A simple statistical model for predicting herbage production from permanent grassland

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Abstract

The considerable year-to-year and seasonal variation in grassland production is of major importance to dairy farmers in Europe, as production systems must allow for the risk of unfavourable weather conditions. A large portion of the variability is caused by weather and its interaction with soil conditions and grassland management. The present study takes advantage of the interactions between weather, soil conditions and grassland management to derive a reliable grassland statistical model (GRAM) for grasslands under various management regimes using polynomial regressions (GRAM-R) and neural networks (GRAM-N). The model performance was tested with a focus on predicting its capability during unusually dry or wet years using long-term experimental data from Austrian sites. The GRAM model was then coupled with the Met&Roll stochastic weather generator to provide estimates of harvestable herbage dry matter (DM) production early in the season. It was found that, with the GRAM-N or GRAM-R methodology, up to 0·78 of the variability in harvested herbage DM production could be explained with a systematic bias of 1·1–2·3%. The models showed stable performance over subsets of dry and wet years. Generalized GRAM models were also successfully used to estimate daily herbage growth during the season, explaining between 0·63 and 0·91 of variability in individual cases. It was possible to issue a probabilistic forecast of the harvestable herbage DM production early in the season with reasonable accuracy. The overall results showed that the GRAM model could be used instead of (or in parallel with) more sophisticated grassland models in areas or sites where complete data sets are not yet available. As the model was tested under various climatic and soil conditions, it is suggested that the proposed approach could be used for comparable temperate grassland sites throughout Europe.

Keywords: modelling, grassland, climate, water stress, Austria

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Introduction

Permanent grasslands, used either for forage production from meadows or as pastures, make up a significant proportion (0·22) of Austria, constituting an important segment of the landscape and are part of agricultural production systems. Managed grasslands in Austria are mostly located in humid regions and are thus not irrigated. The grasslands in the Alpine and near-Alpine regions are distributed over a large range of altitudes (200–2000 m) and are strongly affected by significant climate variability, as are most rain-fed grasslands in Europe. Owing to the weather in individual years and growing seasons, grassland production varies considerably. This is of major importance to dairy farmers, not only in Austria but also throughout Europe, as the whole farming system must allow for the risk of unfavourable weather conditions. In this paper, only meadows, which are defined as well-managed grasslands, cut at least once a year for forage production and without grazing, are investigated. The more general term 'grasslands' is reserved for permanent grasslands used either for mown forage or for grazing (or both). In the case of Austrian meadows, variation in seasonal harvested dry matter (DM) production of at least 0·10 of the mean (and in many cases more than 0·20) is quite common (in every second or third year), while the variation between individual cuts is much greater. Most of this variability in herbage DM production is caused by weather factors and their interaction with soil conditions, sward composition and management.

Analysis of the impact of weather conditions and management measures on stability of production is often hampered by the complexity of the grassland systems and lack of long-term experimental data (Herrmann *et al.*, 2005). As a result, most of the data on the production of meadows is restricted to a few years (Evans *et al.*, 1998; Nolan *et al.*, 2001; Han *et al.*, 2003) and thus they do not properly reflect the effects of variability in weather. Only a limited number of results from long-term experiments have been published (e.g. Williams *et al.*, 2003), but in most cases their relevance has been restricted to a specific management system. Extensive experimental studies that are typically conducted for only a few years, but which include a large number of sites, constitute another valuable source of information. Unfortunately, as in the case of long-term experiments, very few studies have been published recently (e.g. Schapendonk *et al.*, 1998; Topp and Doyle, 2004). The lack of long-term experimental data limits the use of grassland models, as reliable and sufficiently extensive data are essential for their calibration and verification. If properly calibrated, process-oriented growth models could be a valuable tool for the management of grassland production under variable climatic and soil conditions, as is the case in many field crops (e.g. Alexandrov and Hoogenboom, 2000; Žalud *et al.*, 2003). They could also improve the timing of the application of fertilizer and thus reduce nitrogen (N) leaching (e.g. Wu and McGechan, 1998) or provide early warning to farmers, decision makers or insurance companies (Rugget *et al.*, 1998). The development or adaptation of a robust and reliable process-based meadow model that would offer an insight into the underlying physiological processes and inter-species interactions still remains as an ultimate goal of many researchers.

Dynamic crop models are unsuitable to predict annual and seasonal grassland production for Austrian conditions at present for the following reasons: (1) there are inadequate data sets available from representative locations to parameterize complex models; (2) as meadows in Austria vary greatly in their soil conditions, composition and management regimes, each type would require separate parameterization and (3) some models tested fail to simulate realistically the water and N balance at specific grassland sites. The problem with non-existent or incomplete data sets is expected to continue. In order to fill the gap and satisfy the need in Austria for reasonably accurate estimates of herbage production, especially following the drought in 2003, a much simpler approach, relying on the established statistical links between a limited number of daily or seasonal variables, was examined. The main aims of the study were to (1) derive a reliable statistical model for meadows under various management regimes; (2) evaluate the performance of such statistical models during dry and wet years; (3) verify the ability of the models to simulate seasonal growth dynamics and (4) evaluate the ability of the model to predict the production of harvestable DM from herbage early in the season.

Materials and methods

Long-term experimental data and site characteristics

Long-term field data were collected at Gumpenstein (1961–2001), Piber (1971–2001) and Admont (1977–1999) experimental stations. Details of soil and site conditions are given in Table 1. At the first two sites, long-term experiments were conducted with different levels of application of N fertilizer and management regimes (Table 2). These data sets provide a good representation of the variability in weather within the two regions, namely an inner Alpine valley and a southern Austrian region. The soil conditions at these two sites are fundamentally different (Table 1). The soil conditions at the Admont experimental station are similar to those at Gumpenstein experimental station but with an even lower soil retention capacity and an occasional influence of groundwater. Meteorological data were collected continuously throughout the whole experimental period. Table 3 presents monthly accumulated daily mean air temperatures (>0°C), accumulated global solar radiation and accumulated precipitation between March and October (i.e. during the growing season of meadows) at Gumpenstein, Piber and Admont. Although the Admont site is within 25 km of the Gumpenstein experimental station, its annual precipitation is about 0·20 higher than that at Gumpenstein and it has slightly lower annual mean temperatures (0·3°C). The Gumpenstein and Admont weather stations are located directly at the experimental sites, while the closest weather station to the Piber experimental station is 15 km away. Measurements were carried out at Piber during 2002–2004, and the data from this nearest station provide a good representation of the experimental site except for precipitation originating from thunderstorms. Records of daily mean air temperature and precipitation total were available at all three stations. Global solar radiation (R_G) has been directly measured at Gumpenstein since 1999 and measurements of sunshine hours have been made since 1970. Angstrom's equation (Ångström, 1924) was used to complete the solar radiation data for this period. For the remaining period, R_G data were estimated using the equation of Winslow *et al.* (2001), following the results

Table 1 The location, code, longitude, latitude and altitude of the three experimental stations, their long-term mean daily temperatures on an annual basis and total annual precipitation, soil characteristics. Shaded stations provided long-term data (1961–2001 and 1971–2000, respectively) as well as herbage mass dynamics data (2002–2003), whereas at the stations G3 data for period 1977–1999 and one cutting regime were available.

					Climate conditions		Soil conditions					
Location	Code	Latitude (N)	Longitude (E)	Altitude (m)	Temperature (°C)	Precipitation (mm)	Soil type	Soil depth* (cm)	Bulk density ($g\ cm^{-3}$)	Wilting point ($cm^{-3}\ cm^{-3}$)	Field capacity† ($cm^{-3}\ cm^{-3}$)	WHC_{max}‡ (mm)
Gumpenstein	G1	47°29′	14°06′	700	7·6	1010	Sandy loam	100	1·41	0·07	0·26	184
Piber	G2	47°04′	15°04′	591	8·5	934	Silty loam	70	1·43	0·18	0·37	130
Admont	G3	47°34′	14°27′	646	7·5	1247	Sandy loam	90	1·42	0·08	0·24	144

*Depth of the maximum potential rooting depth.
†Mean value for the whole profile (weighted mean).
‡Maximum water-holding capacity of the soil profile (weighted mean value for the whole profile).

of the study conducted by Trnka *et al.* (2005). This method was also used at Admont to estimate R_G for the whole experimental period (1977–1999). In the case of Piber, the R_G between 1990 and 2000 was based on the Graz station observations (located within 30 km) and R_G data for the period from 1971 to 1990 were estimated using the method of Winslow *et al.* (2001). All weather records were checked for homogeneity and consistency using standard statistical methods.

The meadows at all experimental sites were dominated by perennial grasses, and there was also a relatively high proportion of herbs and a significant presence of white clover (*Trifolium repens* L.). There were generally more herb species at variants that were managed under more frequent cutting, whereas a lower cutting frequency led to a higher proportion of white clover. The proportion of grasses, herbs and white clover remained relatively stable for all variants and no statistically significant time trend was noticed. An example of the long-term botanical composition of the meadows is presented in Figure 1. The long-term monitoring of the sward composition showed that during a normal year *Trisetum flavescens* L., *Dactylis glomerata* L., *Phleum pratense* L. and *Festuca pratensis* Huds. were the dominant species at the experimental locations. During dry years, *Festuca rubra* L., *Poa pratensis* L. and *Agrostis capillaris* L. were more prevalent. The conditions in wetter years benefited *Alopecurus pratensis* L. and *Bromus hordeaceus* L., with a reduction in the proportion of the previously mentioned species. The experiments were fertilized by appropriate applications of N fertilizer (as calcium ammonium nitrate) in equal amounts at the onset of each growth cycle after a cut (two to six applications per year). In some treatments at Gumpenstein, the fertilizer application before the last cut was omitted. The effect of higher N application rates reduced the proportion of white clover from 0·25 in plots without the application of mineral N fertilizer to 0·05 when 120 kg N ha^{-1} $year^{-1}$ was applied. In these cases, white clover was replaced by grasses rather than by herb species. The amount of harvested herbage DM produced at the sites failed to show a significant trend over time, suggesting that there were no long-term environmental or management changes taking place during the period. A similar result (i.e. no statistically significant change with time) was also found for the proportions of the main species groups (Figure 1).

