°78'S, 175°32'E; elevation 40 m a.s.l., close to all the North Island sites: less than 2–3 km from No. 2 Dairy and Scott Farm and about 17 km from the hill country sites), the range of values produced for  $\sigma$  are considerably higher than those fitted by McCall in his model for vegetative (0.0065) and



reproductive (0.0131) swards. Also, the seasonal pattern of relative senescence rate is rather different (Fig. 2).

Woodward (1998b), using data reported by Chapman et al. (1984), fitted the function: Leaf death rate =  $0.00158 \times (T_{\text{soil}} + 2.2)$  in kg/kg per day; where  $T_{\text{soil}}$  is 100 mm soil depth temperature. This implies that LLS (in kg/kg per °C-day) has a positive and curvilinear relationship with soil temperature:

$$LLS = \frac{T_{\text{soil}}}{0.00158 \times (T_{\text{soil}} + 202)} \left( \lim_{T_{\text{soil}} \rightarrow \infty} = \frac{1}{0.00158} \right)$$

Eqn (10)

with an asymptote at 632.9°C-days. Within the range of normal temperatures in New Zealand, the values predicted by this function are close to the 507°C-days LLS used here. For example, according to Woodward's function, for  $T_{\text{soil}} = 15^{\circ}\text{C}$ , LLS would be around 552°C-days (9% higher than the value of 507 used here).

### Observed results

The average annual herbage accumulations were 12 205, 7340, 14 571, 12 942, 13 570 and 7208 kg DM/ha per year, for P4, P14, No. 2 Dairy, the plot experiment dataset (Scott Farm), Woodlands and Winchmore, respectively. Of the four sites available for the North Island, P14 was the least productive, which was to be expected since it is on hill country with a history of no fertiliser applications for 8 years. The site at P4 is also on hill country, but was heavily fertilised, while No. 2 Dairy and the site at Scott Farm are flat, regularly fertilised dairy land.

The Winchmore site was the less productive of the two the South Island sites, particularly during the summer-autumn period, which is consistent with the fact that it was a non-irrigated site and with the large response to irrigation expected for that location (McBride 1994).

### Model results

Allowing the optimisation algorithm to fit both AWHC and  $\alpha$  improved model fit for most indicators, and the fitted values for AWHC were markedly different from the default value of 90 mm currently used in the model (Table 2). Interestingly, the value of AWHC fitted for No. 2 Dairy was 211 mm, which is close to the range of values (138–202 mm) fitted by Woodward et al. (2001) for similar soil types (Horotiu and Te Kowhai silt loams). This agreement with the findings by Woodward et al. (2001) highlights the need for further investigation, including

field measurement of soil water content and plant stress indicators.

When both versions of the model were calibrated, the procedure resulted in lower AWHC for both hill country sites (P4 and P14), which is consistent with the shallow soils typical of New Zealand hill country (Bircham & Gillingham 1986). On the other hand, AWHC was greater for No. 2 Dairy, again consistent with the deep volcanic soils and the flat landscape of the site (Gradwell 1968). The hill country sites differed markedly in fertiliser history, and consequently in herbage production potential, which was correctly reflected in the contrasting fitted values for  $\alpha$ . The greater fertility level of P4 (1000 kg/ha per year of superphosphate) compared to No. 2 Dairy was only reflected in  $\alpha$  (Table 2) in the new version of the model.

The model indicated that pasture productivity may have been limited by fertility and AWHC in P14, and by AWHC in P4, compared with No. 2 Dairy. This correlation between parameter calibration and what was expected from knowledge of the sites provides support for the modifications in the model, particularly as these trends were not as clear for the existing version.

In the case of the South Island sites, the fitting produced similar AWHCs for the two versions, both showing lower values for Winchmore compared with Woodlands. This is consistent with soil differences between sites, shallow stony Lismore soil (Thorold et al. 2004) at Winchmore and a deep silt loam soil at Woodlands. The fitted values for AWHC for Winchmore were close to the 61 mm reported by Woodward et al. (2001), although the fitted AWHCs for Woodlands were considerably smaller than the 128 mm reported by those authors. For the current version, the calibration gave values of  $\alpha$  that were unjustifiably much higher than for the North Island sites, particularly for Woodlands. For the new version, on the other hand, the fitted values of  $\alpha$  were similar to those for the flat sites in the Waikato.

### Validation

Table 2 shows the goodness-of-fit indicators against the validation datasets after fitting the parameters  $\alpha$  and AWHC to the calibration datasets. The new version of the model showed better fit than the existing version in eight of the 11 indicators across all datasets. The new version showed more precision, as measured by SSQ, RMSE, MAE and  $r$ . In terms of accuracy, for the new version, the slope between observed and predicted data was consistently closer to 1 than with the existing version. Location shift and

