

Article

# Challenges for Simulating Growth and Phenology of Silage Maize in a Nordic Climate with APSIM

Julien Morel <sup>1,\*</sup>, David Parsons <sup>1</sup>, Magnus A. Halling <sup>2</sup>, Uttam Kumar <sup>1</sup>, Allan Peake <sup>3</sup>, Göran Bergkvist <sup>2</sup>, Hamish Brown <sup>4</sup> and Mårten Hetta <sup>1</sup>

<sup>1</sup> Department of Agricultural Research for Northern Sweden, Swedish University of Agricultural Sciences, 90183 Umeå, Sweden; david.parsons@slu.se (D.P.); uttam.kumar@slu.se (U.K.); marten.hetta@slu.se (M.H.)

<sup>2</sup> Department of Crop Production Ecology, Swedish University of Agricultural Sciences, 75007 Uppsala, Sweden; magnus.halling@slu.se (M.A.H.); goran.bergkvist@slu.se (G.B.)

<sup>3</sup> CSIRO Agriculture and Food, Canberra 2601, Australia; allan.peake@csiro.au

<sup>4</sup> The New Zealand Institute for Plant & Food Research Limited, Private Bag 4704, Christchurch, New Zealand; hamish.brown@plantandfood.co.nz

\* Correspondence: julien.morel@slu.se; Tel.: +46-7676-37129

Received: 18 March 2020; Accepted: 30 April 2020; Published: 2 May 2020



**Abstract:** APSIM Next Generation was used to simulate the phenological development and biomass production of silage maize for high latitudes (i.e.,  $>55^{\circ}$ ). Weather and soil data were carefully specified, as they are important drivers of the development and growth of the crop. Phenology related parameters were calibrated using a factorial experiment of simulations and the minimization of the root mean square error of observed and predicted phenological scaling. Results showed that the model performed well in simulating the phenology of the maize, but largely underestimated the production of biomass. Several factors could explain the discrepancy between observations and predictions of above-ground dry matter yield, such as the current formalization of APSIM for simulating the amount of radiation absorbed by the crop at high latitudes, as the amount of diffuse light and intercepted light increases with latitude. Another factor that can affect the accuracy of the predicted biomass is the increased duration of the day length observed at high latitudes. Indeed, APSIM does not yet formalize the effects of extreme day length on the balance between photorespiration and photosynthesis on the final balance of biomass production. More field measurements are required to better understand the drivers of the underestimation of biomass production, with a particular focus on the light interception efficiency and the radiation use efficiency.

**Keywords:** APSIM model; silage maize; radiation use efficiency; biomass; light interception efficiency; calibration

## 1. Introduction

Maize (*Zea mays* L.) is among the most important crops cultivated globally, with more than 187 Mha produced annually around the world [1]. Maize grain is widely used as human and livestock feed, but also for the production of bioethanol. As a whole crop, maize is also used as silage for cattle-feeding purposes. High biomass production and high starch content are the main reasons for the great interest in maize production [2].

In northern Europe, the importance of maize as a forage for ruminants has markedly increased in recent decades [3]. The expansion of maize cultivation to latitudes higher than  $55^{\circ}$  has been made possible thanks to the breeding of new varieties with shorter growing cycles [4]. In Sweden, the area of silage maize increased from 2500 ha to more than 17000 ha between 2000 and 2017 [5]. The expected increases in temperatures due to climate change [6] increase the probability of maize reaching physiological maturity by the end of the growing season at high latitudes [7].

The increase in maize usage around the world comes concomitantly with a regular and high frequency breeding of new maize cultivars, resulting in a rapid replacement of cultivars: [8] reported an average turnover of 3 years in the United States. This high throughput makes it difficult to estimate how well various cultivars are adapted to different soil and climate conditions, in terms of potential biomass production and quality. As ruminant livestock production relies on both quantity and quality produced, it is beneficial to use tools that would allow farmers to optimize management practices (including the choice of the cultivar) to maximize production.

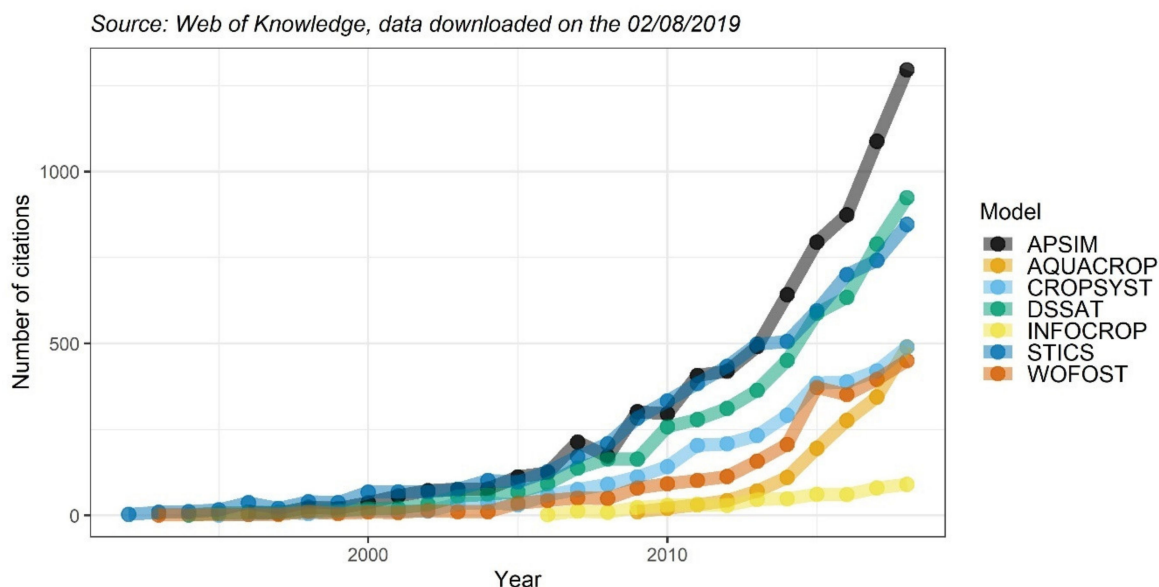
Crop models are widely used to investigate optimum farming practices. Their mathematical framework simulates the growth of a crop by taking into account various crop and environmental input factors and interactions. A wide number of crop models have been developed since the middle of the 20th century and the pioneering work of Cornelis Teunis de Wit [9,10]. Crop models can be used to perform various tasks such as predicting the effects of climate change on crops (e.g., [11–13]), optimization of farming practices for given soil–climate–crop combinations (e.g., [14,15]), understanding the environmental stresses experienced by crops (e.g., [16,17]) or to improve the knowledge of the physiological processes of a plant (e.g., [18]).

Although the modelling of maize growth is widely performed in tropical [19–21] and temperate areas [22–24], there have been few attempts to simulate the growth of silage maize at high latitudes. [25] successfully calibrated the FASSET model against field measurements of several variables (including above-ground biomass, N content and grain yield) to simulate the effects of climate change on the productivity of silage maize in Denmark, ultimately predicting that the projected increase in temperatures and precipitation in Denmark for the next decades will dramatically increase the risk of N leaching in maize cropping systems. In Sweden, two studies have been reported, using the MAISPROQ model [26], which is derived from the FOPROQ model [27] that was originally developed to simulate biomass production and nutrition qualities of grasslands at high latitudes. [7] used maize cultivars predefined in MAISPROQ to assess the impact of climate change and variability on the growth and maturation of silage maize in Sweden. Their results indicate that the effects of expected warming between 2011 and 2100 will increase the likeliness of maize reaching silage maturity in southern Sweden from 17% to 100%, while the chances of reaching silage maturity would increase from 4% to 30% in mid Sweden. However, according to the authors, their results need to be confirmed with Swedish field experiments. [28] calibrated MAISPROQ for Swedish grown cultivars using field measurements and extrapolated the results to future trends for silage maize crops in Sweden based on predicted climate. MAISPROQ reliabilities were shown to be reasonable for the quality estimations ( $R^2$  ranging from 0.25 to 0.54 for the validation subset) but limited for biomass production ( $R^2$  ranging from 0.36 to 0.38 for the validation subset). This is explained by the limited amount of field-sampled data available in the early phase of the growing stages. However, the results lead to similar conclusions as those obtained by [7], with an increasing likeliness of silage maize in Sweden to reach the silage maturity required for feeding to livestock.