Experiments to determine herbage accumulation

During 2002 and 2003, field experiments were conducted at Gumpenstein and Piber in order to provide additional experimental data for verification and testing of the model developed. The growth dynamics were

Table 2 Overview of the series of the long-term experiments at individual locations used in the study.

Location	Cutting frequency	N applied per cut (kg ha^{-1})	Period of the experiment	Annual DM production (t ha^{-1})	Annual DM production (t ha^{-1})	
					Minimum	Maximum
Gumpenstein	Three cuts	40	1961–2002	9·44 (0·97)	7·40	12·31
		60*	1961–2002	10·01 (1·06)	7·56	12·60
	Four cuts	30	1961–2002	8·12 (0·88)	6·59	11·49
	Six cuts	20	1961–2002	6·84 (1·12)	4·83	10·82
Piber	Three cuts	30	1970–1993	8·24 (1·71)	4·66	12·47
		60	1970–1993	11·48 (1·46)	8·81	15·27
		90	1970–1993	13·45 (1·43)	9·61	16·65
	Four cuts	30	1970–1993	7·98 (1·32)	5·66	12·73
		60	1970–1993	10·26 (1·40)	7·59	15·41
		90	1970–1993	12·51 (1·58)	10·13	16·73
	Five cuts	30	1970–1993	7·72 (1·18)	5·63	11·77
		60	1970–1993	10·55 (1·26)	8·44	14·34
		90	1970–1993	12·31 (1·46)	9·99	15·55
	Six cuts	30	1970–1993	7·53 (1·19)	5·53	12·09
		60	1970–1993	10·26 (1·44)	8·08	14·15
		90	1970–1993	11·42 (1·45)	8·30	15·17
Admont	Three cuts	30	1977–1999	7·34 (0·69)	5·85	8·81

For each of the experimental series the following parameters are provided: mean, standard deviation in parentheses, and minimum and maximum annual herbage DM production.
*Only the first two cuts were fertilized.

assessed by weekly measurement of the accumulated herbage DM on selected experimental plots. The first measurements were taken between 23 and 26 April and the last cutting took place between 8 and 10 October in each year. At both sites, experiments included two-, three- and four-cut variants, which were fertilized with 40 kg N ha^{-1} at Gumpenstein and with 30 kg N ha^{-1} at Piber after each cut. The application of P and K fertilizer was based on soil sampling to provide optimum soil concentrations of these nutrients. The sward composition of the sites varied considerably and also depended on the cutting times, with a predomination of grass species in combination with other meadow species. In order to provide detailed monitoring of the environmental conditions, automated weather stations, equipped with CR 10X data loggers and appropriate sensors (Campbell Scientific, Shepshed, UK), were placed at the experimental plots to supplement existing measurements.

Evapotranspiration model

One of the most critical parameters frequently used to characterize growing conditions of field and forage crops is evapotranspiration (ET). In recent decades, the theoretical and applied analysis of this biophysical phenomenon has received much attention (Hatfield, 1988; Monteith and Unsworth, 1990). It is well known that the computational methods for calculating potential evapotranspiration (ET_p) vary in terms of data demands and precision (Eitzinger *et al.*, 2002). After reviewing several models for estimating ET under Austrian conditions, the Penman–Monteith model (Monteith, 1965), as presented by Allen *et al.* (1998), was found to be a reliable method for predicting ET_p or reference evapotranspiration (ET_r). It is defined as evapotranspiration from short grass maintained under optimum soil water content and nutritional conditions and is calculated on a daily basis. The simplified Food and Agriculture Organisation (FAO) method (Allen *et al.*, 1998) also includes daily water balance of the lower rooted layer and allows calculation not only of ET_r but also of the value of the actual evapotranspiration (ET_a) and soil water content. Measurements of soil water content during the 2002–2004 seasons at Piber, Gumpenstein and at two additional sites confirmed the reliability of the ET_a estimated by the FAO model and the ability of the model to correctly simulate soil water content. It was found that the FAO method explained over 0·70 of the daily fluctuation in soil water content at depths of 20 and 40 cm where 0·90 of the root mass is concentrated. This is consistent with the results of similar models (e.g. Woodward *et al.*, 2001) and confirms that the weekly ET_a total closely fits soil water loss from water balance.

Table 3 Overview of the key weather variables and parameter values (accumulations from March to October) at two experimental sites with long-term experiments.

Variables	March	April	May	June	July	August	September	October	Total
Gumpenstein – Gumpenstein weather station									
Daily mean temperature accumulation (°C)									
Mean	124·3	229·5	377·6	459·2	529·6	523·5	409·3	269·1	2922·1
Maximum	227·8	339·7	451·3	513·9	636·1	633·3	499·8	353·6	3197·7
Minimum	47·1	145·2	263·4	378·9	474·3	452·6	297·6	137·2	2518·4
Global solar radiation accumulation (MJ m^{-2})									
Mean	328	438	570	565	574	513	378	263	3630
Max	423	621	1022	898	773	652	514	380	5282
Min	256	340	391	429	446	418	272	180	2733
Rain accumulation (mm)									
Mean	64·7	58·1	87·5	121·8	149·3	127·7	92·6	68·8	770·4
Max	203·0	127·8	207·9	205·4	289·3	274·5	222·8	183·2	1199·7
Min	6·7	12·4	28·5	54·7	42·9	64·3	21·6	1·4	546·6
Piber – Lobming weather station									
Daily mean temperature accumulation (°C)									
Mean	143·8	262·4	413·6	498·1	564·7	553·3	430·6	430·6	3157·5
Max	242·4	365·7	485·1	559·8	647·4	687·1	507·3	507·3	3611·4
Min	47·4	202·2	328·6	424·0	493·8	470·1	321·0	321·0	2847·6
Global solar radiation accumulation (MJ m^{-2})									
Mean	365	523	661	667	676	552	386	386	4215
Max	461	596	772	788	776	648	486	486	5012
Min	251	424	586	544	594	486	317	317	3518
Rain accumulation (mm)									
Mean	56·5	61·5	90·8	129·4	137·3	122·1	88·4	88·4	759·6
Max	194·5	189·6	214·5	262·3	347·3	210·3	191·9	191·9	1105·7
Min	8·8	7·9	32·8	29·5	16·7	41·4	29·4	29·4	471·1
Admont – Admont weather station									
Daily mean temperature accumulation (°C)									
Mean	108·3	218·3	389·1	459·0	532·3	531·5	403·2	280·6	2922·3
Max	205·1	303·1	459·2	542·9	608·6	639·0	489·9	370·4	3187·5
Min	0·0	132·7	266·3	403·4	460·6	466·2	303·9	216·2	2603·5
Global solar radiation accumulation (MJ m^{-2})									
Mean	334	481	644	642	644	544	380	255	3925
Max	399	563	767	704	768	674	466	311	4366
Min	245	353	520	549	466	453	241	193	3612
Rain accumulation (mm)									
Mean	101·4	82·7	96·9	140·5	176·3	140·7	119·3	78·1	935·9
Max	258·6	143·4	164·0	209·0	333·0	311·5	212·9	197·6	1263·0
Min	28·1	20·0	27·4	84·3	70·5	64·8	45·7	20·2	671·5

Data are based on the 1961–2000 daily-observed weather data (Gumpenstein, Gumpenstein-Irdning experimental station; Piber, Lobming experimental station).

Mean value over the period 1961–2000 for Gumpenstein and Piber; the period 1977–2002 was used for Admont.

Design of the statistical model

This study presents and evaluates a model, the grassland statistical model (GRAM), which could be applied both to meadows and grazed grasslands. The model itself is based on the modified approach originally used by Han *et al.* (2003). The GRAM assumes that grass growth depends on the soil water content in the active root zone as well as water stored in the plant tissues. Therefore, the water balance is a significant factor in canopy development. The GRAM further supposes that all of the supply of water can be attributed to rainfall.

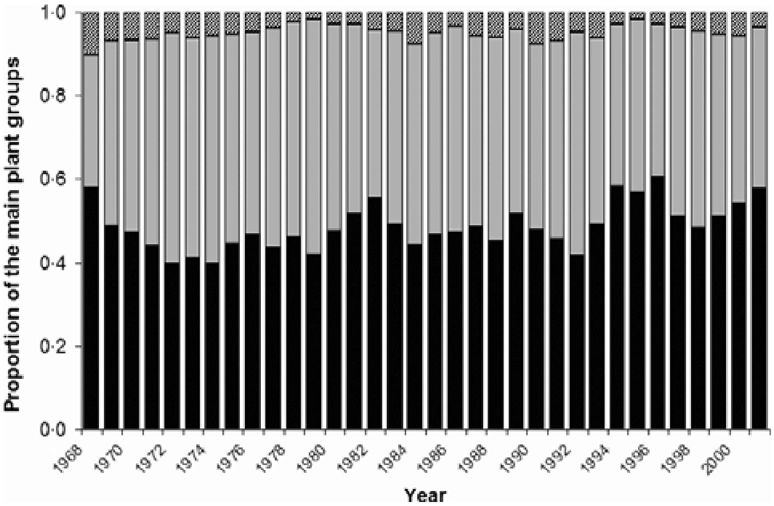

Figure 1 Proportion of the dominant plant species groups (■, grasses; ▒, herbs and ▩, legumes) in the permanent meadow at Gumpenstein experimental station during the long-term experiment (1968–2001) for the three-cut variant (fertilizer N rate of 120 kg N ha^{-1}).