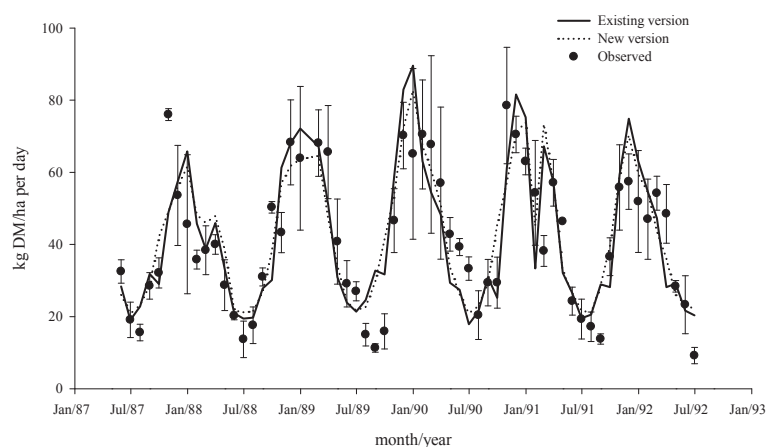
**Table 2** Goodness-of-fit on the validation datasets of Paddock 4 (P4), Paddock 14 (P14), No. 2 Dairy, the plot experiment dataset (Scott Farm), Woodlands (Southland) and Winchmore (Canterbury). Comparison of the existing and new version of the McCall model, fit fitting the parameters efficiency of radiation use ( $\alpha$ ) and available water holding capacity (AWHC). In the plot experiment at Scott Farm, the parameters  $\alpha$  and AWHC were derived from the No. 2 Dairy dataset. SSQ, total sum of squared errors; RMSE, root mean squared error; MAE, mean absolute error. \*Asymptotic value (a) for the new version (see Eqn 9).

Model version →	P4		P14		No. 2 Dairy		Scott Farm		Woodlands		Winchmore	
	Existing	New	Existing	New	Existing	New	Existing	New	Existing	New	Existing	New
Parameters fitted												
$\alpha$ (g DM/MJ)*	0.64	0.62	0.48	0.48	0.66	0.57	0.66	0.57	0.91	0.61	0.82	0.61
AWHC (mm)	95	45	88	35	195	211	195	211	55	70	51	55
Goodness-of-fit												
SSQ*	4787	1575	1847	499	8677	7711	11112	7748	4536	2966	1899	795
RMSE*	18.49	10.61	11.49	5.97	11.93	11.24	15.22	12.7	13.21	10.68	12.58	8.14
MAE*	14.15	9.2	8.32	4.25	9.38	8.71	13.07	10.74	9.84	8.66	10.98	6.52
Correlation	0.66	0.89	0.7	0.9	0.81	0.82	0.72	0.82	0.82	0.88	0.57	0.84
Slope	0.81	1.15	0.71	0.93	0.78	0.88	0.74	0.92	0.84	0.91	0.44	0.66
$\rho_c$ = Concordance	0.59	0.85	0.62	0.88	0.81	0.81	0.71	0.79	0.81	0.88	0.53	0.80
$\mu$ = Location shift	-0.44	0.20	-0.51	0.19	-0.05	-0.09	-0.18	-0.28	0.12	-0.06	0.31	0.22
$\nu$ = Scale shift	1.22	1.28	1.02	1.03	0.96	1.08	1.03	1.11	1.03	1.04	0.77	0.79
$C_b$ = Bias correction factor	0.89	0.95	0.89	0.98	1	0.99	0.98	0.96	0.99	1.00	0.92	0.95
$d_1$ = Modified Index of Agreement	0.58	0.72	0.59	0.79	0.72	0.72	0.62	0.68	0.74	0.78	0.48	0.70
E = Coefficient of Efficiency	0.26	0.76	0.15	0.77	0.6	0.65	0.43	0.6	0.63	0.76	-0.32	0.47

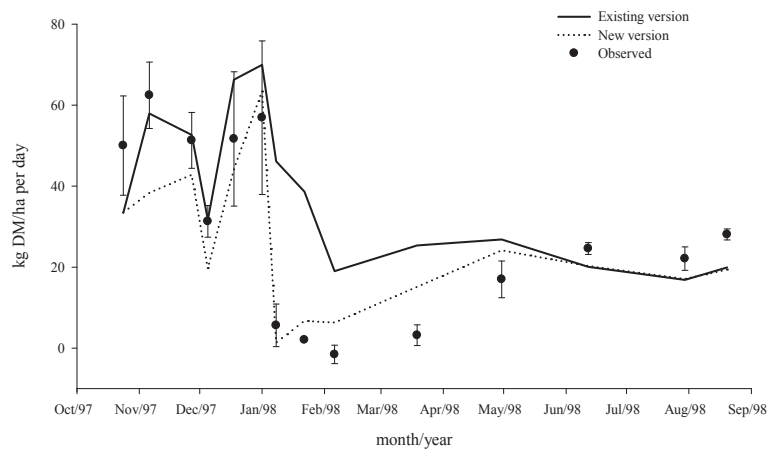
$C_b$  were improved in hill country sites, and  $\nu$  was similar in all the sites between versions. On the other hand, both models showed some scale shift, especially in P4, and in the existing version at Woodlands. A scale shift means that observed and predicted variances are somewhat different. The location shift (indication of the overall bias) was small in general, indicating that observed and predicted means are similar for both versions. The existing version failed to fit the observed monthly trend in Winchmore (even showing a negative E), whereas the new version showed more adequate statistics. When indicators that integrated both precision and accuracy (i.e.,  $\rho_c$ ,  $d_1$ , and E) were applied, all of them favoured the new version in all the validation datasets.