MAISPROQ is a simple, semi-mechanistic model that requires little input data, making it relatively easy to calibrate. However, the trade-off of MAISPROQ's simplicity is a reduction in the capability of the model to take into account various factors that affect the development of the crop. For example, the soil module consists of a simple layer with limited information on the soil structure and water holding capacities, which limits the ability of the model to quantify water stress. Moreover, it assumes that N is non-limiting to crop growth, which prevents investigation of another important limiting factor for the growth and quality of maize. In addition, MAISPROQ does not describe crop phenology, which is critical information (i) for estimating the dynamic of the nutritive quality traits of maize [29], (ii) for understanding the effect of environmental stress on grain production as well as (iii) for estimating optimum harvest dates.

The limitations of MAISPROQ can be overcome using more process-oriented models, such as STICS [30], DSSAT [31], or APSIM [32,33]. Although these models do not simulate the dynamics of starch or other nutritive quality related traits, their structure takes into account the major abiotic

factors that might limit the development of the crop. Of these models, the Australian APSIM model is arguably the most widely used crop model globally (Figure 1), and has recently developed an updated, user-friendly plant modelling framework that simplifies the process required to alter model processes for new applications, such as the quality of maize grain in silage fields.



**Figure 1.** Citations of major crop models (from Web of Knowledge; data downloaded on the 02/08/2019).

Although APSIM-Maize is being widely used in tropical and temperate climate conditions [34–37], it has not been used or calibrated for high latitudes (i.e., over 55° of latitude). Meaningful use of crop models in simulation experiments requires appropriate parameterization for the model to predict field data over the range of experimental conditions [38,39], as demonstrated previously by studies using the APSIM-Maize model to predict irrigation strategies for alternative plant populations [35,40]. At high latitudes, specific conditions such as day length, low temperatures or the solar zenith angle may affect the model’s capability to correctly simulate growth and phenology, as those conditions are out of the domain of prior development of the model. Moreover, the short-duration varieties used in Sweden and more generally at high latitudes have not previously been parameterized for APSIM-Maize. Additionally, APSIM-Maize has been primarily designed to simulate grain production, and its current rules for harvest maturity do not allow simulation of the optimal cutting time for silage maize hybrids.

The aims of this study were therefore (i) to test the ability of APSIM-Maize to simulate the phenological development and above-ground dry matter biomass production of silage maize at high latitudes, and (ii) to identify improvements required to accurately simulate maize at high latitudes.

## 2. Materials and Methods

### 2.1. Field Data

The field data were acquired in 2013 and 2014 at three sites located in southern Sweden: Bajgården, Färjestaden and Önnestad (Figure 2). Each site has a particular soil and climate combination that represents different pedo-climatic conditions encountered in Sweden for silage maize cultivation. The experiments were designed in randomized complete blocks with two replicates and six cultivars with different maturation times. The names and FAO numbers [41] of the six cultivars were Arcade (160), Ramirez (170), Amagrano (200), Atrium (210), LG 30211 (210) and Galbi (220). Farming practices are summarized in Table 1.



**Figure 2.** Location of the experimental sites used for the calibration of APSIM-Maize.

**Table 1.** Farming practices for the different sites and years of the study.

Site (-)	Year (-)	Sowing Date (-)	Sowing Depth (mm)	Sowing Density (seed.m <sup>-2</sup> )	Nitrogen Input at Sowing (kg.ha <sup>-1</sup> )	Row Spacing (mm)
Bajgård	2013	13 May	20	8.5	100	700
	2014	30 April	20	10	100	700
Färjestaden	2013	11 May	20	9	100	750
	2014	28 April	20	8.5	100	750
Önnestad	2013	30 April	20	9	110	750
	2014	26 April	20	9	110	750

Measurements of above-ground dry matter yield and phenological development occurred between late May and early October for each site and year on 1.25 m<sup>2</sup> sampling areas. During this period, a total of 8 measurements of above-ground dry matter yield (ADMY) were made for each replicate. Harvested samples were dried at 60 °C for 48 h or longer until a constant weight was reached. The phenological stage of each treatment was recorded between emergence and anthesis using the **B**iologische **B**undesanstalt, **B**undessortenamt und **C**hemische **I**ndustrie (BBCH) scale [42], with a minimum of two and maximum of four growth stage measurements obtained from each treatment, depending on the experiment.

Soil physical characteristics and organic matter content were measured at each site in September 2017. Samples were taken at depths of 0–10, 10–20, 20–40, 40–60, 60–90 and 90–120 cm and used to determine bulk density, field capacity and wilting point (LL15). The field in Önnestad had a sandy texture (as defined by the USDA soil taxonomy) for the whole profile. In Bajgård, the field had a sandy texture in the first sixty centimeters, then clay texture between 60 and 120 cm. The field in Färjestaden had a sandy loam texture for the whole profile. The soil data used to set up the APSIM soil module are available in a public dataset (<http://dx.doi.org/10.17632/s3r4g8j6jj.1>). A full soil water profile was assumed at sowing due to the snow melt in spring.

Daily climate data including rainfall, solar radiation and minimum and maximum air temperatures were sourced from weather stations located close to the study sites and managed by the Swedish Meteorological and Hydrological Institute (<https://www.smhi.se/en>).

## 2.2. Description of APSIM-Maize

APSIM-Maize (APSIM version 2018.10.10.3136) was used to simulate the growth of the experimental maize plots. This model is part of the APSIM Next Generation suite of crop models [43]. It describes the growth of a homogeneous plot of maize at a daily time step based on soil characteristics, climate data and farming practices. The simulation describes the phenology, leaf development, and biomass production, as well as the partitioning of the dry matter, of maize.

Crop development is based on the Ceres maize model [44], where its duration is divided into 11 phases from germination to harvest. With the exception of the first phase (germination), which is a function of soil water content, all phases are driven by thermal time and affected by water and nitrogen stresses. The thermal time adjustments for low temperatures are included [24]. The leaf development process is also dependent on thermal time accumulation. The leaf area index, computed from the number of leaves that have appeared and their size, is potentially reduced by water, temperature and nitrogen stresses.

APSIM-Maize uses a radiation use efficiency approach for predicting dry matter production [45]. The dry biomass produced is estimated as the product of the amount of solar radiation intercepted by the canopy (through the leaf area index computations) and the radiation use efficiency (*RUE*) of the crop. The *RUE* could be reduced by suboptimal nitrogen, air temperature, water and atmospheric CO<sub>2</sub> concentration stresses. In APSIM, the *RUE* accounts for the dry matter produced for the whole plant (i.e., above and below ground biomass). The partitioning of the dry matter between the different organs of the plant is a function of the phenological stage and is described in detail by [46].

## 2.3. APSIM-Maize Parameterisation

The model was parameterized for each location and each season according to the measured environmental and agronomic data (Table 1). The initial cultivar used within APSIM was the early maturing hybrid NSCM 41. As the cultivars used in this study were bred in northern Europe, with long-day conditions, it can be expected that they were non-photosensitive. Therefore, the duration of the photosensitive stage used in APSIM was set to 0.

The soil module parameterization is critical to correctly simulate the nitrogen and water balance of the soil–crop system. The soil textures, drained upper limits (DULs) and lower limits (LL15) obtained from laboratory measurements were used to set these parameters. The initial water content was set to the soil water storage capacity, as proposed by [7], for simulating post-snow melt soil conditions.

## 2.4. Calibration Protocol

Calibration aimed to optimize the value of one or more parameters of a model by minimizing a cost function describing the error between a simulated and field-measured state variable, also called the adjustment variable. As the aim of this work is to be further assessed with other studies, the calibration was performed on the complete available dataset, with no validation step. The function used was the root mean squared error (*RMSE*) computed as

$$RMSE = \sqrt{\frac{\sum_1^n (p_i - o_i)^2}{n}} \quad (1)$$

where  $n$  is the number of observations used,  $p_i$  is the simulated value of the state variable and  $o_i$  is the measured value of the state variable.

A set of parameters related to the phenology was defined (see Table 2) for each cultivar using the BBCH phenological stage [42] as the adjustment variable.

