# Modeling the biomass production of grasslands of Wallonia according to their functional type

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## Abstract

Permanent grasslands are complex ecosystems which respond with a great variability - in terms of specific richness - to soil type and management strategies. Modelling is a valuable tool to explore these relationships. Our work consisted in adapting the Moorepark St Gilles grass growth model (MoSt GG) designed to model *Lolium perenne* plant functional type (PFT) pastures (PFT A) to a different PFT (*Dactylis glomerata*, PFT B) through literature-based parametrization. The model was evaluated under Walloon (Belgium) conditions using growth trials from 2014 to 2018 in two sites with contrasting pedo-climatic conditions. Three to five cuts were performed over the course of the growing seasons depending on the rainfall yielding a total of 20 and 25 biomass measurements (kg of DM per ha), for PFT A and B respectively. No site effects were observed in the performance of the model. The relative root mean square error (RRMSE), normalized deviation (ND) and model efficiency (EF) across all cuts, sites and PFTs were 33%, 3% and 68% respectively. PFT B was better simulated than A for the criteria RRMSE (33% vs 33%), ND (4% vs. 9%), and EF (75% vs. 54%). Although this first evaluation was satisfactory, a complementary parametrization for additional pedoclimatic conditions and PFTs is called for to use the model under the diversity of Walloon conditions

## Introduction

Permanent grasslands are complex plant communities with a high number of species that can vary greatly depending on soil and climatic conditions and management practices. Grouping these different species into functional types can facilitate the diagnosis of the value of the grasslands and the implementation of optimal management strategies. Addressing such question, Cruz et al. (2002, 2010) proposed the grouping of temperate grasslands species in 6 plant functional types (PFTs), A (e.g., *Lolium perenne*), B (e.g., *Dactylis glomerata*), b (e.g., *Poa trivialis*), C (e.g., *Festuca rubra*), D (e.g., *Briza media*) and d (e.g., *Deschampsia cespitosa*), based on the following functional traits (leaf life span, specific leaf area, leaf dry matter content, start date and duration of the reproductive period, maximum sward height and leaf resistance to breakage). Modeling, through its ability to represent complex ecosystems, can also help to better understand the dynamics of grasslands. Several models already address the dynamics of grasslands, mostly dominated by *Lolium perenne* or often in mixtures with legumes, under cutting or grazing conditions. Simulation of future situations, difficult to achieve under experimental conditions, can allow farmers to anticipate and limit the effects of weather uncertainty and climate change on grassland stability. Expanding the ability of models to simulate a wider range of grasslands with different specific composition is of utmost importance in this respect owing the connection between plant functional traits and their response to changing environmental conditions and management practices including cutting/grazing regime and fertilization.

Jouven et al. (2006) proposed a first model to simulate four PFT (ModVege model). This model was later completed by Ruelle et al. (2018) (MoSt GG model) to consider the impact of fertilization applied during the growing season focusing only on one PFT of ModVege. In this paper, we adapted MoSt-GG and evaluated its ability to predict the biomass production of PFT A and B grasslands in Wallonia (Belgium) by comparing simulation to field results. The hypothesis is that the adapted model when properly parameterized, correctly simulates the dynamics of grasslands growth for both PFT.

## Methods and Study sites

The MoSt GG model simulates grassland growth based on the biomass contained in four plant compartments: green vegetative, green reproductive, dead vegetative and dead reproductive. The growth potential calculated from the intercepted photosynthetically active radiation is reduced depending on the limitations imposed by the environmental conditions. The actual growth in then split in the two green compartments depending on the time of the year and parts of the green material move to their respective dead compartments when aging through senescence. Similarly, parts of the dead material disappear from the vegetation by abscission with increasing age. Driving variables of the model are the daily environmental conditions (temperature (T), rainfall (PP), potential evapotranspiration (PET) and solar radiation (Ra)) and management (fertilization, cutting dates and height). The model yields among others the evolution of the biomass accumulated in the different compartments, their organic matter digestibility, as well as the water and nitrogen dynamics in the soil compartment.