In addition to the statistical indicators in Table 2, a visual examination indicates that the fit of both versions of the model to the validation dataset was acceptable for No. 2 Dairy (Fig. 3) and Woodlands (Fig. 7). At the hill country sites and Winchmore, the models did not fit the validation datasets as well (Fig. 4, 5, 7, 8). In particular, the existing version over-predicted growth for P4 and P14 during the summer of 1998, when the observed green growth was low because of dry and hot weather. This bias was notably reduced with the new version, possibly because of the inclusion of the water infiltration component (Eqn 7) and the effect of temperature on the new senescence function. In the case of Winchmore (Fig. 8) the observed data showed very low growth from January to August, with a marked peak in spring and an abrupt fall in December, both versions showed over-predictions in summer, but the existing version also under-predicted in early spring.

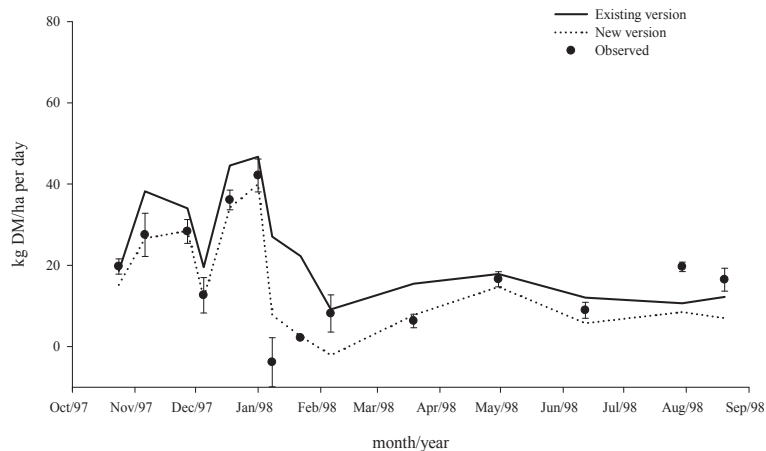
**Fig. 3** Observed (dots) and predicted (lines) average daily herbage accumulation (kg DM/ha per day,  $\pm$  SD) in the No. 2 Dairy validation dataset for the existing and the new version of the model.

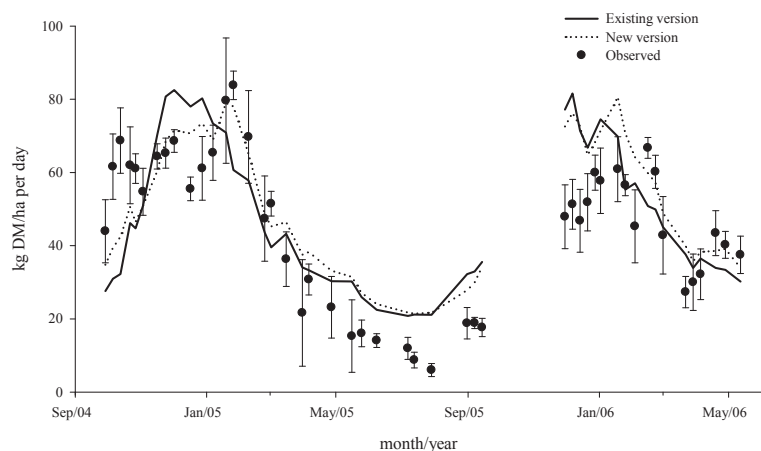


**Fig. 4** Observed (dots) and predicted (lines) average daily herbage accumulation (kg DM/ha per day,  $\pm$  SD) in the Paddock 4 validation dataset for the existing and the new version of the model.

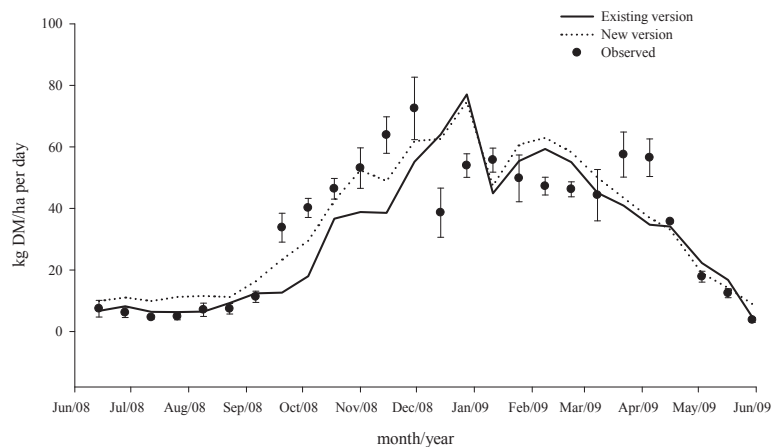


**Fig. 5** Observed (dots) and predicted (lines) average daily herbage accumulation (kg DM/ha per day,  $\pm$  SD) in the Paddock 14 validation dataset for the existing and the new version of the model.