**Table 2.** Cultivar parameters used for calibration.

Parameter Name (Abbreviation)	Short Description
Emergence lag (ShootLag)	Thermal time target (°C) from germination to the emergence of the plant
Juvenile phase (JUV)	Thermal time target (°C) from emergence to the beginning of the photosensitive stage
Phyllochron (PC x)	Number of leaf tips that have appeared
Phyllochron (PC y)	Leaf rate appearance (°C <sup>-1</sup> )

All the potential values of the parameters were defined within a realistic range (see Table 3) based on the existing values provided for the early cultivars of the APSIM catalogue and combined to create a full factorial simulation, consisting of a single matrix of 192 lines (i.e., unique combinations of parameter values) and 3 columns (i.e., the parameters to recalibrate). This matrix was then used to run APSIM-Maize simulations for each site and year of the recorded dataset, consisting of a total of 1152 simulations.

**Table 3.** Range (minimum and maximum) of values used for each parameter to calibrate.

Parameter Name (Abbreviation)	Range (Minimum–Maximum)
Emergence lag (ShootLag)	15–45
Juvenile phase (JUV)	100–205
Phyllochron (PC x)	1 4 4.2 10.5 11–1 4 11 15
Phyllochron (PC y)	26 26 40 40 60–26 40 70 90

APSIM-Maize results were then analyzed with R (version 3.6.1, R Foundation for Statistical Computing, Vienna, Austria, 2019). Field observations and APSIM-Maize predictions were matched according to the site and date of sampling to compute RMSE (Equation (1)) and the combination of parameters with the lowest RMSE was extracted for each cultivar. The coefficient of determination  $R^2$ , the index of agreement proposed by [47] and the normalized root mean square error were also used as statistical indicators of the performance of the model to simulate the phenology and biomass production of silage maize. The index of agreement (IoA) was computed as

$$IoA = 1 - \left( \frac{\sum_{i=1}^n (p_i - o_i)^2}{\sum_{i=1}^n (|p_i - \bar{o}| + |o_i - \bar{o}|)^2} \right) \quad (2)$$

with  $\bar{o}$  being the average of the observed values.

The normalized root mean square error (NRMSE) was computed as

$$NRMSE = \frac{RMSE}{\bar{o}} \quad (3)$$

For each cultivar, the calibration was performed using the complete observation dataset to maximize the robustness of the model. In order to evaluate the performance of calibration, a leave-one-out cross validation (LOOCV) was performed. The six combinations of year and site were used for calibration (five combinations) and validation (one combination) so that each of the combinations was used for validation. For each loop of the LOOCV, the set of parameters with the lowest RMSE value was identified, and the corresponding validation RMSE was calculated with the

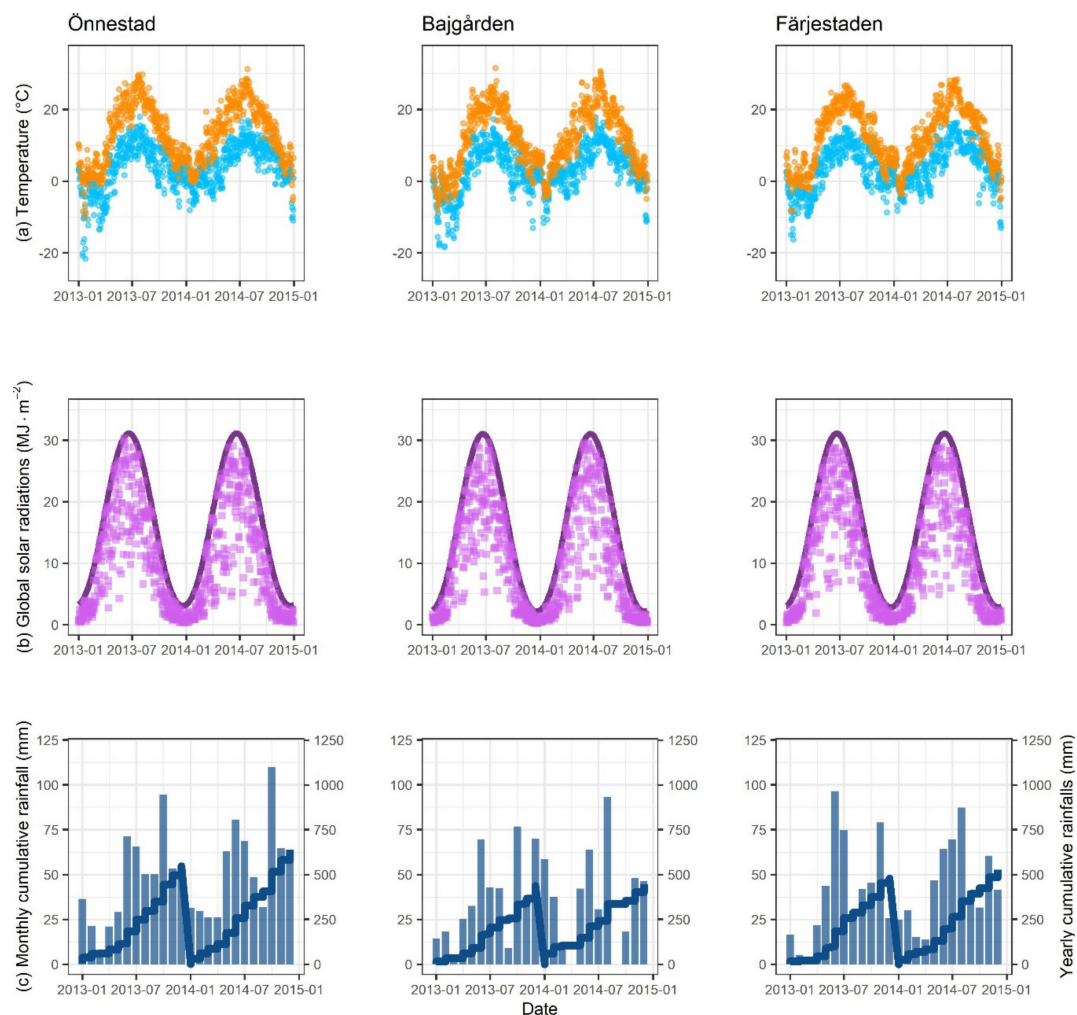


remaining combination of site and year. This resulted in six RMSEs for each cultivar which could be compared with the RMSEs obtained with the calibration.

### 3. Results

#### 3.1. Weather Data

The climate data for each location are presented in Figure 3. Minimum and maximum temperature values fell into the expected ranges and did not exhibit any scattering or pattern that would indicate abnormal recordings. Global (i.e., direct and diffuse) radiation data did not exhibit any positive or negative offset when compared to computed clear sky radiation [48]. Rainfall data were also consistent with expectations.

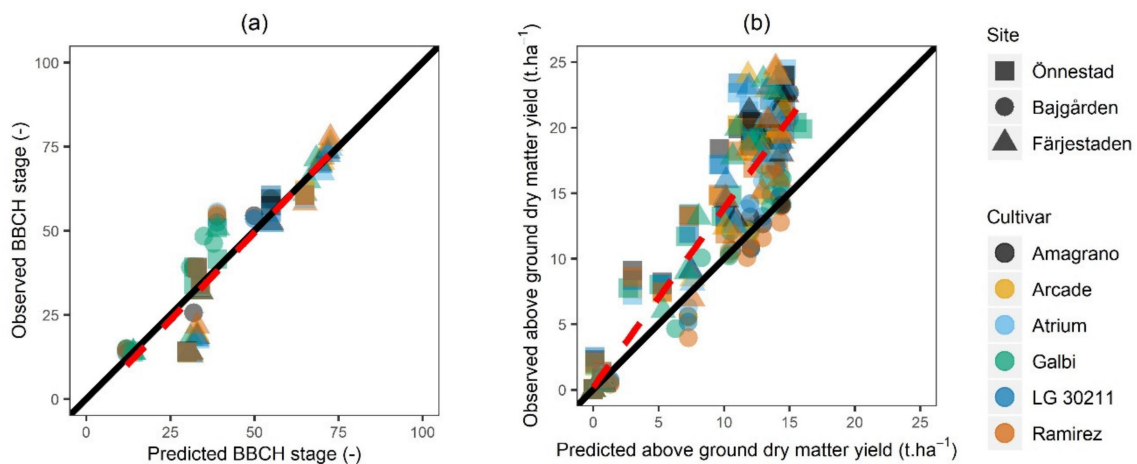


**Figure 3.** Climate data used in this study. (a) The daily minimum and maximum temperatures (°C); (b) the global solar radiations (MJ·m<sup>-2</sup>), as measured from the station (symbols), and computed clear sky radiation (lines); (c) the monthly rainfalls (bars) and yearly cumulative rainfalls (lines).