Water uptake is then divided mainly between the plant transpiration and the soil evaporation, with adjustments for surface runoff, drainage and interception. Comparing with the original method proposed by Han *et al.* (2003), the ratio of ET_a and ET_r, calculated by the FAO model, was used, with the assumption that the soil–plant water content of a meadow at any moment at a given location depends mainly on the historical precipitation and R_G profiles. One of the advantages of using the ET model is that it takes into account the influence of soil conditions on the water balance. As suggested by Han *et al.* (2003), GRAM retains two time-related water availability factors. The first of these, long-term water availability factor W_L (mm mm^{-1}), was set to reflect the long-term water supply and losses over the growing season, and is defined as

$$W_L = t_{CL}\frac{ET_{aSE}}{ET_{rSE}} \quad (1)$$

where ET_{aSE} is the actual ET accumulation (in mm) from the start of the growing season, as calculated by the FAO model (Allen *et al.*, 1998), and ET_{rSE} the corresponding reference ET value. The start of the growing season is defined as the first day of at least five consecutive days without snow cover during which the daily minimum air temperature is higher than −3°C, while the mean daily air temperature is at least 2°C. The approach presented performed better in the tests than the threshold proposed by Broad and Hough (1993) and which was used in a study that included most of Europe by Topp and Doyle (2004). The parameter t_{CL} (threshold of long-term water availability) was set according to the experiments carried out at Piber and Gumpenstein sites during the 2002–2004 seasons. The reduction of biomass accumulation starts when ET_{aSE} is less than 0·5 of ET_{rSE} (i.e. $t_{CL} = 2·0$). In addition, a short-term water availability factor W_S was introduced to account for short-term water supply and water loss status on a given day:

$$W_S = t_{CS}\frac{ET_{aW}}{ET_{rW}} \quad (2)$$

For each day in the season, ET_{aW} (mm) and ET_{rW} (mm) are actual and reference evapotranspiration accumulated in the previous 6 d, respectively, with t_{CS} as the threshold for short-term water availability set at 2·0. Water availability at any time is dependent on both the long- and short-term water availabilities, and thus the water availability factor, W_A, introduces a composite water availability value for canopy growth on a given day. It is defined as a function of W_L and W_S in the form of

$$W_A = [CW_L^M + (1 - C)W_S^M]^{1/M} \quad (3)$$

In Equation 3, C ($0 < C < 1$) and M are model coefficients dependent on site characteristics (slope or aspect), soil properties (water hydraulic conductivity, etc.), herbage water storage capacity and history of the vegetative cover (Table 4). These coefficients reflect the relative importance of water availability factors with regard to the current water availability. Whether the

Table 4 Comparison of the coefficients used for the Austrian conditions with the original values proposed by Han *et al.* (2003).

	Coefficient value				
	C	***M***	***α***	***β***	***γ***
Han *et al.* (2003)	0·84	2·0	−2·9	−2·1	16·0
Present study	0·55	3·0	−2·9	−2·1	8·0

studied grass canopy can achieve the potential growth rate on a given day is determined not only by the inherent sward properties but also by the actual temperature and radiation, on the assumption that adequate water is available (at this stage the influence of other factors has been disregarded). To describe this relationship, Han *et al.* (2003) introduced a growth-supporting factor g_S:

$$g_S = \exp^{\alpha \exp^{\beta W_a^{\gamma}}} \tag{4}$$

where α, β and γ are empirical model coefficients (Table 4). The growth-supporting factor is calculated for each day based on the actual value of W_A at a given time. It is introduced as an indicator as to whether the grass sward achieves its potential growth rate with limited water availability levels. As W_A increases, g_S will eventually approach 1·0, which indicates that adequate water supply is available and sward growth will not be restricted by water stress. The equation is exponential because manifestations of water stress in the growth of the herbage DM cannot be accurately modelled with accumulation of temperature and global solar radiation using linear statistical models. In order to use a similar modelling approach and to take into account the effect of water deficit on canopy growth, the GRAM uses the water deficit level together with the accumulation of mean daily air temperature (T_{AVG}) and R_G in the modelling of herbage growth. The symbols T and G were assigned to the accumulated values of T_{AVG} and R_G assuming no water stress (i.e. $g_S = 1$). By introducing the growth-supporting factor (g_S), it is possible to define the effective accumulation of air temperature T_e and effective accumulation of global solar radiation G_e as

$$T_e = \int_{t_0}^{t_n} T_{AVG} g_S \, dt \tag{5}$$

and

$$G_e = \int_{t_0}^{t_n} R_G g_S \, dt \tag{6}$$

The values of T_e and G_e for a specific time are the accumulation of the growth-supporting factor discounted by the mean air temperature or global solar radiation from the growth starting day to the time concerned. Provided that there is sufficient soil water content (reflected by high ET_a/ET_r ratio and consequently g_S value close to unity), T_e and G_e become dependent only on the accumulation of daily mean temperature and global radiation respectively. The start of the growing season was determined so as to simulate the herbage mass of the first cuts. In order to take account of the influence of the duration of snow cover on accumulated DM herbage, the simple snow pack model proposed by Running and Coughlan (1988), and calibrated for Austrian conditions by Thornton *et al.* (2000), was used. The number of snow days from 1 October of the previous year to the beginning of the new growing season was calculated and used as an input for the subsequent calculations.

The final step was to quantify the relationship between the set of independent variables that included effective accumulated temperature, effective accumulated solar radiation, duration of growth under each particular cutting, mineral N application, cut number and, in some cases, the number of snow days during the preceding cold season (starting on 1 October of the previous year). In all cases, the first-order interactions of variables and their squares were also included as independent variables. This approach provided stable models with relatively high prediction power. However, the role of the individual parameters could not be quantified, as this is open to misinterpretation (e.g. Connolly and Wachendorf, 2001). Polynomial regression function and neural-network-based methods were used to derive the relationship between the set of independent variables and the amount of harvested DM of herbage set as the dependent variable. Each data set used was randomly split into two groups regardless of the site; the first sample being used for model calibration and the second for model evaluation with the independent data set. As the values T_e and G_e are dependent on coefficients C and M in Equation 3, the subset of data from the Gumpenstein location (2000–2003) was used to calibrate the model. The values of the constants α and β were retained at the levels proposed by Han *et al.* (2003), while the remaining γ was lowered somewhat to suit the Austrian conditions. The overview of the coefficients used is listed in Table 4.

The stepwise regression procedure of the UNISTAT 5.1 statistical package (UNISTAT Ltd, London, UK) was used for analysis of the calibration data subset. The models with the highest variability explained and the lowest mean square errors were regarded as the most accurate. The best set of equations for a given data subset is referred to as grassland statistical model – multiple regression (or GRAM-R). In the second step, this model was used to calculate the amount of harvested DM of herbage for the verification subset and compared with the experimental results. The same set of independent variables was used to derive grassland statistical model – neural networks version (GRAM-N). In this case, the back-propagation neural network method provided by NNModel® version 1.40 was used (Neural Fusion, Middetown, NY, USA). After training on the calibration data set, the most suitable network was used to predict the behaviour of the verification data subset.

Additionally, those years that could be classified as dry or wet were selected from the verification subset. The performance of each model version was also assessed under conditions of dry and wet years. Despite its original focus on the simulation of seasonal herbage accumulation, the GRAM is able to simulate daily increments of DM and this option was tested in the following verification step. For this purpose, the increments of DM were measured at Gumpenstein and Piber during 2002. The final step of the verification focused on the transferability of GRAM from the sites at which the models were originally calibrated (i.e. Gumpenstein and Piber) to another location (Admont). In order to test the performance of both GRAM modifications during extreme years, the seasons within the database used for the model verification were divided into three data subsets. Two of the subsets included seasons characterized by either unusually dry or unusually wet weather conditions, while the third group included seasons that were close to normal. The accumulated Standard Precipitation Index (SPI) value (McKee *et al.*, 1993) was used to determine which category a particular season belonged to. The 1-month SPI values were calculated for the period from April to September and individual values were totalled. Years with accumulated SPI values >−1·0 were regarded as dry, and years with an accumulated SPI of >+1·0 were considered wet (Svoboda *et al.*, 2002). Of forty-one seasons examined at the Gumpenstein site, 16 years were dry (with year 1986 the driest) and 10 years were wet (culminating in the 1970 season). Of the 31-year series at Piber, 12 years were dry (the most extreme season was 1976) and 8 years were classified as wet (with 1972 being the wettest). It should be kept in mind that the SPI value is determined on the basis of the long-term weather record at a particular location and the assigned index value is relative only to the station's long-term precipitation distribution. As both stations had relatively high precipitation sums over the growing season, the low SPI value does not necessarily transform into drought conditions in terms of deficiency in soil water content. The analysis of the dry years showed relatively low T_e and G_e values compared with the T and G values, while during the wet years $T_e \sim T$ and $G_e \sim G$. At the same time, the wet years showed below-average mean air temperatures and lower solar radiation sums, contrary to dry years that were mostly characterized by an above-average temperature and higher solar radiation intensity.

Evaluation of the GRAM outputs

As the main objective of this study was to assess the reliability of the simulated outputs, several statistical methods were used to compare the simulated and observed results. These included a comparison of the basic descriptive statistics, e.g. mean, median, extreme values and coefficient of variance, as well as further examination by the mean bias error (MBE), root mean square error (RMSE) and modelling efficiency index (MEI) according to Wilmot (1982) and Theil's inequality coefficient (U) (Theil *et al.*, 1970). The main reason for reporting the results in terms of several statistical methods was to allow comparison with the results of other authors and at the same time to enable other researchers to make the same comparison. As some of these methods cannot be compared directly (e.g. MEI and U), values for each of them are provided.

The MEI is a very useful indicator specifically derived in order to assess the performance of models compared with the experimental data and is formulated as follows:

$$\mathrm{MEI} = 1 - \left[\frac{\sum_{i=1}^{n} (Y_{\mathrm{est}} - Y_{\mathrm{obs}})^2}{\sum_{i=1}^{n} |Y_{\mathrm{est}} - Y_{\mathrm{est-mean}}||Y_{\mathrm{est}} - Y_{\mathrm{obs-mean}}|} \right] \quad (7)$$

where Y_{obs} and Y_{est} are the observed and estimated amounts of DM of herbage harvested (kg ha^{-1}) respectively. The values have to be totalled for each possible pair of estimated and observed values. The index results in a number between 0 and 1. The closer it is to 1, the better the fit between the model and field observations. MEI refers to the accuracy of prediction, where accuracy is regarded as the degree to which model predictions approach the magnitude of their observed counterparts.