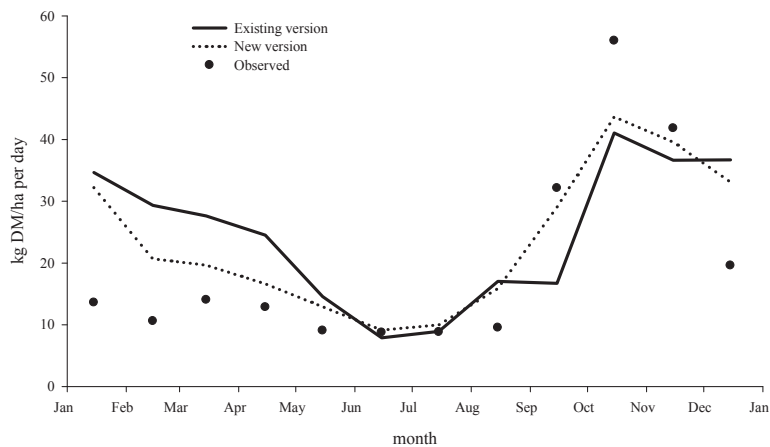




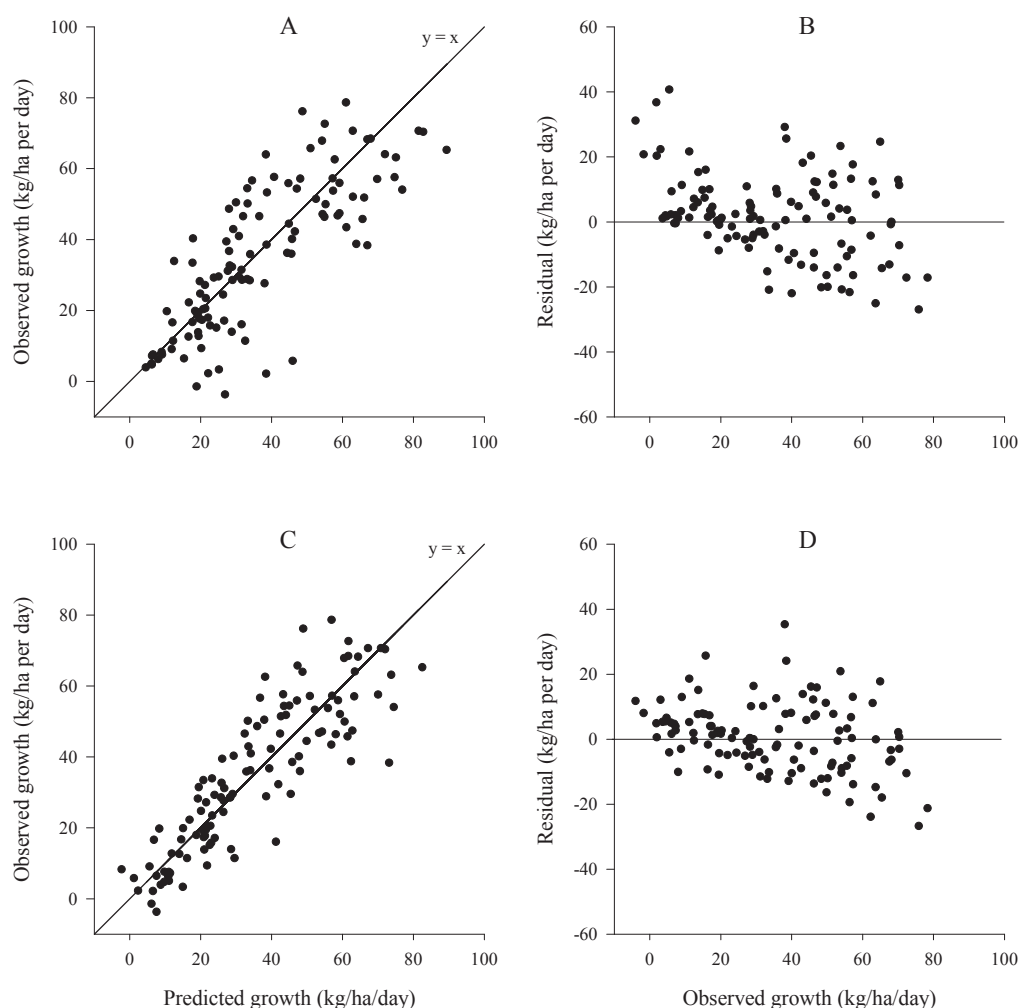
**Fig. 6** Observed (dots) and predicted (lines) average daily herbage accumulation (kg DM/ha per day,  $\pm$  SD) in the plot experiment (Scott Farm) validation dataset for the existing and the new version of the model.



**Fig. 7** Observed (dots) and predicted (lines) average daily herbage accumulation (kg DM/ha per day,  $\pm$  SD) in the Woodlands validation dataset for the existing and the new version of the model.



**Fig. 8** Observed (dots) and predicted (lines) monthly average (1998–2003) of daily herbage accumulation (kg DM/ha per day) in the Winchmore validation dataset for the existing and the new version of the model.



**Fig. 9** Observed versus predicted herbage growth and residuals (predicted-observed) using the existing **A**, and **B**, respectively) and the new version of the model, **C**, and **D**, respectively) for the combined validation datasets of Paddock 4, Paddock 14, No. 2 Dairy, the plot experiment (Scott Farm) and Woodlands (Southland).