Önnestad had the warmest and wettest weather of the three sites. Bajgården was the most northern site, with the lowest amount of solar radiation, and was also the coldest and the driest of the three sites. Färjestaden exhibited intermediate levels of rainfall and temperatures compared to Önnestad and Bajgården.

### 3.2. Calibration of the Phenological Parameters

The optimization of the phenological parameters for each cultivar shows that the overall prediction of the BBCH stage by APSIM is satisfactory (Figure 4a);  $R^2 = 0.81$ , RMSE = 8.8 phenological units and NRMSE = 0.23 (see Table 4). The regression exhibited a slope of 1.04 (significantly  $>1$ ,  $p < 0.001$ ) with an intercept of  $-2.5$  (not significantly different to zero,  $p = 0.2$ ). Deviation from the 1:1 line is evident at approximately BBCH stage 30 (i.e., during stem elongation), where the simulations for Färjestaden and Bajgården tend to overestimate the actual BBCH stage, and simulations for Önnestad tend to underestimate the phenological stage.



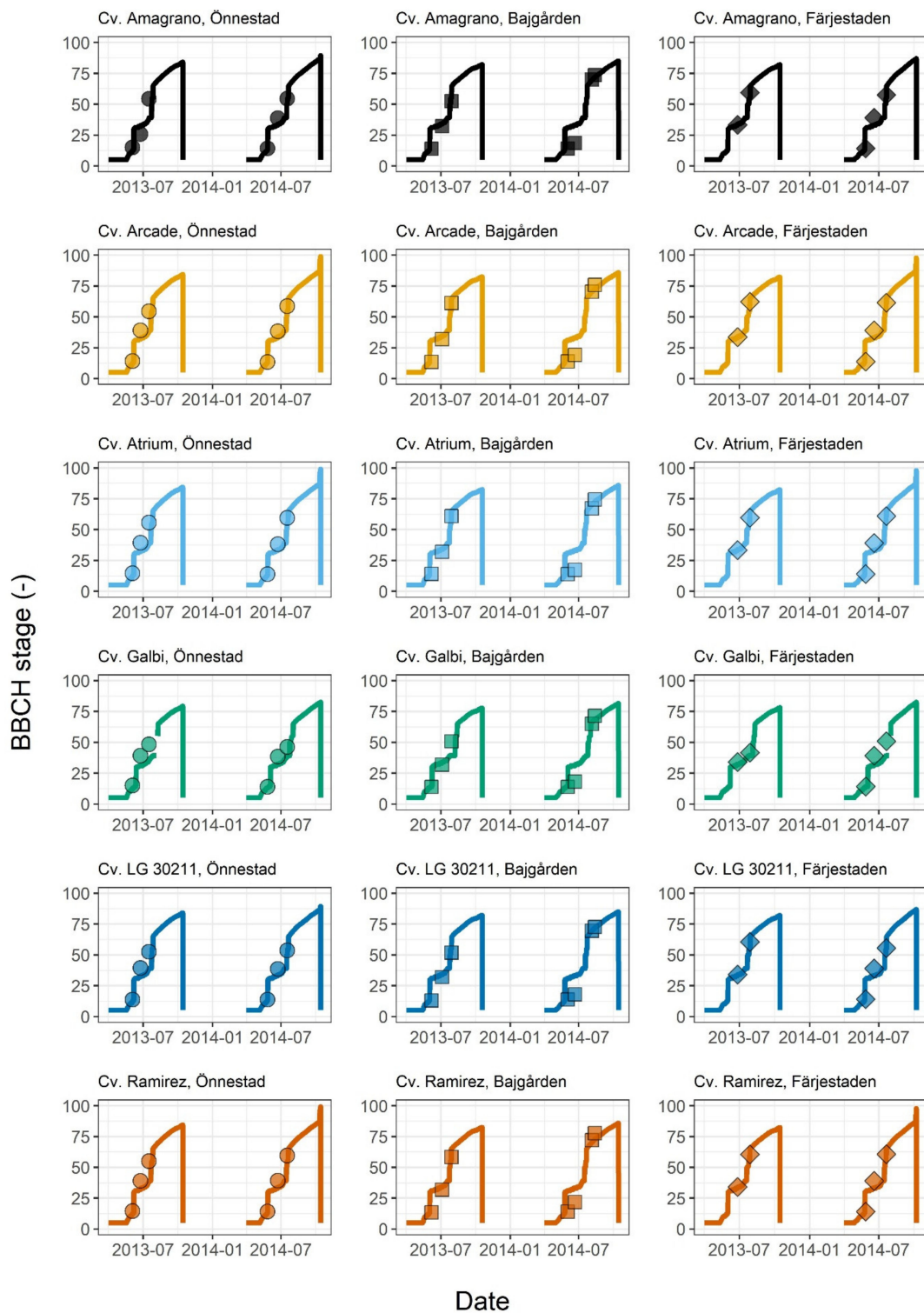
**Figure 4.** Scatterplots of simulation results and field observations for **B**iologische **B**undesanstalt, **B**undessortenamt und **C**hemische **I**ndustrie (BBCH) stage (a) and above-ground dry matter yield (b). The red dashed lines show the linear regression. The black lines indicate the 1:1 regression line.

**Table 4.** Statistical indicators of APSIM performance. ADMY stands for above-ground dry matter yield,  $n$  indicates the number of available measurements, and  $a$  and  $b$  are the slope and the intercept of the linear regressions, respectively. p.u. stands for BBCH phenological units.

Variable	$n$	$a$	$b$	$R^2$	RMSE	NRMSE	Index of Agreement
BBCH	108	1.04	$-2.5$	0.81	8.8 p.u.	0.23	0.94
ADMY	282	1.32	0.12	0.87	5.2 t.ha <sup>-1</sup>	0.41	0.87

The dynamics of phenological developments for each cultivar confirm that there is good agreement between predicted and observed values of BBCH stages (Figure 5), although a systematic overestimation can be observed in Bajgården in 2014 for the first stages of development.





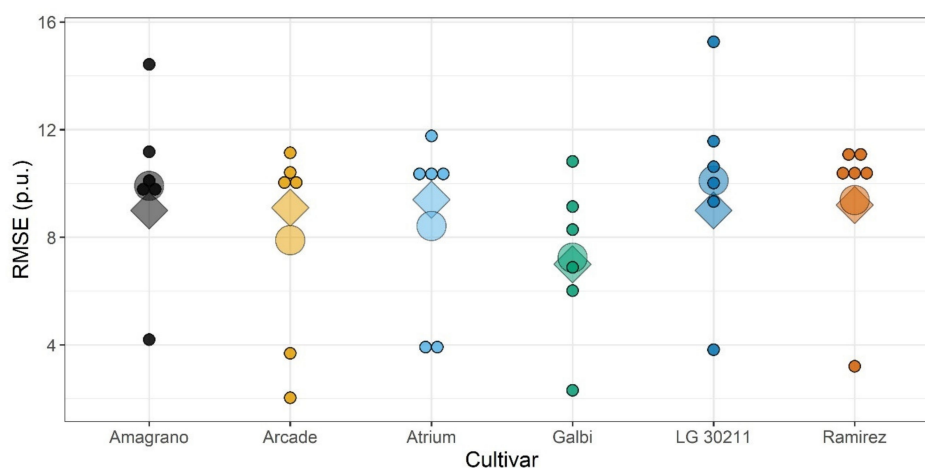
**Figure 5.** Observed (symbols) and simulated (dashed lines) BBCH stage values as a function of the date. The color varies according to the cultivar, and the shape of the symbols varies according to the site.

The results for calibrated parameter values suggest that all cultivars develop at a similar rate until floral development (Table 5), with the exception of the Galbi cultivar, which requires a longer thermal time target to complete the juvenile phase. The RMSEs of the cultivars show consistent values, ranging from 7.0 (Galbi cv.) to 9.4 (Atrium cv.)

**Table 5.** Optimal values of the phenology related cultivar parameters. ShootLag and JUV stand for the emergence lag and juvenile phase, respectively (see Table 2 for definition). PC x and PC y define the phyllochron used, with PC x being the number of leaf tips that have appeared and PC y being the degree days necessary for a new leaf tip to appear. As PC x and PC y change depending on the number of leaf tips that have already appeared, values listed in this table indicate the dynamic relationship between both variables (<https://apsimnextgeneration.netlify.com/modeldocumentation/>). The corresponding RMSEs of measured vs. predicted BBCH scaling are provided as an indication of the accuracy of the calibrated parameters.