Theil's inequality coefficient (U) penalizes large errors more than small ones and it also assesses a model's ability to duplicate a turning point or rapid changes in the data (Topp and Doyle, 2004). It is formulated as follows:

$$U = \frac{\sqrt{(1/n) \sum (Y_{\mathrm{est}} - Y_{\mathrm{obs}})^2}}{\sqrt{(1/n) \sum {Y_{\mathrm{est}}}^2} + \sqrt{(1/n) \sum {Y_{\mathrm{obs}}}^2}} \quad (8)$$

The value of U ranges from 0 (indicating perfect fit) to 1 (indicating a total absence of any fit between the simulated and observed values). One of the main advantages of the coefficient is the possibility of calculating proportions of estimated bias (U_B), variance (U_S) and covariance (U_C). While U_B indicates systematic error, U_S measures the ability of the model to replicate the degree of variability in the data. Any remaining error, after accounting for the bias and variance effects, is called the covariance proportion (U_C). The ideal distribution of inequality over these three sources is for the bias and variance effects to equal 0, and the covariance to equal 1 (Theil *et al.*, 1970).

In addition to comparison of the estimated vs. observed values for the amount of herbage DM produced, both GRAM-R and GRAM-N versions were evaluated with respect to the production of patterns in residuals against N fertilizer application rate, year, cut number, location, length of the growing season, date of the previous cut, number of snow days, G, G_e, T_e, T and total precipitation during the period of sward growth. The validation data subset was used to search for patterns. The occurrence of patterns in the residuals was analysed with IRENE_DLL (Filla *et al.*, 2003), which allows for automated calculation of the range-based pattern index (PI) proposed by Donatelli *et al.* (2004). The minimum number of residuals in each group was set to 5%, and two to five macro-pattern groups were targeted at the $P = 0{\cdot}05$ significance level.

Probabilistic yield forecasting

The probabilistic forecast of herbage production of meadows is based on the methodology applied in the PERUN forecasting system (Dubrovský *et al.*, 2003). It relies on the Met&Roll stochastic weather generator (Dubrovský, 1997; Žalud and Dubrovský, 2002). The newly introduced six-variate version of Met&Roll (Dubrovský *et al.*, 2004) allows for generation of $T_{\max}$, $T_{\min}$, R_G, precipitation, wind speed and water vapour pressure for an arbitrary number of seasons. In this study, the parameters of the weather generator were derived from observed data series at Gumpenstein between 1961 and 2001. If the probabilistic forecast is issued on 1 July, it relied on the observed weather data until 30 June and generated a data series from 1 July. The generated data were continuously fitted to the observed weather series. The PERUN system makes it possible either to generate weather series in accordance with the weather of a given site (i.e. based on the long-term weather conditions) or to take into account mid- or long-term weather forecasts (i.e. modifies the range of weather variables according to the actual seasonal forecast). In the example presented, the PERUN system was set to issue ninety-nine daily weather series on each of ten forecasting dates based on the long-term weather of the site. These data series of weather were used as inputs for the GRAM-R version and herbage accumulation was calculated for each of the ninety-nine seasons.

Results

Water availability factor and effective temperature (radiation) during the growing season

The W_A value depends on coefficients C and M (Equation 3) and is composed of the long- and short-term components (Figure 2). For example, the year 1990 (from 6 March to 31 October) at Gumpenstein was characterized by sufficient and well-distributed precipitation and drought index values indicating normal-to-wet weather conditions. On the contrary, during 1968

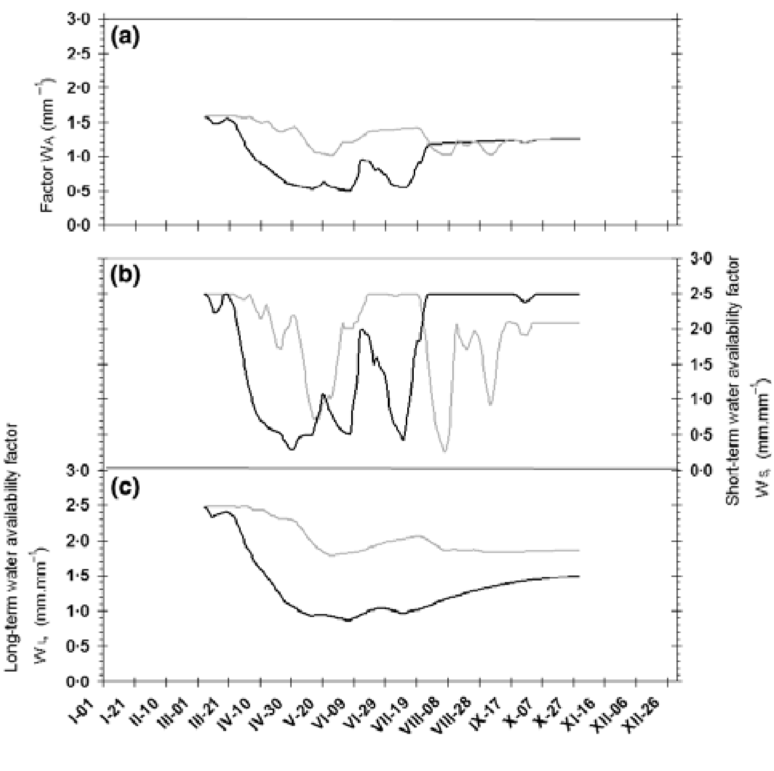

Figure 2 Example of water availability factor W_A (mm mm^{-1}) values (a) during normal (6 March to 3 October 1990) and severely dry (21 April to 30 October 1968) seasons at Gumpenstein experimental site; the daily W_A value is calculated from short- (b) and long-term (c) water availability factors (mm mm^{-1}) for each day. The W_L and W_S values are presented for the same normal and severely dry seasons as the W_A factor.

(from 21 April to 30 October) the weather was extremely dry with drought index values reaching extreme threshold levels several times. During 1968, the value of W_A was substantially lower than in 1990 (Figure 2). This disparity was also seen in the effective solar radiation and temperature values in these 2 years. The seasons with a balanced water regime showed no difference between potential and effective accumulated temperatures and global radiation total. On the contrary, during dry years this effective total was significantly lower. While the amount of global solar radiation potentially available to the canopy during 1968 was approximately 3·5 GJ m^{-2}, the effective value was only 1·5 GJ m^{-2}. The difference between the potential and effective accumulated temperatures was of approximately the same magnitude. While the difference between the potential and effective accumulated temperatures in 1990 was only proportionately 0·02, during 1968 the effective temperature total was 0·48 lower than the potential value. The low T_e and G_e values then resulted in low estimates of herbage mass by both GRAM-R and GRAM-N versions through their use as independent input variables.

Herbage accumulation estimates under a three-cut management regime

As a large number of meadows in Austria are cut three times a year, the GRAM-R and GRAM-N versions were first derived and tested over the data set collected under a three-cut management regime. The accuracy of GRAM-R over the calibration subset was relatively

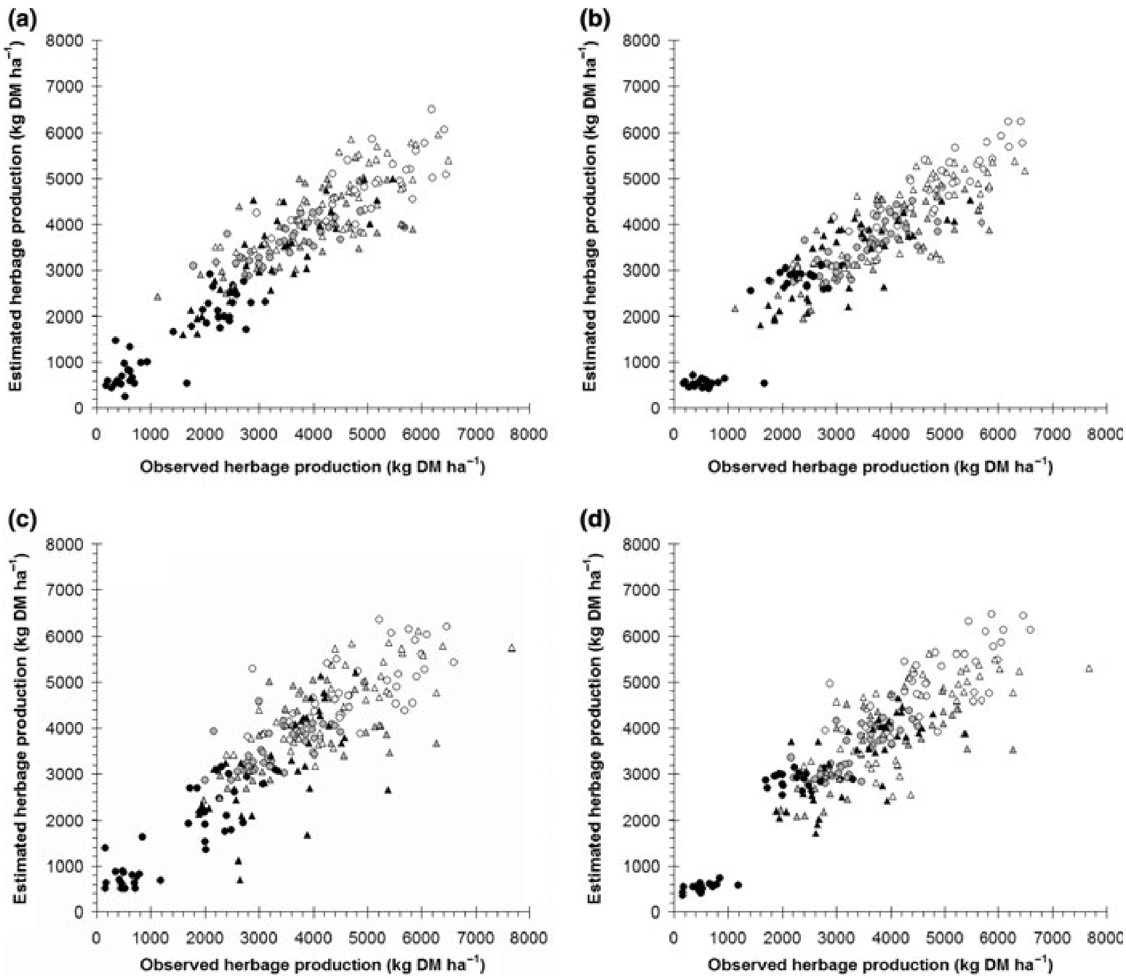

Figure 3 Results of the calibration (a, b) and verification (c, d) of the GRAM-R (a, c) and GRAM-N (b, d) models. Both models were derived for those experiments that were cut three times a year (n = 468). Circles represent results obtained at Gumpenstein experimental station; triangles from the Piber station. Herbage harvested at first, second and third cuts shown as white, grey and black symbols respectively.

high, with 0·82 of the variability explained (Figure 3a). The satisfactory performance of this version can also be seen in the high MEI index values (0·79) and low relative MBE and RMSE values (Table 5). Most of the herbage production values (0·85) were simulated with an absolute error equal to or smaller than 900 kg DM ha^{-1}, which may be considered as an acceptable range in the light of earlier studies. When used over the calibration subset, GRAM-N performed even better (Table 5) than the GRAM-R version, with 0·83 of the variability explained (Figure 3b).