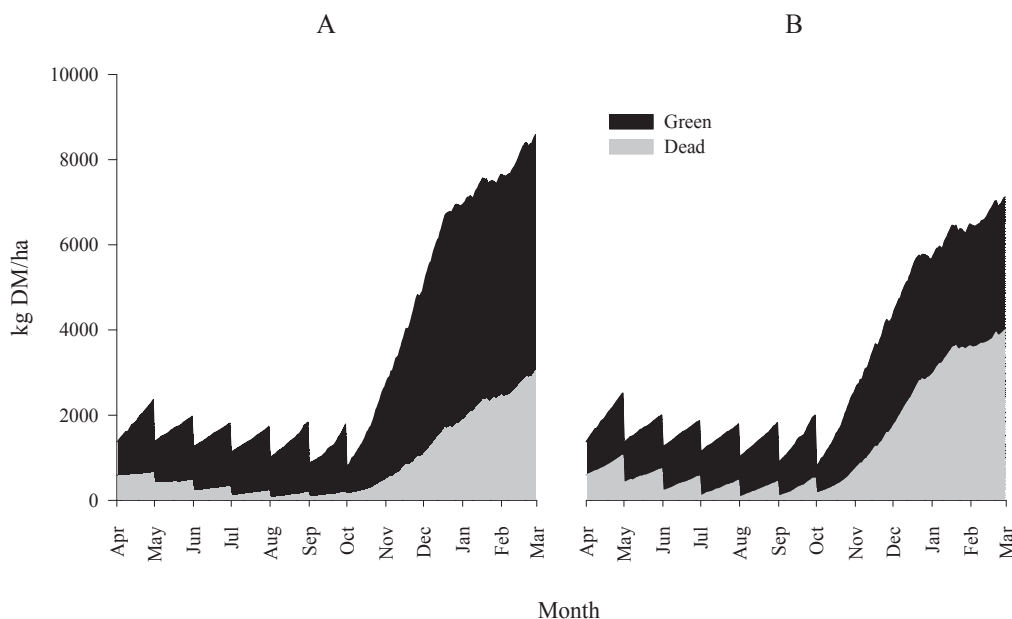
In the Scott Farm dataset validation, values for parameters  $\alpha$  and AWHC were those obtained by calibration for No. 2 Dairy, assumed to be the most similar site. The new version of the model outperformed the existing version on eight of the goodness-of-fit indicators considered in this study (including  $\rho_c$ ,  $d_1$ , and E), with the other three indicators being similar between model versions (Table 2, Fig. 6).

Combining the four North Island datasets and Woodlands (i.e., where individual regrowth data

were available), the observed versus predicted plots and the residual plots showed a bias with the existing version of the model, with predominantly positive residuals at low growth rates and negative residuals at high growth rates (Fig. 9A,B). This trend was less obvious with the new version of the model (Fig. 9C,D).

It is noteworthy that the testing performed here used data from pastures maintained in a vegetative state by frequent cutting or grazing (up to 1 month





**Fig. 10** Simulated green and dead material accumulation on a pasture undisturbed from October through the summer using the existing **A**, and the new version **B**, of the model.

of regrowth). It was not clear how the proposed changes to the model would affect simulations of pastures subjected to infrequent grazing regimes, such as pastures left undisturbed for a long period of time for deferred grazing or hay cropping. For this reason, a simulation was done of an undisturbed herbage growth (after cutting once a month since April) from the first of October through to the end of February. It showed that the new version of the model produced more realistic results, based on ceiling green yields similar to those found by Korte et al. (1982). The existing version of the model seemed to accumulate proportionally too much green material (Fig. 10). For example, by the end of January (i.e., after 4 months of closure), the existing version predicted that the pastures should contain about 30% dead material above ground, while the new version predicted a more realistic figure of 50%. Again, the new version was more in line with the results reported by Korte et al. (1982).

### Results in context

Håkanson (1995) argued that if the variability within a system is large, many samples are needed to determine a representative mean value. This implies

that such a mean would be difficult to predict, since there may be many causes of system variability. This is the normal situation found with herbage accumulation estimates, where spatial variability, and large measurement errors both contribute to the variability in the observed data. In the present study, the coefficient of variation between samples for herbage growth estimates at any given sampling date (calculated at each sampling date as daily growth/average SD  $\times$  100 and then averaged for each site) were on average 21, 24, 17 and 13% for No. 2 Dairy, P4, P14, and Woodlands respectively. Even in a highly controlled situation like the Scott Farm plot experiment, the average coefficient of variation between plots was 16%. Climate data are also not free from errors. Model predictions were not perfect, but considering the uncertainty in observed data and inputs, and the simple nature of the McCall model, it can be argued that the present model is fit for use in grazing system design and analysis. Substantial further improvements would be difficult.

Finding reliable herbage accumulation data, along with soil and management information for more regions and for at least two seasons per site would be necessary to develop this model further. Such data

have not been regularly collected, and in many cases crucial details of the experimental procedures have not been preserved. With the need to be able to simulate herbage growth accurately for a broad spectrum of functions (ranging from helping with new grazing system design to aiding short-term decision making) it will become increasingly important to validate this pasture growth model for other locations and pasture types.