In this work, the Most GG model, initially parameterized by Ruelle et al. (2018) for PFT A, was parametrized for PFT B using the parameters from Jouven et al. (2006). Key parameters are the specific leaf area, the percentage of laminae, the minimum and maximum organic matter digestibility of the green compartments, the leaf lifespan and the sum of the temperatures for the beginning and the end of the reproductive period. To evaluate the model, we compared the biomass yield per cut to data obtained plant cultivar growth trials conducted by the ASBL Fourrages Mieux on the sites of Louvain-la-Neuve (LLN, 50°67'N 4°64'E) and Tinlot (TLT, 50°50'N 5°39'E) in Wallonia between 2014 and 2018. PFT A was represented by perennial ryegrass (*Lolium perenne)* and PFT B by orchard-grass (*Dactylis glomerata)*. The biomass yield per cut for each plant cultivar is the average of 4 replications. Yield per replication was not always available for all cuts. Hence the absence of error bars for the PFT A cuts where only the average yield per cut was available. Overall, 45 cut yields (20 for PFT A and 25 for PFT B) were available with an average of 3 cut yields per season. All plots received an average of 200 kg of N/ha/year in 3 inputs: 80 kg before the first cut, 60 kg after the first cut and 60 kg after the second cut. Only the PFT B trial at the LLN site did not receive any fertilization. Phosphorus and potassium were applied almost systematically at an average rate of 100 kg $P_2O_5$ and 200 kg $K_2O$ per hectare per trial. Each site had a dedicated weather station within 100 m of the experimental plots collecting weather data during the experiments and this data was provided by the Agriculture, Land and Technology Integration Unit of the Walloon Agricultural Research Centre (CRA-W) (Table 1).

**Table. 1: weather data collected at Louvain-la-Neuve (LLN) and Tinlot (TLT) sites during the trial years with standard deviation in brackets**

| | PFT | T (°C) | Ra (MJ/m$^2$/d) | PP (mm) | PET (mm) |
|---|---|---|---|---|---|
| | | | **LLN** | | |
| **2014** | B | 11.6 (5.38) | 10.26 (7.14) | 692 | 689 |
| **2015** | B | 10.83 (5.91) | 10.82 (8.58) | 640 | 725 |
| **2016** | A, B | 10.49 (6.51) | 10.46 (7.21) | 667 | 664 |
| **2017** | A | 10.92 (6.58) | 10.37 (7.6) | 605 | 724 |
| **2018** | A | 11.59 (7.35) | 11.26 (8.11) | 499 | 815 |
| | | | **TLT** | | |
| **2014** | B | 11.87 (5.61) | 10.38 (7.69) | 808 | 661 |
| **2015** | B | 11.28 (6.32) | 11.42 (8.69) | 668 | 684 |
| **2016** | A, B | 10.64 (6.9) | 10.88 (7.59) | 712 | 637 |
| **2017** | A | 10.03 (6.75) | 10.61 (7.93) | 677 | 661 |
| **2018** | A | 10.9 (7.46) | 11.53 (8.33) | 600 | 755 |

The statistical indicators used to evaluate the quality of the model are: the relative root mean square error (RRMSE), the normalized deviation (ND) and the model efficiency (EF). The RRMSE is obtained by dividing the RMSE by the mean of the observed data. The model is considered good for values of RRMSE ≤ 0.30, ND approaching 0, and EF approaching 1. The equation to calculate these indicators are given hereafter:

$$RRMSE = \frac{1}{\bar{O}} \times \sqrt{\frac{\sum_{i=1}^{n}(Si - Oi)^2}{n}} \quad ; \quad ND = \frac{\sum_{i=1}^{n} Oi - \sum_{i=1}^{n} Si}{\sum_{i=1}^{n} Oi} \quad ;$$

$$EF = \frac{\sum_{i=1}^{n}(Oi - \bar{O})^2 - \sum_{i=1}^{n}(Si - Oi)^2}{\sum_{i=1}^{n}(Oi - \bar{O})^2}$$

where $\bar{O}$ denotes the mean of the observations, $Oi$ and $Si$ the observed and simulated biomass yield per cut, respectively.

## Results and Discussion

The simulation results were, overall, very close to the field results. The correlation between the simulated data and the field data was stronger for PFT A than for PFT B where the model tends to overestimate biomass production (Fig. 1).

### *Total biomass production*

The average biomass exported per cut in dry matter per hectare over the whole period shows a very high variability, more than one ton, in both observed and simulated data. This is partly explained by the fact that the highest yield is generally obtained at the first cut and progressively decreases for the following cuts. The simulated average biomass per cut remains very close to that of the field, with a difference of less than 0.1 ton per hectare. The EF above 50% shows that the model prediction is better than the average observation for the average dry matter yield per cut. When comparing simulated yields to observed yields on a cut-by-cut basis, the model also had good prediction quality with an absolute ND of less than 5%. The prediction error of the model when compared to the average yield per cut is higher than 30% but remains lower than 35%. The prediction of the model is therefore good.