In addition to the calibration, the performance of both versions on independent data sets is also important. For the majority of parameters, the GRAM-N slightly outperformed the GRAM-R version, but the differences were not significant (Figure 3c–d). The U_B and U_S values of 0·01 and 0·01 in GRAM-R indicate almost perfect fit in both bias and variability when reported using Theil's inequality coefficient. Results for GRAM-N were very similar, leading to the conclusion that most of the deviations were caused by random and not systematic error, as is also apparent from the MBE and RMSE values in Table 5. Figure 3 also shows that all cases with an underestimation of herbage mass greater than 0·20 were to be found at Piber. This can be explained by the biases contained in the weather data, and consequently in the ET_r and ET_a calculations, which are inherent to the site owing to the distance of 15 km to the closest weather station in combination with the specific soil conditions. This had an influence on the daily ET_a calculations, despite the fact that the weekly precipitation total at Piber and the nearest weather station showed a high degree of agreement during three seasons of parallel measurements.

Additional testing included data from the study at Admont (1977–1999) with one level of fertilizer application (80 kg N ha^{-1}). Using GRAM-R over the data set, a relatively large MBE value (0·100) was found when compared with the verification data set from Gumpenstein and Piber. However, the MEI and R^2 values of 0·83 and 0·72, respectively, reflect the overall satisfactory fit at this site. The GRAM-N version yielded a significantly better fit, with both higher MEI and R^2 values and a lower Theil's inequality coefficient value. The less satisfactory performance of both models in some parameters compared with data from Gumpenstein and Piber can be explained in part by the influence of the underground water table, which is known to vary from season to season at the site and is not accounted for in the GRAM. As the impact of groundwater can be found at many meadow locations in Austria (especially in the valley basins), its negative effect on the GRAM estimates will be considered in subsequent studies.

Analysis of residuals vs. number of independent variables did not reveal any statistically significant patterns in either GRAM version. However, when the residuals vs. observed amounts of harvested herbage DM were examined, a clear trend was found, indicating

Table 5 Variation explained [R^2 and R_0^2 (with the regression line forced through 0)], mean bias error (MBE) and root mean squared error (RMSE), modelling efficiency index (MEI), Theil's inequality coefficient (U) and proportions of cases with deviations from the simulated dry matter production of greater than 0·25 (P_1) and 600 kg DM ha^{-1} (P_2), respectively, after fitting the GRAM-R and GRAM-N versions to a range of data sets from Gumpenstein and Piber experimental stations.

Models and data sets tested	n		R^2		R_0^2		MBE × 10^{-2}		RMSE		MEI*		U†		P_1		P_2	
	Cal	Ver	Cal	Ver	Cal	Ver	Cal	Ver	Cal	Ver	Cal	Ver	Cal	Ver	Cal	Ver	Cal	Ver
GRAM-R model																		
Three-cut variant	232	236	0·82	0·75	0·78	0·71	0·7	2·0	0·177	0·211	0·79	0·87	0·10	0·10	0·82	0·76	0·77	0·72
Variant (all cuts except first cut)	255	1306	0·73	0·70	0·64	0·64	1·7	2·3	0·267	0·272	0·76	0·93	0·12	0·12	0·67	0·71	0·81	0·84
Variant (first cut only)	263	235	0·71	0·71	0·71	0·61	0·5	−13·8	0·247	0·306	0·65	0·58	0·12	0·14	0·58	0·57	0·53	0·50
GRAM-N model																		
Three-cut variant	232	236	0·83	0·78	0·79	0·74	−0·4	1·1	0·172	0·196	0·80	0·87	0·08	0·09	0·80	0·79	0·77	0·74
Variant (all cuts except first cut)	255	1306	0·75	0·72	0·67	0·65	−1·0	1·7	0·256	0·262	0·76	0·94	0·14	0·15	0·71	0·65	0·83	0·84
Variant (first cut only)	263	235	0·62	0·65	0·62	0·65	−26·2	−38·7	0·389	0·479	0·12	0·0	0·12	0·15	0·35	0·29	0·40	0·32

*Modelling efficiency index (Wilmot, 1982) indicates the goodness-of-fit of the predicted values. The value of the coefficient lies between 0 and 1, with 1 indicating perfect fit.

†Theil's inequality coefficient tests the goodness-of-fit of the predicted values. The value of the coefficient lies between 0 and 1, with 0 indicating perfect fit.

that the models in general underestimated high values and overestimated low ones (shown in Figure 3). Further comparisons of the GRAM-R and GRAM-N versions showed that neither was markedly superior to the other. The overall fit with the verification data set was found to be surprisingly good, given the simplicity of the model used. It should also be noted that, despite the relatively high predictive power of the models, it is site-dependent to a certain extent, especially if the site is influenced by factors that are not accounted for in the GRAM methodology.

Herbage accumulation estimates under various cutting management regimes – general model

As one of the aims was to derive a model that could be used under most management regimes practised in Austria, all data in the database, including both first and subsequent cuts, were pooled. From this data set one tenth of the values were randomly selected for the model calibration and a larger subset (0·9) was set aside for the model verification. It was found that for this subset neither GRAM-R version nor GRAM-N version performed well, probably because of differences in the importance of independent variables for biomass production, improper modelling of the spring growth initiation period and different species composition of the first cut. This is supported by PI values, which clearly indicate the presence of macro-patterns in the residuals of model estimates vs. cut number in this data subset. As a result, the first cut was excluded and the remaining data pooled. As further attempts to improve the universal model failed, two separate models were derived instead. The first one was designed for the second to *n*th cut (where *n* ranged from 2 to 6), while a separate model was derived for the estimation of herbage mass at the first cut. The subsequent analysis of residuals vs. independent variables (as listed above) did not reveal any patterns except when *D* was used as an independent variable in the first-cut model. It was concluded that the method of initiation of the season needs further research, as neither the methods used here nor the threshold proposed by Broad and Hough (1993) improved the model.

In order to derive GRAM models for the production of the second to sixth cut, the effective temperature and total solar radiation, N fertilizer application rate and cut number were retained in the database and used as independent variables. The data set was split into two parts with the smaller subset ($n = 255$) being used for calibrating both GRAM versions. The remaining part of the data set ($n = 1306$) was used for independent verification of the model's performance. As expected, the calibration and verification using all data within the database led to significantly worse results than in the three-cut variant only. However, the GRAM-R version was still able to explain a large part of the variability in the harvested herbage DM with relatively small systematic error (Table 5). When the GRAM-R version was applied to the additional data set from the Admont site ($n = 46$), it underestimated herbage mass by approximately 0·05 with a relative random error of 0·26. In other parameters, the GRAM-R version also performed slightly worse for Admont than for Gumpenstein and Piber. As in the case of the three-cut variants, the GRAM-N version proved to be slightly more efficient than the GRAM-R version (Table 5).

A specific GRAM version was developed separately for the determination of the accumulation of first-cut herbage. For this purpose, all available data from this

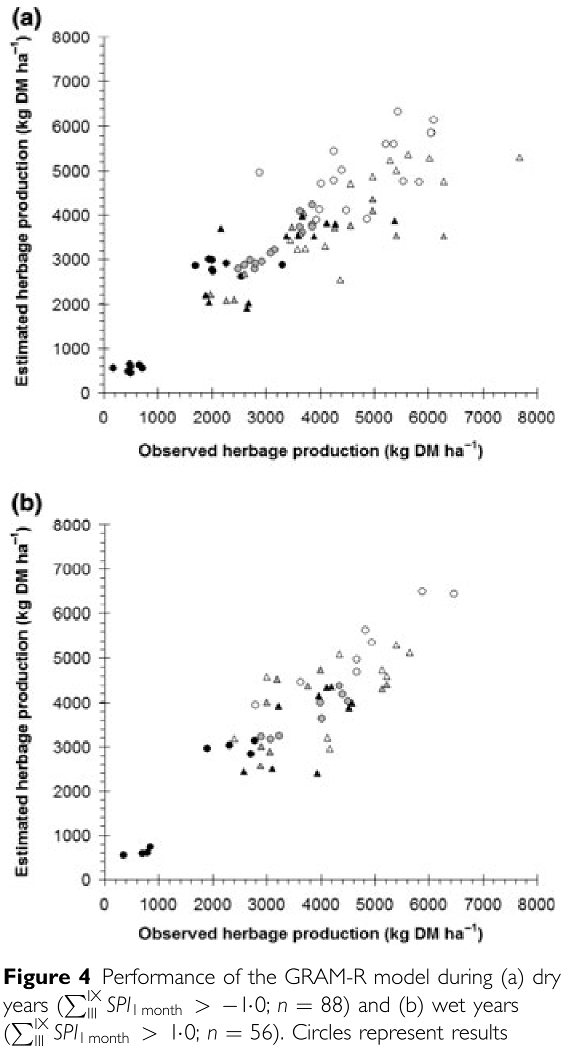

Figure 4 Performance of the GRAM-R model during (a) dry years ($\sum_{\mathrm{III}}^{\mathrm{IX}} SPI_{1\ \mathrm{month}} > -1\cdot0$; $n = 88$) and (b) wet years ($\sum_{\mathrm{III}}^{\mathrm{IX}} SPI_{1\ \mathrm{month}} > 1\cdot0$; $n = 56$). Circles represent results obtained at Gumpenstein experimental station and triangles the Piber station. Herbage harvested at first, second and third cuts shown as white, grey and black symbols respectively.