## CONCLUSION

Considering the suite of goodness-of-fit indicators and visual assessments used in this study, the proposed changes to the McCall model improved prediction of herbage production in five datasets, one of them totally independent (i.e., without specific calibration), and both versions were similar in the sixth dataset. Such improvement was achieved without adding excessive complexity to the model, or the necessity for more input variables. More importantly, the use of more mechanistic solutions eliminated some correction factors that require site calibration instead of using values obtained from independent research. The existing senescence algorithm in the model needs four parameters;  $\sigma$  for vegetative ( $\sigma_v$ ) and reproductive ( $\sigma_R$ ) swards and the dates to change from vegetative to reproductive phase ( $t_F$ ) and vice versa ( $t_D$ ), all of which required empirical calibration. The new senescence function needs only one parameter (i.e., the leaf lifespan), which is species/cultivar specific, can be measured independently, and has a clear biological meaning.

It is concluded that the new improved version of the model can be confidently used as a replacement for the existing version.

## ACKNOWLEDGMENTS

The authors thank Barbara Dow, Errol Thom and John Roche for their invaluable help in reviewing this paper. Also special thanks to Simon Woodward for the useful discussions. Many thanks to Chris Smith (AgResearch) and Ballance Agri-nutrients, for the Woodlands data. And thanks to Todd White and Ray Moss (AgResearch) for the Winchmore data. This research was funded by the New Zealand Foundation for Research, Science and Technology and DairyNZ.

## REFERENCES

- Alberda T, Sibma L 1968. Dry matter production and light interception of crop surfaces. III. Actual herbage production in different years as compared with potential values. *Journal of the British Grassland Society* 23: 206–215.
- Bahmani I, Hazard L, Varlet-Grancher C, Betin M, Lemaire G, Matthew C, Thom ER 2000. Differences in tillering of long- and short-leaved perennial ryegrass genetic lines under full light and shade treatments. *Crop Science* 40: 1095–1102.
- Barker DJ 1983. The effect of summer moisture stress and its interaction with spring cutting management on the production and persistence of a ryegrass (*Lolium perenne* L.) sward. Unpublished PhD thesis, Massey University, New Zealand. 146 p.
- Beukes PC, Clark CEF, Romera AJ, Levy G, Lee JM 2008. Using a climate-driven farm model to predict pasture mass for individual paddocks on New Zealand dairy farms. *Proceedings of the New Zealand Grassland Association* 70: 159–163.
- Bircham JS, Gillingham AG 1986. A soil water balance model for sloping land. *New Zealand Journal of Agricultural Research* 29: 315–323.
- Cayley JWD, Bird PR, Chin JF 1980. Death and decay of perennial pastures as affected by season. *Proceedings of the Australian Society of Animal Production* 13: 469.
- Chapman DF, Clark DA, Land CA, Dymock N 1984. Leaf and tiller or stolon death of *Lolium perenne*, *Agrostis* spp. and *Trifolium repens* in set stocked and rotationally grazed hill pastures. *New Zealand Journal of Agricultural Research* 27: 303–312.
- Cooper JP 1970. Potential production and energy conversion in temperate and tropical grasses. *Herbage Abstracts* 40: 1–15.
- Cros M-J, Duru M, Garcia F, Martin-Clouaire R 2003. A biophysical dairy farm model to evaluate rotational grazing management strategies. *Agronomie* 23: 105–122.
- Davies A, Thomas H 1983. Rates of leaf and tiller production in young spaced perennial ryegrass plants in relation to soil temperature and solar radiation. *Annals of Botany* 57: 591–597.
- Donaghy DJ 1998. Improving the production and persistence of temperate pasture species in subtropical dairy regions of Australia. Unpublished PhD thesis, University of New England, Australia.
- Donaghy DJ, Turner LR, Adamczewski KA 2008. Effect of defoliation management on water-soluble carbohydrate energy reserves, dry matter yields, and herbage quality of tall fescue. *Agronomy Journal* 100: 122–127.