Cultivar	ShootLag	JUV	PC x	PC y	RMSE	FAO Number
Amagrano	45	100	1 4 4.2 10.5 11	26 26 40 40 65	9.0	200
Arcade	45	100	1 4 4.2 10.5 11	26 26 40 40 60	9.1	160
Atrium	45	100	1 4 4.2 10.5 11	26 26 40 40 60	9.4	210
Galbi	35	160	1 4 4.2 10.5 11	26 26 40 40 60	7.0	220
LG 30211	45	100	1 4 4.2 10.5 11	26 26 40 40 65	9.0	210
Ramirez	45	100	1 4 4.2 10.5 11	26 26 40 40 60	9.2	170

The performance of the models calibrated with the complete dataset was compared to the performance obtained for the LOOCV. Although the mean RMSEs slightly differ for the calibration based on the complete dataset and the LOOCV, results are comparable (Figure 6). RMSEs obtained from the calibration procedure lie within the range of RMSEs obtained from the LOOCV and are comparable to the mean RMSEs of the LOOCV. This suggests that the calibration performed with the complete dataset provides an accurate estimation of the considered parameters while avoiding overfitting. The sets of best parameters obtained for each iteration of the LOOCV are also comparable to the ones obtained from the calibration over the complete dataset: the best set from LOOCV was the same as for the calibration 6 times out of 6 for cvs. Arcade, Atrium and Ramirez, 5 times out of 6 for cv. Amagrano, 4 times out of 6 for cv. Galbi and 3 times out of 6 for cv. LG 30211.



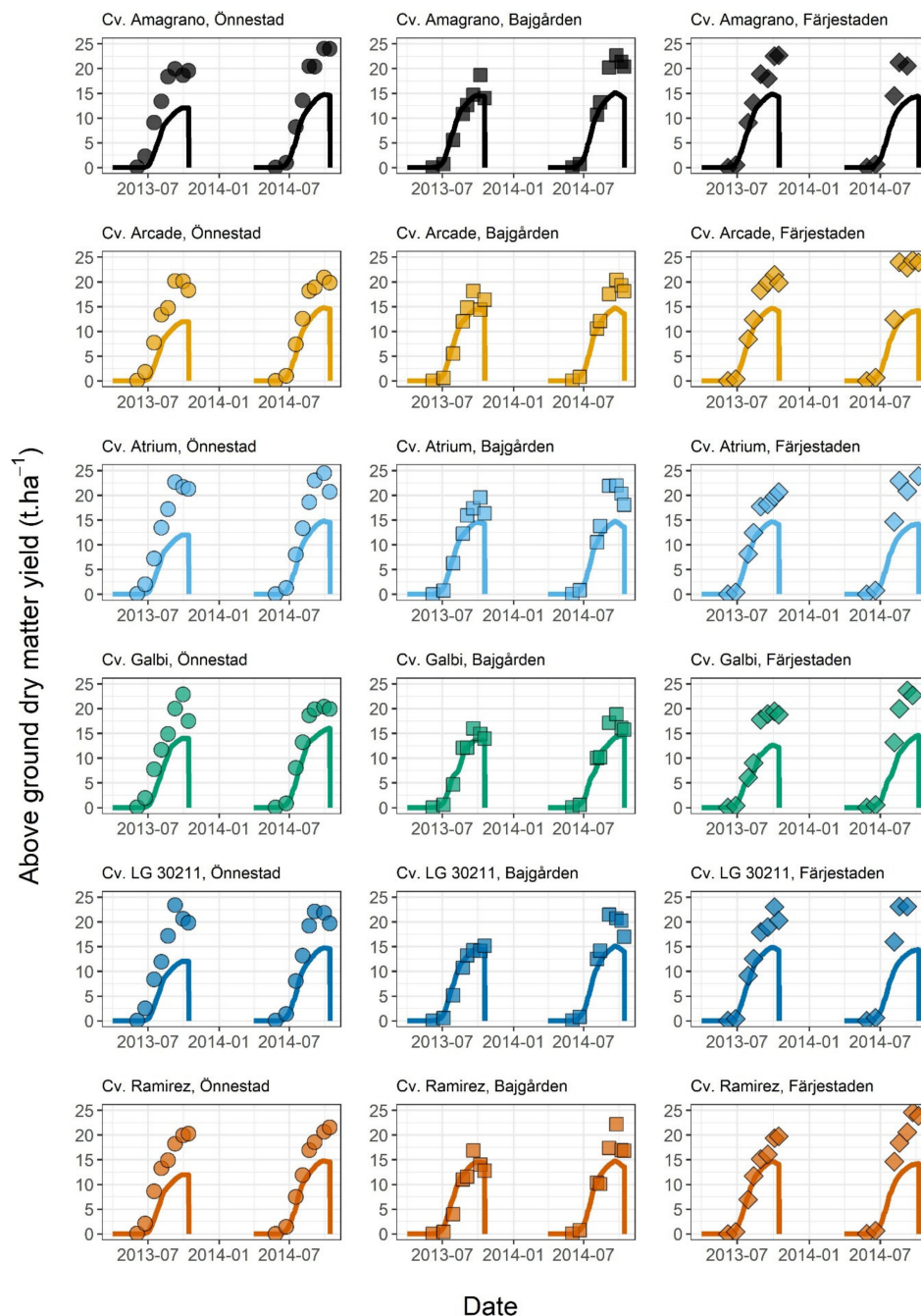
**Figure 6.** Comparison of the RMSEs of calibration using the whole dataset (diamonds) with the RMSEs computed from the leave-one-out cross validation (LOOCV). Large circles indicate the mean value of the RMSEs computed with the LOOCV, and small circles indicate the individual values of the RMSEs of the LOOCV. p.u. stands for BBCH phenological units.

### 3.3. Simulation of Above-Ground Dry Matter Yield

Once the phenological parameters were calibrated, predicted values of above-ground dry matter yield were extracted and compared with field measurements (Figure 4b). Despite the successful calibration of cultivar phenology, APSIM largely underpredicted above-ground biomass prediction, with a regression exhibiting a slope of 1.39 (significantly  $>1$ ,  $p < 0.001$ ) and an intercept value of 0.12

(not significantly different to zero,  $p = 0.7$ ). Although the prediction of ADMY shows an acceptable relationship ( $R^2 = 0.87$ ), the accuracy is low (RMSE = 5.2 t.ha<sup>-1</sup> and NRMSE = 0.41), with a large spread of the data around the regression line and an obvious bias for overprediction.

The simulated dynamics of ADMY presented in Figure 7 confirm the results of Figure 4b, with a clear underestimation of biomass production by the model. However, the differences appear to be less in Bajgården, especially in 2013.



**Figure 7.** Observed (symbols) and simulated (dashed lines) above-ground dry matter yields as a function of the date. The color varies according to the cultivar, and the shape of the symbols varies according to the site.

## 4. Discussion

### 4.1. Calibration of the Phenological Parameters

A factorial experiment was created to combine a set of predefined values for each cultivar parameter to calibrate. Minimization of the RMSE was used to select the optimal set of values for each cultivar. Although several calibration approaches are available [49], we selected this one because of its time efficiency and its ease of reproducibility. The results of the calibration of the phenology related parameters, with an overall error less than 10 BBCH units, can be considered as satisfactory.

BBCH values predicted by APSIM are, overall, in good agreement with field observations. The deviation observed at approximately stage 30 can be due to an operator bias, as this stage corresponds to the end of the leaf development and the beginning of the stem elongation. Evaluating the number of nodes that have appeared can be a difficult task, especially in the first steps of stem elongation, and can therefore be subject to a strong operator bias. Another reason that could explain this deviation is that we used averaged values of replicates. Consequently, a replicate that was affected by a non-reported stress would be included in the average calculations and result in an underestimation of the BBCH stage. This explanation is particularly sound for results in Färjestaden (Figure 4a).

Individual cultivar RMSEs all fall within a similar range, at approximately 9 BBCH units, with the exception of Galbi cv, with a RMSE of 7 BBCH units. The values for the parameters ShootLag and JUV are the same for all cultivars except the Galbi cultivar. The obtained values of the JUV parameter are lower than the ones reported in the APSIM-Maize catalogue of cultivars, which is consistent with our expectations for the early to very early cultivars used at high latitudes. The values for the ShootLag parameter are also lower than the default one used in APSIM-Maize (i.e., 55 degree days). This would also be consistent with cultivars bred to meet requirements of shorter growing seasons. The set of values for the phyllochron shows little variation among cultivars and is close to the set of values proposed for the Atrium cultivar already present in the APSIM-Maize catalogue of cultivars. Interestingly, the reported value for the JUV parameter of Atrium cv. in the APSIM-Maize catalogue is higher than the reported value resulting from the present calibration. It would be interesting to compare the data used for the initial calibration of Atrium cv. with the data used in this study and determine whether these differences can be explained. The reader is referred to the documentation (<https://apsimnextgeneration.netlify.com/modeldocumentation/>) for further information on the catalogue of cultivars and related default values of parameters.