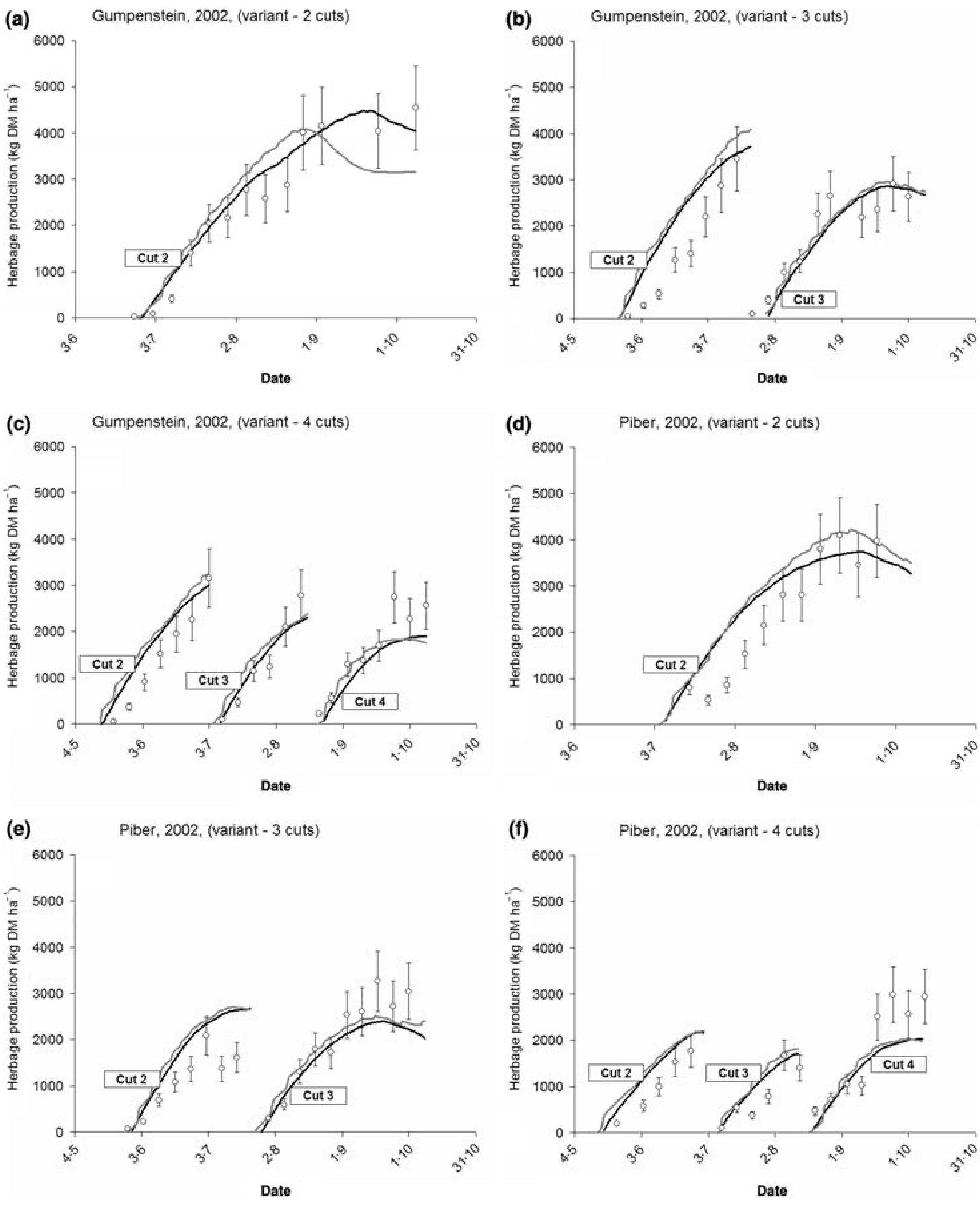

Figure 5 Comparison between prediction of biomass dynamics by GRAM-R (black line) and GRAM-N (grey line) at Gumpenstein (a–c) and Piber (d–f) stations during 2002. Three management strategies are included, i.e. two cuts per year (a, d); three cuts per year (b, e) and four cuts per year (c, f). The first cut is excluded from the simulations. The lines at the observed data points indicate errors of measurement known to be in the range of ±15%.

cut were pooled, with one data subset serving for method calibration and the other for verification. The calibration of both GRAM-R and GRAM-N using the harvested herbage DM from the first cut ($n = 263$) produced a poorer fit than all the previous GRAM versions (Table 5). The MBE value depicting the systematic error was the highest of all tested subsets, indicating that more research in the first-cut initiation sub-routine is needed.

Model performance during dry and wet years

The analysis of the performance of the GRAM-R version (using three-cut data only), using the verification data set during years characterized by dry weather (i.e. accumulated SPI $< -1{\cdot}0$), showed that approximately the same proportion of variability was explained, with similar MBE and RMSE values as the whole data set. No statistically significant difference was found in GRAM-R performance during dry years compared with the whole data set (Figure 4a). Cases of GRAM-R failure resulting in significant underestimation of herbage accumulation (more than 0·35) occurred during dry years almost exclusively at the Piber site (Figure 4a). Similar results were found when the same approach was applied to the data set of wet years. The GRAM-R version showed more outliers than the GRAM-N version and a higher systematic bias. In general, both GRAM modifications were found to perform better under wet conditions (Figure 4b) than under dry ones.

Simulation of the sward growth dynamics

In order to verify the performance of the models, their ability to reproduce sward growth dynamics was tested. As Figure 5 shows, the increase in above-ground biomass was overestimated in almost all cases at the beginning of the growth period and underestimated close to the harvest date. Such behaviour is a direct consequence of the model design, as it relies only on T_e and G_e and the length of the regrowth as driving variables. The overestimation of the growth rate in 2002 was the highest during months with high T and G total, i.e. at the end of June and July, whereas growth rate during the following months (especially in case of the fourth cut) was underestimated. Apparently, the method does not take into account sink/source relationships within the canopy, the changing physiological properties of the plants associated with the phenological growth or changes in species composition between cuts. The overall performance of both GRAM modifications was nevertheless found to be surprisingly good (Figure 5). The GRAM-R and GRAM-N versions were able to explain between 0·63 and 0·96 of the weekly variability in herbage growth.

Estimating dry matter production early in the season

In the final part of the study, the GRAM-R version was coupled with the Met&Roll weather generator and a number of tests were performed, using Gumpenstein station data collected during the 2002 season. It was found that the statistical forecast of the second cut based on the long-term statistical data (Stat_A) produced relatively high uncertainty (2200 kg DM ha^{-1}) in the possible production range, with underestimation of the mean value by 550 kg DM ha^{-1} (Figure 6). Improvements gained by matching long-term statistical records with the 2002 season characteristics (Stat_B or Stat_C) led to a narrower range of harvestable DM herbage estimates, but this value still had high uncertainty. The probabilistic herbage growth forecast issued on the first day of the sward regrowth showed a smaller bias and lower uncertainty than the conventional statistical forecast. The prognoses continued to improve, and about 30 d before harvest the herbage mass could be estimated with high accuracy (i.e. uncertainty of less than 1000 kg DM ha^{-1}) and good estimation of the mean value. The mean herbage mass estimate issued 3 d before harvest was within 90 kg DM ha^{-1} of the harvested DM

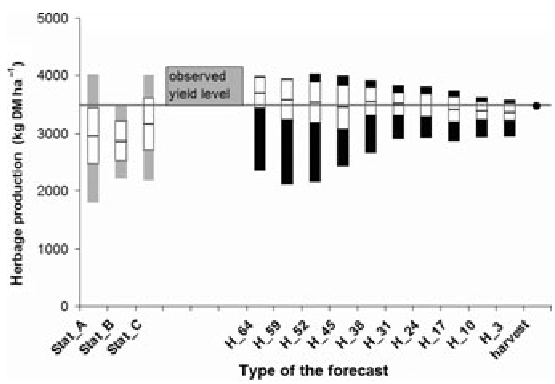

Figure 6 Example of the herbage mass forecast for cut 2 (from 22 May to 26 July 2002) at Gumpenstein experimental station. The horizontal line represents the level of the observed dry matter herbage mass at the site. The grey vertical bars represent predictions of the herbage mass based on the long-term statistics [Stat_A: long-term herbage production characteristics for period 1961–2002; Stat_B: based on herbage production of ten seasons with the sward regrowth starting around 22 May; Stat_C: based on the ten seasons with the accumulated (April to June) SPI value closest to 2002 season]. The black bars represent probabilistic forecasts, each based on the ninety-nine GRAM-R model runs issued on the given day preceding harvest. The *x*-axis description depicts the number of days to the harvest. The lowest and highest parts of each bar represent minimum and maximum predicted values. The white part of each bar indicates mean value ± s.d.

herbage. Almost identical results were found in an additional ten seasons tested in a separate study using the same GRAM-R (M. Trnka, unpublished results). It was also found that the precision of the forecast could be significantly improved by issuing a probabilistic forecast that incorporated the long-term weather forecast for the rest of the season for the generated weather series.

Discussion

The results attained with GRAM correspond closely to the original work of Han *et al.* (2003) in terms of approach and model accuracy. However, GRAM also takes into account the number of days with snow cover, cut number and mineral N application rate per cut as independent variables. This agrees in principle with the findings of numerous authors that intercepted photosynthetic radiation (or measured global radiation), soil water availability and N supply largely explain the variability in herbage mass (e.g. Cookson *et al.*, 2000; Akmal and Janssens, 2004). An evaluation of the model using long-term experimental results indicates that it can be used with reasonable precision over a wide range of management systems of meadows.

While the variability explained in the study of Han *et al.* (2003) was significantly higher (0·85–0·93) than those reported by this study, it should be borne in mind that the findings in this study included experimental data sets with much higher variability in terms of soil and weather conditions, management practices and years of record. When the GRAM versions were calibrated over a single site using data from a single cut, the results in terms of explained variability were much closer to those reported by Han *et al.* (2003). On the contrary, in contrast to the original findings it was noted that the use of T and G parameters, instead of effective temperature and global radiation values (i.e. T_e and G_e), yielded significantly worse results than those obtained by the use of T_e and G_e. This can be explained by the higher sensitivity of the Austrian sites to fluctuations in soil water content because of different soil conditions or smaller maximum rooting depth of grass sward. Besides the use of ET_r and ET_a as variables to define W_A, the ratio of global radiation and precipitation was also tested, as proposed by Han *et al.* (2003). Interestingly, when this ratio was used to determine W_A at one site only, both versions of GRAM models performed slightly better than the calculations using evapotranspiration values. However, the predictive power of the model at multiple sites decreased significantly, which seems to point to the fact that the ET_a/ET_r ratio additionally takes account of the influence of the local soil conditions, air humidity and wind speed.