- Fernandes Cauduro G, Carvalho PCF, Barbosa CMP 2006. Morphogenetic and structural traits of Italian ryegrass (*Lolium multiflorum* Lam.) sward managed under different grazing intensities and methods. *Revista Brasileira de Zootecnia* 35: 1298–1307.
- Gillingham AG, Richardson S, Power IL, Riley J 1990. Long term effects of withholding phosphate application on North Island hill country: Whatawhata Research Centre. *Proceedings of the New Zealand Grassland Association* 51: 11–16.
- Gradwell MW 1968. The moisture-holding properties of Waikato soils and methods of their determination. *New Zealand Journal of Agricultural Research* 11: 631–654.
- Håkanson L 1995. Optimal size of predictive models. *Ecological Modelling* 78: 195–204.
- Hanna MM, Steyn-Ross DA, Steyn-Ross M 1999. Estimating biomass for New Zealand pastures using optical remote sensing techniques. *Geocarto International* 14: 89–94.
- I-Kuei Lin L 1989. A concordance correlation coefficient to evaluate reproducibility. *Biometrics* 45: 255–268.
- Johnson IR, Thornley JHM 1983. Vegetative crop growth model incorporating leaf area expansion and senescence, and applied to grass. *Plant, Cell Environment* 6: 721–729.
- Johnson IR, Riha SJ, Wilks D 1995. Modelling daily net canopy photosynthesis and its adaptation to irradiance and atmospheric CO<sub>2</sub> concentration. *Agricultural Systems* 50: 1–35.
- Johnson IR, Chapman DF, Snow VO, Eckard RJ, Parsons AJ, Lambert MG, Cullen BR 2008. DairyMod and EcoMod: biophysical pasture simulation models for Australia and New Zealand. *Australian Journal of Experimental Agriculture* 48: 621–631.
- Korte CJ, Watkin BR, Harris W 1982. Use of residual leaf area index and light interception as criteria for spring-grazing management of a ryegrass-dominant pasture. *New Zealand Journal of Agricultural Research* 25: 309–319.
- Lee JM, Elborough K, Catto WD, Donaghy DJ, Roche JR 2008. Effect of surface-applied glycine betaine application on herbage production and quality of perennial ryegrass-white clover pastures. *Australian Journal of Experimental Agriculture* 48: 687–694.
- Legates DR, McCabe GJJ 1998. Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resources Research* 35: 233–241.
- Lemaire G, Agnusdei M 2000. Leaf tissue turnover and efficiency of herbage utilization. *Grassland eco-physiology and grazing ecology*. Wallingford, UK, CABI Publishing. Pp. 265–287.
- Lemaire G, Chapman D 1996. Tissue flows in grazed plant communities. In: Hodgson J, Illius AW ed. *The ecology and management of grazing*. Wallingford, UK, CAB International. Pp. 3–37.
- McBride SD 1994. Pasture yield responses to irrigation in Canterbury. *Proceedings of the New Zealand Grassland Association* 56: 168–168.
- McCall DG 1984. A systems approach to research planning for North Island hill country. Unpublished PhD thesis, Massey University, New Zealand. 261 p.
- McCall DG, Bishop-Hurley GJ 2003. A pasture growth model for use in a whole-farm dairy production model. *Agricultural Systems* 76: 1183–1205.
- Meffert K, Rotstan N 2008. JGAP—Java Genetic Algorithms and Genetic Programming Package. Available from <http://jgap.sf.net> (date accessed 6 November 2009).
- Neil PG, Bright KP, Sherlock RA 1997. Integrating legacy components into an object-oriented model. In: McDonald AD, Smith ADM, McAller M ed. *Proceedings of the International Conference on Modelling and Simulation, Modelling and Simulation Society of Australia. MODSIM 97, December 1997, Hobart, Australia*. Pp. 1133–1138.
- Oltjen JW, Ahmadi A, Romera AJ, Drake DJ, Woodward SJR 2008. PRANCH: cow-calf herd simulation system. In: Ninomiya TNAS ed. *Proceedings of Joint Conference of the 12th World Congress of the International Association of Agricultural Information Specialists (IAALD), the 6th Conference of the Asian Federation of Information Technology in Agriculture (AFITA) and the 6th World Congress on Computers in Agriculture (WCCA), Agricultural Information and IT. Proceedings of IAALD AFITA WCCA, Tokyo University of Agriculture, Japan*. Pp. 123–126.
- Pell GS, King MD, Proctor E, Thomas DL, Lythgoe MF, Gadian DG, Ordidge RJ 2003. Comparative study of the FAIR technique of perfusion quantification with the hydrogen clearance method. *Journal of Cerebral Blood Flow & Metabolism* 23: 689–699.
- Peri PL, Moot DJ, McNeil DL 2003a. A canopy photosynthesis model to predict the dry matter production of cocksfoot pastures under varying temperature, nitrogen and water regimes. *Grass and Forage Science* 58: 416–430.