### 4.2. Simulation of Above-Ground Dry Matter Yield

APSIM underestimated the ADMY of most experiments, with the only exception being that of Bajgården in 2013. This particular case could be due to an unobserved stress, as it is observed in all cultivars for this particular site and year. Apart from the simulations for Bajgården in 2013, the reported underestimation is unusual given that phenological development was specified correctly and that in such situations, crop models typically overestimate the dry matter yield due to reducing factors such as pests, diseases or nutrient limitations [50] unaccounted for by the model.

In order to investigate other potential causes of this error, it is necessary to consider the method that APSIM uses to compute the daily production of dry matter yield. It does so using an adapted version of the efficiency model proposed by [45]:

$$\Delta_{DM} = RUE \times \varepsilon_i \times GR \quad (4)$$

where  $\Delta_{DM}$  is the daily production of dry matter for a unit area ( $g_{DM} \cdot m^{-2} \cdot d^{-1}$ ),  $RUE$  is the radiation use efficiency ( $g_{DM} \cdot MJ^{-1}$ ),  $\varepsilon_i$  is the light interception efficiency (arbitrary units) and  $GR$  is the daily global solar radiation ( $MJ \cdot m^{-2} \cdot d^{-1}$ ).

In this equation, we consider  $GR$  values to be reliable, as they have been validated by the Swedish Meteorological Board and are close to the computed maximum data for each location. Therefore, it is



likely that APSIM parameters for the radiation use efficiency and the light interception efficiency could be affected by specific weather conditions or the sun angles achieved at high latitudes.

#### 4.2.1. The Radiation use Efficiency

The radiation use efficiency, as used in APSIM-Maize, has a default potential value of  $2 \text{ g}_{DM} \cdot \text{MJ}^{-1}$  (<https://apsimnextgeneration.netlify.com/modeldocumentation/>) and integrates the biomass production of the whole plant (below and above ground). APSIM uses the global radiation to compute biomass production, and therefore applies a 0.5 multiplier to *RUE* to compensate for the fact that only half of the global radiation is used by the plant for photosynthesis (the so called photosynthetically active radiation). The assumption of using a constant value for *RUE* might be a limitation for high latitude simulations. [51] showed that in the case of wheat cultivated along a north–south transect in Australia, the *RUE* value increases southward, with 1.1% per degree of latitude due to the increase in the fraction of diffuse light (that is, the part of the light that is scattered by the atmosphere) toward higher latitudes [52,53]. The diffuse light eventually reaches the highly efficient lower layers of the canopy [51]. It is possible that a similar mechanism also occurs for maize at Northern latitudes. [54] also showed that a redistribution of the solar energy from highly exposed leaves to shaded leaves resulted in an increased dry matter production for cabinet-grown tomato plants, indicating that plants exposed to more diffuse light should increase their dry matter production. It is likely that a similar effect would affect maize grown at high latitudes. As the current parameterization of APSIM does not take into account the influence of diffused light, the influence of latitude on *RUE* might partly explain why it underestimates the biomass produced.

APSIM uses several reduction factors to take into account the effects of abiotic stresses on *RUE*, including water, nitrogen, atmospheric  $\text{CO}_2$  concentration, vapor pressure deficit and temperature stresses. Simulations showed no water, nitrogen,  $\text{CO}_2$  or vapor pressure deficit-related stress. However, temperature stresses were reported for all sites, resulting in a reduction in the theoretical maximum yield ranging between 15% and 4%. This temperature-related stress, however, does not fully explain the differences between observed ADMY and predicted ADMY.

It can be assumed that the effects of water, nitrogen, atmospheric  $\text{CO}_2$  concentration and vapor pressure deficit are independent of latitude. However, APSIM assumptions on how temperature affects *RUE* might need to be investigated. Indeed, the temperature stress *FT* is computed as a function of the daily averaged temperature and a set of cardinal temperatures that defines the potential (from 8 to 50 °C) and optimal (from 15 to 35 °C) ranges for growth. The daily averaged temperature is itself computed as a function of a weighting coefficient that accounts for the length of day. The default value of this parameter is 0.75, which might be insufficient to take into account the extreme length of days at high latitude during the growing season.

#### 4.2.2. Light Interception Efficiency

The light interception efficiency  $\varepsilon_i$  is computed as follows

$$\varepsilon_i = 1 - e^{(-k \times LAI)} \quad (5)$$

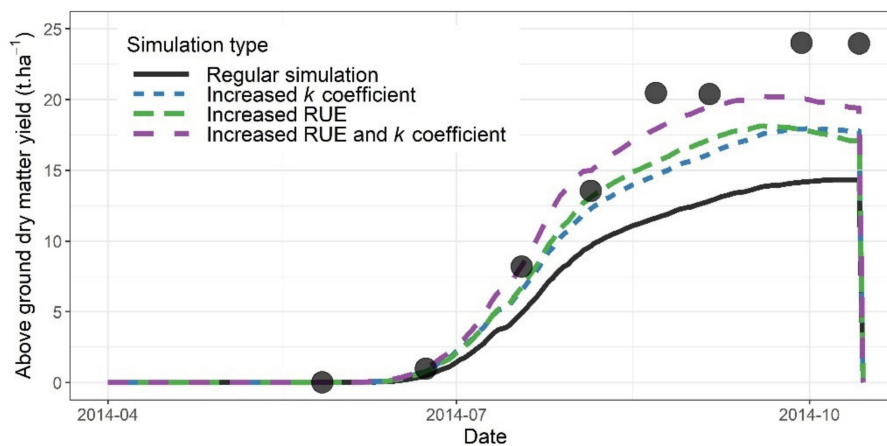
where  $k$  is the coefficient of extinction (–) and *LAI* is the leaf area index ( $m_{leaf}^{-2} \cdot m^{-2}$ ).

$k$  can be expected to be latitude dependent, as the smaller solar elevation angle of high latitudes in summer enables more light to penetrate the canopy. In APSIM-Maize,  $k$  is a function of row spacing and water stress (leaf curling). As latitude effects are unaccounted for,  $k$  might be underestimated, which induces an underestimated amount of light used for photosynthesis and, consequently, an underestimation of biomass production.

*LAI* is defined as the ratio of one-sided green leaf area to ground area [55]. In APSIM, *LAI* is a function of the number of leaves and of the leaf-specific area. *LAI* is affected by water and nitrogen stresses, which are latitude independent. *LAI* is also affected by the stress related to temperature, in a

similar way as described for *RUE*. Similar to *k*, *LAI* has a direct influence on biomass production, as it determines the amount of light intercepted by the canopy. Although the post-tasseling simulated values of *LAI* are within the usual range of 4 to 8, as reported by, e.g., [55,56], a proper evaluation of these simulated values could not be performed due to the absence of measurements related to the leaf area of the crop (such as *LAI* or leaf number) in the dataset.

Based on these statements, we performed a simple evaluation of the effects of *RUE* and *k* values to evaluate how an increase in these variables would help to reduce the gap between simulated and observed ADMY in Önnestad in 2014 for the Amagrano cultivar. *RUE* was increased to  $2.66 \text{ g}_{DM} \cdot \text{MJ}^{-1}$  based on the evidence from [51], and *k* values were increased to 0.8, 0.7 and 0.6 (previously 0.7, 0.5 and 0.4) for 20, 50 and 100 cm, respectively, of row spacing (<https://apsimnextgeneration.netlify.com/modeldocumentation/>). Although the increased values of these parameters logically result in an increase in ADMY, this approach did not fully close the gap between observations and simulations (Figure 8). This could be because the values of these parameters should be further increased, or other factors are currently unaccounted for by the model, such as the effect of day length on photorespiration.



**Figure 8.** Attempt to reduce the gap between predicted (lines) and observed (dots) above-ground dry matter yields by increasing the radiation use efficiency (*RUE*) and the coefficient of extinction *k* (Önnestad, 2014, Amagrano cv.)