The results showed that the GRAM-R and GRAM-N versions are comparable to the performance of widely applied process-oriented models in terms of the ability to estimate herbage production from meadows, both for the total season and for the individual cuts. As both GRAM versions rely on a different set of rules than process-oriented models, GRAM versions could be used in parallel with them in early warning systems (e.g. Rugget *et al.*, 1998), as an alternative method of herbage mass prediction, or in cases when the input data are insufficient for more sophisticated techniques to be used. The test of the performance of GRAM versions during dry and wet years also shows that it is relatively reliable under such conditions.

The results attained with GRAM in terms of deviations between the estimated and harvested DM herbage production are consistent with those reported by Schapendonk *et al.* (1998) using the LINGRA model. The data sets in both studies are comparable in terms of variability of weather. While the LINGRA study used data records of 1–5 years from single-species plots at thirty-five experimental sites throughout Europe, the GRAM data set consists of data records of 23–40 years, with multiple cut and fertilizer treatments, large inter-annual weather variation in particular seasons and in some cases very different sward composition. However, compared with the study mentioned earlier, the total N fertilizer application rate was much lower in most cases (from 80 to 540 kg N ha^{-1} year^{-1}). This difference resulted in higher variability in herbage production and much lower values for total DM production (from 3·3 to 12·5 t DM ha^{-1}) in the Austrian data set, compared with the LINGRA study, where the N fertilizer application rate was 600 kg N ha^{-1} year^{-1} and non-irrigated plots yielded over 16 t DM ha^{-1}. The modified version of LINGRA designed for the simulation of growth and herbage production of timothy (*P. pratense*) and reported an R^2 value of 0·75 for ten pairs of simulated and measured herbage mass (Höglind *et al.*, 2001), which closely resembles the results attained with GRAM. On the contrary, the performance of the OSYAQ model (Herrmann and Schachtel, 2001) or the canopy photosynthesis model designed to predict DM production of cocksfoot (*D. glomerata*) pastures (Peri *et al.*, 2003) was significantly better than that achieved by GRAM. Despite the undoubted precision of the OSYAQ model (e.g. Herrmann *et al.*, 2005), it should be borne in mind that the data set used for testing the model comprised data collected during 3 years at one location and were thus limited in terms of weather or soil heterogeneity. The similar scale of data limitation was also true for the model of Peri *et al.* (2003). When the GRAM versions were calibrated and tested with a similar data set (only one location with 40 years of data, split in half for calibration and evaluation, one cutting regime and one level of fertilizer application), it yielded similar results to the models referred above, with R^2 values of over 0·90.

The GRAM versions compare favourably also with the results of other studies (Topp and Doyle, 1996; Riedo *et al.*, 1998) as far as estimates of herbage mass of DM are concerned. The former study reported a U value under UK conditions of 0·18–0·24 with pure grass stands. This is almost double the U values found in this study (Table 5). Interestingly, when the Topp and Doyle (2004) model was applied to fifteen sites in northern Europe, the U value ranged from 0·19 to 0·42 on irrigated sites and 0·20 to 0·51 on non-irrigated sites, with a tendency to systematically overestimate DM production. The reported U_B and U_S values for non-irrigated sites ranged from 0 to 0·37 and 0 to 0·28, respectively, which are more than those obtained in the case of the GRAM versions. The study by Riedo *et al.* (1998), which used an enhanced version of the HURLEY PASTURE (HP) model (Thornley and Verberne, 1989) for 2 years of data from two Swiss sites, reported total biomass production estimates per season that differed from −0·06 to 0·21 of the observed values. This model was able to explain 0·79 of the variation in herbage mass at these sites, which is similar to the GRAM versions. But even relatively complex models sometimes fail to represent the real-world process, as can be seen from the differences between the herbage DM harvested for individual cuts and the HP model estimates. In this case, deviations ranged from −0·47 to 0·87 (Riedo *et al.*, 1998), similar to the GRAM versions. These high deviations could be attributed to processes that were not described (or not described adequately) within the model. The modification of the HP model, including a more detailed N submodel (Wu and McGechan, 1998), resulted in estimates of −0·22 to 0·43 but without any statistical correlation between the observed and estimated values. It should be stressed, however, that the latter study focused more on the validation of the N submodel than on precise representation of herbage mass and that the database used was very limited. The results above demonstrate that the derivation of fairly simple and regionally specific models (similar to GRAM) remains a viable option, particularly for the purpose of describing regional herbage production. This type of model could easily be incorporated into complex farm models as it represents well variability in site and seasonal herbage mass compared with the methods currently used (e.g. Berentsen *et al.*, 2000) without significantly increasing the required input data.

The GRAM was not designed to compete with dynamic models that are far more versatile tools with great potential in research, decision making or the forecasting of herbage mass, but to provide an alternative to these models, especially when the necessary inputs for complex models are not available for the given time or region. One important advantage of the GRAM models is their relative algorithmic simplicity enabling the model to be embedded directly in a Geographic Information System environment and thus permitting truly spatial herbage accumulation monitoring and forecasting with relatively affordable computer hardware. A combination of the spatial assessment with GRAM capability to be used for herbage production forecasting early in the season makes it a relatively inexpensive option in comparison with more complex models. One of the practical examples of GRAM-R application is its application to estimate the impact of droughts on the herbage DM production nationwide in Austria. In this framework, the GRAM versions have been successfully tested at twenty-five locations with various climate and soil conditions and with different types of sward composition. As these sites represent a broad range of grassland types that occur in Europe, it seems plausible to apply the methodology to other regions that have comparable grasslands. The GRAM versions might also be used to estimate climate threshold for herbage production under conditions of future climate change, or to optimize N fertilizer application, as the GRAM is capable of accounting for effects of both drought and N stress.

There are, nevertheless, a number of caveats associated with this simplified approach, which relies more on statistical links than on a simulation of the key processes. As the model outcome is almost entirely based on previous experimental results rather than a detail description of all the key processes, it can perform reasonably only within the range of environmental conditions for which it has been calibrated and verified. This disadvantage could be mitigated using extensive experimental data sets, as was carried out in this study. It should also be considered that the experiments used in this work were based on the data from experimental stations. These sites are characterized by higher adherence to the rules of good farming practice and higher standards in terms of the homogeneity and quality of the management than might reasonably be expected for commercial farms. However, some of the earlier experiments, especially those at site G2, were treated using inputs of N fertilizers that would not be allowed under current official regulations and, therefore, the estimates provided by the GRAM-R version might be slightly higher than those actually attained under field conditions. Finally, the GRAM versions do not provide any information on herbage quality or N content, as they are designed as support tools to other dynamic crop models in areas where sufficient data for these models are not currently available.

Conclusions

The results of the study demonstrate that the productivity of meadows in Austria is highly dependent on a combination of available soil water, global radiation, air temperature, applied N and management regime (number of cuts per season) and this is also likely to be true for other similar temperate grassland regions. These factors explain up to 0·78 of the variability in herbage mass and are useful in determining the production potential of selected sites. The GRAM has proved to be a suitable tool that takes these strong links into account and may thus be used for various practical purposes, with no significant difference between GRAM-R and GRAM-N approaches. It has been shown that the GRAM versions are capable of reproducing herbage accumulation variation during extreme seasons and could thus be used in the assessment of the possible impact of dry or extremely wet years on the herbage mass of DM of grassland. The approach can be used to establish critical environmental threshold for herbage production at a range of sites. In combination with the data on climate change scenarios, it could eventually be used to extrapolate the potential impact of future climate change on herbage production. As both versions of GRAM can be easily integrated into a GIS, it might be used for the spatial evaluation of such impacts and the identification of areas likely to be most vulnerable, provided that spatially defined input data are available. This could provide information for stakeholders in government or for insurance purposes as well as for individual farmers or their representatives. The spatial analysis outputs could also be used to identify areas potentially vulnerable to drought events and quantify such risk in terms of probability and possible loss in herbage production. Additionally, the GRAM versions, in combination with a stochastic weather generator, are effective tools for issuing predictions early in the season, thus allowing decision makers or farmers to take the necessary steps prior to a potential bad or good harvest. The predictions based on the GRAM-R version were shown to be superior to estimates based on conventional forecasting methods. The main advantage of the GRAM is the possibility of incorporating the algorithm in a conventional spreadsheet programme, calibrating it with a very limited data set compared with complex models of meadows and delivering relatively satisfactory estimates of herbage production.

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References

Akmal M. and Janssens M.J.J. (2004) Productivity and light use efficiency of perennial ryegrass with contrasting water and nitrogen supplies. *Field Crops Research*, **88**, 143–155.

Alexandrov A. and Hoogenboom G. (2000) The impact of climate variability and change on crop yield in Bulgaria. *Agriculture and Forest Meteorology*, **104**, 315–327.

Allen G.A., Pereira L.S., Raes D. and Smith M. (1998) Crop evapotranspiration – guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper 56, pp. 78–86. Rome, Italy: FAO.

Ångström A. (1924) Solar and terrestrial radiation. *Quarterly Journal of the Royal Meteorological Society*, **50**, 121–125.

Berentsen P.B.M., Giesen G.W.J. and Renkema J.A. (2000) Introduction of seasonal and spatial specification to grass production and grassland use in dairy farm model. *Grass and Forage Science*, **55**, 125–137.

Broad H.J. and Hough M.N. (1993) The growing and grazing season in the United Kingdom. *Grass and Forage Science*, **48**, 26–37.

Connolly J. and Wachendorf M. (2001) Developing multi-site dynamic models of mixed species plant communities. *Annals of Botany*, **88**, 703–712.

Cookson W.R., Rowarth J.S. and Cameron K.C. (2000) The response of a perennial ryegrass (*Lolium perenne* L.) seed crop to nitrogen fertilizer application in the absence of moisture stress. *Grass and Forage Science*, **55**, 314–325.

Donatelli M., Acutis M., Bellocchi G. and Filla G. (2004) New indices to quantify patterns of residuals produced by model estimates. *Agronomy Journal*, **96**, 631–645.