- Peri PL, Moot DJ, McNeil DL, Lucas RJ 2003b. Modelling the net photosynthesis rate of field-grown cocksfoot leaves to account for growth duration. *New Zealand Journal of Agricultural Research* 46: 105–115.
- Piggot GJ 1997. Pasture production in the northern dairy farms. *Proceedings of the New Zealand Grassland Association* 59: 103–106.
- Rawnsley RP, Donaghy DJ, Fulkerson WJ, Lane PA 2002. Changes in the physiology and feed quality of cocksfoot (*Dactylis glomerata* L.) during regrowth. *Grass and Forage Science* 57: 203–211.
- Robson MJ, Deacon MJ 1978. Nitrogen deficiency in small closed communities of S24 ryegrass. II. Changes in the weight and chemical composition of single leaves during their growth and death. *Annals of Botany* 42: 1199–1213.
- Robson MJ, Ryle GJA, Woledge J 1988. The grass plant. In: Jones MB, Lazenby A ed. *The grass crop*. London, Chapman & Hall. Pp. 26–83.
- Romera AJ, Morris ST, Hodgson J, Stirling WD, Woodward SJR 2004. A model for simulating rule-based management of cow-calf systems. *Computers and Electronics in Agriculture* 42: 67–86.
- Romera AJ, Morris ST, Hodgson J, Stirling WD, Woodward SJR 2005a. Comparison of haymaking strategies for cow-calf systems in the Salado Region of Argentina using a simulation model. 1. Effect of herbage mass at cutting and cow stocking rate under a rigid system of management. *Grass and Forage Science* 60: 399–408.
- Romera AJ, Morris ST, Hodgson J, Woodward SJR, Stirling WD 2005b. Risk-efficiency assessment of haying. In: Murphy JJ ed. *Utilization of grazed grass in temperate animal systems*. *Proceedings of a satellite workshop of the XXth International Grassland Congress*, Wageningen Academic Publishers, Cork, Ireland. P. 224.
- Schijf M, Deurer M, Clothier B, Aslam T, van der Dijssel C 2008. What impact has soil water repellency on the buffering of soil water? *WISPAS* 100: 1–2.
- Seligman NG 1993. Modelling as a tool for grassland science progress. *Proceedings of the XVII International Grassland Congress* 1: 743–748.
- Snow VO, Zyskowski RF, Cichota R, Lilburne LR, Jamieson PD 2007. The effect of temporal aggregation on modelling pasture growth and nitrate leaching from urine patches. In: Oxley L, Kulasiri D ed. *MODSIM 2007 International Congress on Modelling and Simulation*. Modelling and Simulation Society of Australia and New Zealand, Christchurch, New Zealand. Pp. 1646–1652.
- Tait A, Henderson R, Turner R, Zheng X 2006. Thin-plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. *International Journal of Climatology* 26: 2097–2115.
- Thorrold BS, Bright KP, Palmer MJ, Wastney M 2004. Modelling the effects of irrigation reliability on pasture growth in a dairy system in Canterbury. *Proceedings of the New Zealand Grassland Association* 66: 61–34.
- Turner LR, Donaghy DJ, Lane PA, Rawnsley RP 2006. Effect of defoliation interval on water-soluble carbohydrate and nitrogen energy reserves, regrowth of leaves and roots, and tiller number of cocksfoot (*Dactylis glomerata* L.) plants. *Australian Journal of Agricultural Research* 57: 243–249.
- Willmott CJ 1981. On the validation of models. *Physical Geography* 2: 184–194.
- Woledge J, Dennis WD 1976. Effect of temperature on photosynthesis of ryegrass and white clover leaves. *Annals of Botany* 50: 25–35.
- Woodward SJR 1998a. Dynamic systems models and their application to optimizing grazing management. In: Peart RM, Curry BR ed. *Agricultural system modeling and simulation*. United States of America, Marcel Dekker Inc. Pp. 419–474.
- Woodward SJR 1998b. Quantifying different causes of leaf and tiller death in grazed perennial ryegrass swards. *New Zealand Journal of Agricultural Research* 41: 149–159.
- Woodward SJR, Barker DJ, Zyskowski RF 2001. A practical model for predicting soil water deficit in New Zealand pastures. *New Zealand Journal of Agricultural Research* 44: 91–109.

APPENDIX

---

Concordance Correlation Coefficient ( $0 \leq \rho_c \leq 1$ ; I-Kuei Lin 1989)

$$\rho_c = \frac{2S_{op}}{S_o^2 + S_p^2 + (\bar{Y}_o - \bar{Y}_p)^2}$$

where:

$S_o^2, S_p^2$ : Variance of the observed and predicted datasets, respectively

$\bar{Y}_o, \bar{Y}_p$ : Mean of the observed and predicted datasets, respectively

$$S_{op} = \frac{1}{n} \sum_{i=1}^n (Y_{io} - \bar{Y}_o)(Y_{ip} - \bar{Y}_p)$$

$Y_{io}, Y_{ip}$ : *ith* value on the observed and predicted datasets, respectively

Bias Correction Factor ( $0 \leq C_b \leq 1$ , I-Kuei Lin 1989)

$$C_b = \left( \frac{\left( v + \frac{1}{v} + \mu^2 \right)}{2} \right)^{-1} \quad \text{A value of 1 for } C_b \text{ indicates no deviation from the } Y = X \text{ line (perfect accuracy).}$$

where:

$$v = \frac{S_o}{S_p} : \text{Scale shift (ideal value 1)}$$

$$\mu = \frac{(\bar{Y}_o - \bar{Y}_p)}{\sqrt{S_o S_p}} : \text{Location shift relative to the scale (ideal value 0)}$$

$S_o, S_p$ : Standard deviation of the observed and predicted datasets, respectively

Note also that  $\rho_c = r \times C_b$

Coefficient of Efficiency ( $-\infty \leq E \leq 1$ ; Legates & McCabe 1998)

$$E = 1 - \frac{\sum_{i=1}^n (Y_{io} - Y_{ip})^2}{\sum_{i=1}^n (Y_{io} - \bar{Y}_o)^2}$$

where  $n$  is the number of observation/simulation pairs

Modified Index of Agreement ( $0 \leq d_1 \leq 1$ ; Willmott 1981)

$$d_1 = 1 - \frac{\sum_{i=1}^n |Y_{ip} - Y_{io}|}{\sum_{i=1}^n |Y_{ip} - \bar{Y}_o| + |Y_{io} - \bar{Y}_o|}$$


---