#### 4.2.3. The Light Interception Efficiency

Another factor that might affect the accuracy of APSIM in the simulation of ADMY is the increased duration of day length at high latitudes. APSIM uses an adapted version of the efficiency model proposed by [45] to compute the daily biomass accumulation. This approach simulates net photosynthesis and does not separate the energy produced through photosynthesis from the energy used for photorespiration. Although this approach provides accurate results for tropical and temperate conditions, the extreme day length of the growing season at high latitudes might affect the accuracy of the biomass production model used in APSIM, as the effects of photorespiration are largely reduced due to the very short nights.

## 5. Conclusions

APSIM Next Generation (version 2018.10.10.3136) was used to simulate the growth of six maize silage cultivars at high latitudes ( $>55^\circ \text{ N}$ ). The relevant phenology parameters were calibrated to optimize the RMSE value of measured and simulated BBCH scaling. Although the accuracy of the simulation of the phenology was satisfactory, the above-ground dry matter simulated by the model largely underestimated the measured values. This underestimation can be due to several factors, with the first being the way in which APSIM assesses the effects of high latitude on the light interception of radiation. Indeed, the model does not account for the amount of diffuse light for the production of biomass. As the ratio of diffuse light increases with latitude, it can be expected that the model



underestimates biomass production. The effect of the low sun angle of high latitudes, also unaccounted for by APSIM, might also partly explain the underestimation of the biomass. Another factor that potentially affects the performance of the model is the increased day length observed at high latitudes that might eventually affect the balance between photorespiration and photosynthesis as currently simulated by APSIM. It appears that more measurements need to be performed to overcome the current issues, with a particular focus on leaves (leaf area index, leaf number, etc.) and radiation use efficiency measurements. These results address the question of the current limitations of the model structure used in APSIM and more generally in crop models for the simulation of biomass production. As little work has been performed at such high latitudes, especially for C4 plants, it is necessary to focus on the physical mechanisms that drive the light interception of radiation by the canopy and, eventually, the biomass production of the crop.

**Author Contributions:** Conceptualization, J.M.; methodology, J.M., D.P., A.P. and H.B.; software, J.M., A.P. and H.B.; formal analysis, J.M., D.P., U.K., A.P. and H.B.; data curation, J.M., M.A.H. and A.P.; writing—original draft preparation, J.M.; writing—review and editing, J.M., D.P., M.A.H., U.K., A.P., G.B., H.B. and M.H.; visualization, funding acquisition, M.H. and M.A.H. All authors have read and agreed to the published version of the manuscript.

**Funding:** This study was financed by the Swedish University of Agricultural Sciences, the Lantmännen Research Foundation (grant number 20120035), the Swedish Farmers' Foundation for Agricultural Research (grant number SLF H1260158) and Partnerskap Alnarp (grant number PA 677/12/Anim).

**Acknowledgments:** STRÅNG data used here are from the Swedish Meteorological and Hydrological Institute (SMHI) and were produced with support from the Swedish Radiation Protection Authority and the Swedish Environmental Agency. Acknowledgments are made to the APSIM Initiative, which takes responsibility for quality assurance and a structured innovation program for APSIM. APSIM is provided free for research and development use (see [www.apsim.info](http://www.apsim.info) for details).

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. FAO; FAOSTAT. CROPS (Dataset). (Latest Update: 28/05/2018). Available online: <http://www.fao.org/faostat/en/#data/QC> (accessed on 6 July 2018).
2. Filya, I. Nutritive value and aerobic stability of whole crop maize silage harvested at four stages of maturity. *Anim. Feed Sci. Technol.* **2004**, *116*, 141–150. [[CrossRef](#)]
3. Fogelfors, H.; Wivstad, M.; Eckersten, H.; Holstein, F.; Johansson, S.; Verwijst, T. *Strategic Analysis of Swedish Agriculture*; Institutionen för växtproduktionsekologi, Sveriges lantbruksuniversitet: Uppsala, Sweden, 2009; ISBN 91-86197-55-X.
4. Givens, D.I.; Deaville, E.R. Comparison of major carbohydrate fractions and cell wall digestibility in silages made from older and newer maize genotypes grown in the UK. *Anim. Feed Sci. Technol.* **2001**, *89*, 69–82. [[CrossRef](#)]
5. Jordbruksverket. Swedish Board of Agriculture. (In Swedish). 2018. Available online: <http://www.jordbruksverket.se/amnesomraden/odling/jordbruksgridor/majs/skordestatistik.html> (accessed on 6 July 2018).
6. Pachauri, R.K.; Allen, M.R.; Barros, V.R.; Broome, J.; Cramer, W.; Christ, R.; Church, J.A.; Clarke, L.; Dahe, Q.; Dasgupta, P. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; IPCC: Geneva, Switzerland, 2014; ISBN 92-9169-143-7.
7. Eckersten, H.; Herrmann, A.; Kornher, A.; Halling, M.; Sindhøj, E.; Lewan, E. Predicting silage maize yield and quality in Sweden as influenced by climate change and variability. *Acta Agric. Scand. Sect. B—Soil Plant Sci.* **2012**, *62*, 151–165. [[CrossRef](#)]
8. Atlin, G.N.; Cairns, J.E.; Das, B. Rapid breeding and varietal replacement are critical to adaptation of cropping systems in the developing world to climate change. *Glob. Food Secur.* **2017**, *12*, 31–37. [[CrossRef](#)]
9. Bouman, B.A.M.; Van Keulen, H.; Van Laar, H.H.; Rabbinge, R. The 'School of de Wit' crop growth simulation models: A pedigree and historical overview. *Agric. Syst.* **1996**, *52*, 171–198. [[CrossRef](#)]