Dubrovský M. (1997) Creating daily weather series with use of the weather generator. *Environmetrics*, **8**, 409–424.

Dubrovský M., Žalud Z., Eitzinger J., Trnka M. and Semerádová D. (2003) PERUN system and its application for assessing the crop yield potential of the Czech Republic. *Proceedings of 28th General Assembly of European Geosciences Union*, Nice, France, 6–11 April, 2003.

Dubrovský M., Buchtele J. and Žalud Z. (2004) High-frequency and low-frequency variability in stochastic daily weather generator and its effect on agricultural and hydrologic modelling. *Climatic Change*, **63**, 145–179.

Eitzinger J., Marinkovic D. and Hösch J. (2002) Sensitivity of different evapotranspiration calculation methods in different crop-weather models. In: Rizzoli A.E. and Jakeman A.J. (eds) *Proceedings of the International Environmental Modelling and Software Society Meeting, Integrated Assessment and Decision Support, Lugano, Switzerland, 24–27 June 2002*, p. 395.

Evans D.R., Williams T.A., Jones S. and Evans S.A. (1998) The effect of cutting and intensive grazing management on sward components of contrasting ryegrass and white clover types when grown in mixtures. *Journal of Agriculture Science, Cambridge*, **130**, 317–322.

FILLA G., BELLOCCHI G., DONATELLI M. and ACUTIS M. (2003) IRENE_DLL: a class library for evaluating numerical estimates. *Agronomy Journal*, **95**, 1330–1333.

HAN D., O'KIELY P. and SUN D.W. (2003) Application of water-stress models to estimate the herbage dry matter yield of a permanent grassland pasture sward regrowth. *Biosystems Engineering*, **84**, 101–111.

HATFIELD J.L. (1988) Research priorities in ET: evolving methods. *Transactions of the American Society of Agricultural Engineers*, **31**, 490–495.

HERRMANN A. and SCHACHTEL G.A. (2001) OSYAQ, an organ-specific growth model for forage grasses. *Grass and Forage Science*, **56**, 268–284.

HERRMANN A., KELM M., KORNHER A. and TAUBE F. (2005) Performance of grassland under different cutting regimes as affected by sward composition, nitrogen input, soil conditions and weather – a simulation study. *European Journal of Agronomy*, **22**, 141–158.

HÖGLIND M., SCHAPENDONK A.H.C.M. and VAN OIJEN M. (2001) Timothy growth in Scandinavia: combining quantitative information and simulation modelling. *New Phytologist*, **151**, 761–766.

MCKEE T.B., DOESKEN N.J. and KLEIST J. (1993) The relationship of drought frequency and duration to time scales. *Procedings of the 8th Conference on Applied Climatology*, pp. 179–184. Anaheim, CA, USA: American Meteorological Society.

MONTEITH J.L. (1965) Evaporation and environment. *Proceedings of the 19th Symposia of the Society for Experimental Biology*, 8–12 September 1964, Swansea, pp. 205–234. Cambridge UK: University of Cambridge Press.

MONTEITH J.L. and UNSWORTH M.H. (1990) *Principles of Environmental Physics*, 2nd edn, p. 291. London, UK: Edward Arnold.

NOLAN T., CONNOLLY J. and WACHENDORF M. (2001) Mixed grazing and climatic determinants of white clover (*Trifolium repens L.*) content in a permanent pasture. *Annals of Botany*, **88**, 713–724.

PERI P.L., MOOT D.J. and MCNEIL D.L. (2003) 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.

RIEDO M., GRUB A., ROSSET M. and FUHRER J. (1998) A pasture simulation model for dry matter production and fluxes of carbon, nitrogen, water and energy. *Ecological Modelling*, **105**, 141–183.

RUGGET F., DELÉCOLLE R. and TIERS N. (1998) Estimating alarm situations on grassland production at regional scale. *Proceedings of the 7th ICCTA, Computer Technology in Agricultural Management and Risk Prevention*, Florence, Italy, 15–18 November 1998, p. 130 (Abstract).

RUNNING S.W. and COUGHLAN J.C. (1988) A general model of forest ecosystem processes for regional applications. I. Hydrological balance, canopy gas exchange and primary production processes. *Ecological Modelling*, **42**, 125–154.

SCHAPENDONK A.H.C.M., STOL W., VAN KRAALINGEN D.W.G. and BOUMAN B.A.M. (1998) LINGRA: a sink/source model to simulate grassland productivity in Europe. *European Journal of Agronomy*, **9**, 87–100.

SVOBODA M.D., LECOMTE D., HAYES M.J., HEIM R., GLEASON K., ANGEL J., RIPPEY B., TINKER R., PALECKI M., STOOKSBURY D., MISKUS D. and STEVENS S. (2002) The drought monitor. *Bulletin of the American Meteorological Society*, **83**, 1181–1190.

THEIL H., CRAMER J.S., MOERMAN H. and RUSSCHEN A. (1970) *Economic Forecast and Policy*, 2nd edn. Amsterdam, The Netherlands: North-Holland Publishing Company.

THORNLEY J.H.M. and VERBERNE E.L.J. (1989) A model of nitrogen flows in grassland. *Plant, Cell and Environment*, **12**, 863–886.

THORNTON P.E., HASENAUER H. and WHITE M.A. (2000) Simultaneous estimation of daily solar radiation and humidity from observed temperature and precipitation: an application over complex terrain in Austria. *Agriculture and Forest Meteorology*, **104**, 255–271.

TOPP C.F.E. and DOYLE C.J. (1996) Simulating the impact of global warming on milk and forage production in Scotland: 1. Effect on dry-matter yield of grass and grass-white clover swards. *Agricultural Systems*, **52**, 213–243.

TOPP C.F.E. and DOYLE C.J. (2004) Modelling the comparative productivity and profitability of grass and legume systems of silage production in northern Europe. *Grass and Forage Science*, **59**, 274–292.

TRNKA M., ŽALUD Z., EITZINGER J. and DUBROVSKÝ M. (2005) Global radiation in Central European lowlands estimated by various empirical formulae. *Agricultural and Forest Meteorology*, **131**, 54–76.

WILLIAMS T.A., EVANS D.R., RHODES I. and ABBERTON M.T. (2003) Long-term performance of white clover varieties grown with perennial ryegrass under rotational grazing by sheep with different nitrogen applications. *Journal of Agricultural Science, Cambridge*, **140**, 151–159.

WILMOT C.J. (1982) Some comments on the evaluation of model performance. *Bulletin of the American Meteorological Society*, **64**, 1309–1313.

WINSLOW J.C., HUNT E.R. and PIPER S.C. (2001) A globally applicable model of daily solar irradiance estimated from air temperature and precipitation data. *Ecological Modelling*, **143**, 227–243.

WOODWARD S.J.R., BARKER D.J. and ZYSKOWSKI R.F. (2001) A practical model for predicting soil water deficit in New Zealand pastures. *New Zealand Journal of Agricultural Research*, **44**, 91–109.

WU L. and MCGECHAN M. (1998) Simulation of biomass, carbon and nitrogen accumulation in grass to link with a soil nitrogen dynamics model. *Grass and Forage Science*, **53**, 233–249.

ŽALUD Z. and DUBROVSKÝ M. (2002) Modelling climate change impacts on maize growth and development in the Czech Republic. *Theoretical and Applied Climatology*, **72**, 85–102.

ŽALUD Z., MCMASTER G.S. and WILHELM W. (2003) Parameterization of SHOOTGRO 4.0 for simulating winter wheat phenology and yield in the Czech Republic. *European Journal of Agronomy*, **19**, 497–509.

Appendix

List of symbols, constants, coefficients and abbreviations used in the article. The nomenclature of the article tries to follow the original symbols used by Han *et al.* (2003) or other studies mentioned in the article.

Symbol	Description	Units	Equation*
C	Coefficient in water availability model	–	3
D	Number of days from the regrowth starting day to the time concerned	Days	
ET_a	Actual daily evapotranspiration calculated by model of Allen *et al.* (1998)	mm day^{-1}	
ET_{aSE}	Actual daily evapotranspiration accumulated a from the beginning of the growing season	mm	1
ET_{aW}	Actual daily evapotranspiration accumulated during on the given day and previous six days	mm	2
ET_r	Reference evapotranspiration from the well water short grass canopy	mm day^{-1}	
ET_{rSE}	Reference daily evapotranspiration accumulated a from the beginning of the growing season	mm	1
ET_{rW}	Reference daily evapotranspiration accumulated on the given day and previous 6 days	mm	2
G	Global radiation accumulation in D under no water stress	GJ m^{-2}	
G_e	Accumulation of water-stress-dependent effective global radiation in D	GJ m^{-2}	6
g_S	Water-stress-dependent growth-supporting factor	–	4–6
M	Coefficient in water availability model		3
MBE	Mean bias error		
MEI	Modelling efficiency index		7
N	Nitrogen		
PI	Pattern index		
R^2	Model coefficient of determination (based on the best fitting linear regression line)		
R_0^2	Model coefficient of determination (based on the linear regression line forced through the origin)		
R_G	Daily global solar radiation measured/estimated at the given experimental site	MJ m^{-2} day^{-1}	6
RMSE	Root mean square error		
T	Daily mean air temperature accumulation in D under no water-stress accumulation	°C	
T_{AVG}	Mean daily temperature at the given experimental site	°C	5
t_{CL}	Coefficient determining threshold of long-term water availability	–	1
t_{CS}	Coefficient determining threshold of short-term water availability	–	2
T_e	Accumulation of water-stress-dependent effective daily temperature in D	°C	5
T_{max}	Daily maximum temperature measured at the given site	°C	
T_{min}	Daily minimum temperature measured at the given site	°C	
U	Theil's inequality coefficient		8
U_B	Proportions of estimated bias of U		
U_C	Proportions of estimated covariance of U		
U_S	Proportions of estimated variance of U		
W_A	Water availability factor	–	3
W_L	Long-term water availability factor	–	1
W_S	Short-term water availability factor	–	2
α	Coefficient in growth-supporting factor submodel	–	4
β	Coefficient in growth-supporting factor submodel	–	4
γ	Coefficient in growth-supporting factor submodel	–	4

*Equation number in this column is given only if the parameter is used in the specific equation.