**Table. 2: Comparison between field and simulated biomass. Mean values (Kg DM ha$^{-1}$) are presented with the standard variance between brackets. C1, C2, C3, C4, and C5 represent the cuts from 1 to 5. A, B are plant functional types (PFT).**

| | Total (n=45) | A (n=20) | B (n=25) | C1 (n=12) | C2 (n=12) | C3 (n=11) | C4 (n=8) | C5 (n=2) |
|---|---|---|---|---|---|---|---|---|
| **Observed** | 2515 (1497) | 2990 (1473) | 2135 (1433) | 3889 (1359) | 2398 (1195) | 2164 (1329) | 1512 (1039) | 918 (339) |
| **Simulated** | 2437 (1463) | 2711 (1464) | 2219 (1453) | 4254 (1098) | 2274 (643) | 1644 (1158) | 1417 (694) | 963 (84) |
| **RRMSE** | 0.33 | 0.33 | 0.33 | 0.23 | 0.39 | 0.41 | 0.35 | 0.33 |
| **\|ND\|** | 0.03 | 0.09 | 0.04 | 0.09 | 0.05 | 0.24 | 0.06 | 0.05 |
| **EF** | 0.68 | 0.54 | 0.75 | 0.52 | 0.32 | 0.52 | 0.7 | -0.59 |

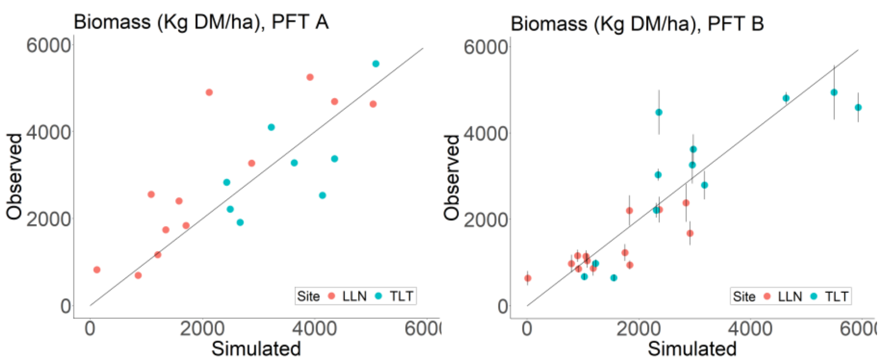


**Fig. 1. Comparison of observed and simulated biomass per cut for the two plant functional types (PFT) A and B and the two sites Louvain-la-Neuve (LLN) and Tinlot (TLT). Each point is the mean of 4 measurements (replications). The error bar reflects the variability between these replications.**

### *Biomass production by PFT*

The prediction error of the model in terms of yield per cut for PFTs A and B remains acceptable with a RRMSE value under 35%. The model predicts yield per cut well compared to the field data with a ND of less than 10%. The EF value greater than 50% shows that the prediction of the model remains better than the average of the observations for PFT A. The average DM yield per hectare obtained per cut for orchard-grass (PFT B) over the 25 cuts also remains highly variable for both simulated and observed data. In contrast to PFT A, the model tends to slightly overestimate the biomass production of PFT B for almost all cuts (Fig. 1). This can be explained in part by the current parameterization of PFT B, which remains very close to PFT A, while the plants in the two PFTs grow very differently in the field. However, the model has a good predictive quality when comparing simulated yields to observed yields on a cut-by-cut basis, with an absolute ND of less than 5%. The prediction of the model is also better than the global average of the observations with an efficiency of more than 70%. Overall, the model predicts the DM yield of PFT B better than PFT A.

### *Biomass per cut*

The simulated and observed average yields for the two PFTs are close at first cut, less than 0.5 ton difference in DM per hectare. The prediction error of the model compared to the average of the observations remains very low, less than 30%. The biomass yield at each first cut is well simulated with a ND less than 10%. The EF above 50% shows that the model also predicts the first cut yield better than the average of observations. Compared to the first cut, the biomass yield of the second cut is relatively less well predicted with an EF value above 30% but still below 50% and an RRMSE of 40%. However, the ND inferred at 10% shows that the prediction quality of the model remains good if we consider each second cut separately. The yield at the third cut is also less well predicted compared to the first cut. Although the EF is higher than 50%, the ND and RRMSE values remain higher than 20% and 40% respectively. The biomass yield of cut 4 is better predicted compared to cut 5. However, the lower number of data available for these last two cuts can account for poorer predictions.

## Conclusion

The initial assumption that the model can accurately predict the forage production of Walloon grasslands over a growing season is partly confirmed. Indeed, the model is able to predict well the biomass production of grasslands dominated by ryegrass (PFT A) and the dynamics of grasslands dominated by orchard-grass (PFT B). Whatever the composition of the grassland, the model predicts with a good accuracy the yield at the first cut; beyond that, the prediction remains unsatisfactory. In order to assist farmers in adapting to climate change, it is important to accurately predict the yield of each cut. Additional reparameterization and calibration work in particular of plant nitrogen demand and vertical distribution of biomass according to the PFT, based on a larger database, is necessary to improve the quality of the model.

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