10. Di Paola, A.; Valentini, R.; Santini, M. An overview of available crop growth and yield models for studies and assessments in agriculture: Overview of crop models for agriculture. *J. Sci. Food Agric.* **2016**, *96*, 709–714. [[CrossRef](#)]
11. Bassu, S.; Brisson, N.; Durand, J.-L.; Boote, K.; Lizaso, J.; Jones, J.W.; Rosenzweig, C.; Ruane, A.C.; Adam, M.; Baron, C.; et al. How do various maize crop models vary in their responses to climate change factors? *Glob. Chang. Biol.* **2014**, *20*, 2301–2320. [[CrossRef](#)]
12. Phelan, D.C.; Harrison, M.T.; Kemmerer, E.P.; Parsons, D. Management opportunities for boosting productivity of cool-temperate dairy farms under climate change. *Agric. Syst.* **2015**, *138*, 46–54. [[CrossRef](#)]
13. Phelan, D.C.; Parsons, D.; Lisson, S.N.; Holz, G.K.; MacLeod, N.D. Beneficial impacts of climate change on pastoral and broadacre agriculture in cool-temperate Tasmania. *Crop Pasture Sci.* **2014**, *65*, 194. [[CrossRef](#)]
14. Mesbah, M.; Pattey, E.; Jégo, G. A model-based methodology to derive optimum nitrogen rates for rainfed crops—A case study for corn using STICS in Canada. *Comput. Electron. Agric.* **2017**, *142*, 572–584. [[CrossRef](#)]
15. Phelan, D.C.; Harrison, M.T.; McLean, G.; Cox, H.; Pembleton, K.G.; Dean, G.J.; Parsons, D.; do Amaral Richter, M.E.; Pengilly, G.; Hinton, S.J.; et al. Advancing a farmer decision support tool for agronomic decisions on rainfed and irrigated wheat cropping in Tasmania. *Agric. Syst.* **2018**, *167*, 113–124. [[CrossRef](#)]
16. Peake, A.S.; Das, B.T.; Bell, K.L.; Gardner, M.; Poole, N. Effect of variable crop duration on grain yield of irrigated spring-wheat when flowering is synchronised. *Field Crops Res.* **2018**, *228*, 183–194. [[CrossRef](#)]
17. Peake, A.S.; Gilmour, A.; Cooper, M. The 1BL/1RS translocation decreases grain yield of spring wheat germplasm in low yield environments of north-eastern Australia. *Crop Pasture Sci.* **2011**, *62*, 276. [[CrossRef](#)]
18. Setiyono, T.D.; Weiss, A.; Specht, J.; Bastidas, A.M.; Cassman, K.G.; Dobermann, A. Understanding and modeling the effect of temperature and daylength on soybean phenology under high-yield conditions. *Field Crops Res.* **2007**, *100*, 257–271. [[CrossRef](#)]
19. Gaiser, T.; de Barros, I.; Sereke, F.; Lange, F.-M. Validation and reliability of the EPIC model to simulate maize production in small-holder farming systems in tropical sub-humid West Africa and semi-arid Brazil. *Agric. Ecosyst. Environ.* **2010**, *135*, 318–327. [[CrossRef](#)]
20. Jones, P.; Thornton, P. The potential impacts of climate change on maize production in Africa and Latin America in 2055. *Glob. Environ. Chang.* **2003**, *13*, 51–59. [[CrossRef](#)]
21. Scopel, E.; Da Silva, F.A.M.; Corbeels, M.; Affholder, F.; Maraux, F. Modelling crop residue mulching effects on water use and production of maize under semi-arid and humid tropical conditions. *Agronomie* **2004**, *24*, 383–395. [[CrossRef](#)]
22. Constantin, J.; Beaudoin, N.; Launay, M.; Duval, J.; Mary, B. Long-term nitrogen dynamics in various catch crop scenarios: Test and simulations with STICS model in a temperate climate. *Agric. Ecosyst. Environ.* **2012**, *147*, 36–46. [[CrossRef](#)]
23. Teixeira, E.I.; George, M.; Herreman, T.; Brown, H.; Fletcher, A.; Chakwizira, E.; de Ruiter, J.; Maley, S.; Noble, A. The impact of water and nitrogen limitation on maize biomass and resource-use efficiencies for radiation, water and nitrogen. *Field Crops Res.* **2014**, *168*, 109–118. [[CrossRef](#)]
24. Wilson, D.R.; Muchow, R.C.; Murgatroyd, C.J. Model analysis of temperature and solar radiation limitations to maize potential productivity in a cool climate. *Field Crops Res.* **1995**, *43*, 1–18. [[CrossRef](#)]
25. Ozturk, I.; Kristensen, I.S.; Baby, S. Sensitivity of silage-maize to climate change in Denmark: A productivity analysis using impact response surface. *Eur. J. Agron.* **2018**, *98*, 55–64. [[CrossRef](#)]
26. Herrmann, A.; Kornher, A.; Taube, F. A new harvest time prognosis tool for forage maize production in Germany. *Agric. For. Meteorol.* **2005**, *130*, 95–111. [[CrossRef](#)]
27. Torssell, B.W.R.; Kornher, A. Validation of a yield prediction model for temporary grasslands [Sweden]. *Swed. J. Agric. Res. Swed.* **1983**, *13*, 125–135.
28. Nkurunziza, L.; Kornher, A.; Hetta, M.; Halling, M.; Weih, M.; Eckersten, H. Crop genotype-environment modelling to evaluate forage maize cultivars under climate variability. *Acta Agric. Scand. Sect. B—Soil Plant Sci.* **2014**, *64*, 56–70. [[CrossRef](#)]
29. Hetta, M.; Mussadiq, Z.; Gustavsson, A.-M.; Swensson, C. Effects of hybrid and maturity on performance and nutritive characteristics of forage maize at high latitudes, estimated using the gas production technique. *Anim. Feed Sci. Technol.* **2012**, *171*, 20–30. [[CrossRef](#)]
30. Brisson, N.; Gary, C.; Justes, E.; Roche, R.; Mary, B.; Ripoche, D.; Zimmer, D.; Sierra, J.; Bertuzzi, P.; Burger, P.; et al. An overview of the crop model stics. *Eur. J. Agron.* **2003**, *18*, 309–332. [[CrossRef](#)]

31. Jones, J.; Hoogenboom, G.; Porter, C.; Boote, K.; Batchelor, W.; Hunt, L.; Wilkens, P.; Singh, U.; Gijsman, A.; Ritchie, J. The DSSAT cropping system model. *Eur. J. Agron.* **2003**, *18*, 235–265. [[CrossRef](#)]
32. Holzworth, D.P.; Huth, N.I.; deVoil, P.G.; Zurcher, E.J.; Herrmann, N.I.; McLean, G.; Chenu, K.; van Oosterom, E.J.; Snow, V.; Murphy, C.; et al. APSIM—Evolution towards a new generation of agricultural systems simulation. *Environ. Model. Softw.* **2014**, *62*, 327–350. [[CrossRef](#)]
33. Keating, B.A.; Carberry, P.S.; Hammer, G.L.; Probert, M.E.; Robertson, M.; Holzworth, D.; Huth, N.; Hargreaves, J.N.; Meinke, H.; Hochman, Z.; et al. An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.* **2003**, *18*, 267–288. [[CrossRef](#)]
34. Archontoulis, S.V.; Miguez, F.E.; Moore, K.J. Evaluating APSIM Maize, Soil Water, Soil Nitrogen, Manure, and Soil Temperature Modules in the Midwestern United States. *Agron. J.* **2014**, *106*, 1025. [[CrossRef](#)]
35. Peake, A.S.; Robertson, M.J.; Bidstrup, R.J. Optimising maize plant population and irrigation strategies on the Darling Downs using the APSIM crop simulation model. *Aust. J. Exp. Agric.* **2008**, *48*, 313. [[CrossRef](#)]
36. Pembleton, K.G.; Cullen, B.R.; Rawnsley, R.P.; Harrison, M.T.; Ramilan, T. Modelling the resilience of forage crop production to future climate change in the dairy regions of Southeastern Australia using APSIM. *J. Agric. Sci.* **2016**, *154*, 1131–1152. [[CrossRef](#)]
37. Seyoum, S.; Rachaputi, R.; Chauhan, Y.; Prasanna, B.; Fekybelu, S. Application of the APSIM model to exploit G × E × M interactions for maize improvement in Ethiopia. *Field Crops Res.* **2018**, *217*, 113–124. [[CrossRef](#)]
38. Passioura, J.B. Simulation Models: Science, Snake Oil, Education, or Engineering? *Agron. J.* **1996**, *88*, 690. [[CrossRef](#)]
39. Sinclair, T.R.; Seligman, N.G. Crop Modeling: From Infancy to Maturity. *Agron. J.* **1996**, *88*, 698. [[CrossRef](#)]
40. Peake, A.S.; Huth, N.I.; Kelly, A.M.; Bell, K.L. Variation in water extraction with maize plant density and its impact on model application. *Field Crops Res.* **2013**, *146*, 31–37. [[CrossRef](#)]
41. Zscheischler, J.; Estler, M.; Staudacher, W.; Groß, F.; Burgstaller, G.; Streyl, H.; Rechmann, T. *Handbuch Mais: Umweltgerechter Anbau, Wirtschaftliche Verwertung*; 4. vollkommen überarbeitete Auflage; DLG-Verlag: Frankfurt (Main), Germany, 1990; ISBN 978-3-7690-0473-1.
42. Lancashire, P.D.; Bleiholder, H.; Boom, T.V.D.; Langelüddeke, P.; Stauss, R.; Weber, E.; Witzemberger, A. A uniform decimal code for growth stages of crops and weeds. *Ann. Appl. Biol.* **1991**, *119*, 561–601. [[CrossRef](#)]
43. Holzworth, D.; Huth, N.I.; Fainges, J.; Brown, H.; Zurcher, E.; Cichota, R.; Verrall, S.; Herrmann, N.I.; Zheng, B.; Snow, V. APSIM Next Generation: Overcoming challenges in modernising a farming systems model. *Environ. Model. Softw.* **2018**, *103*, 43–51. [[CrossRef](#)]
44. Jones, C.A.; Kiniry, J.R.; Dyke, P.T. (Eds.) *CERES-Maize: A Simulation Model of Maize Growth and Development*, 1st ed.; Texas A&M University Press: College Station, TX, USA, 1986; ISBN 978-0-89096-269-5.
45. Monteith, J.L. Solar Radiation and Productivity in Tropical Ecosystems. *J. Appl. Ecol.* **1972**, *9*, 747. [[CrossRef](#)]
46. Brown, H.E.; Huth, N.I.; Holzworth, D.P.; Teixeira, E.I.; Wang, E.; Zyskowski, R.F.; Zheng, B. A generic approach to modelling, allocation and redistribution of biomass to and from plant organs. *Silico Plants* **2019**, *1*, diy004. [[CrossRef](#)]
47. Willmott, C.J. On the validation of models. *Phys. Geogr.* **1981**, *2*, 184–194. [[CrossRef](#)]
48. Allen, R.G. Assessing Integrity of Weather Data for Reference Evapotranspiration Estimation. *J. Irrig. Drain. Eng.* **1996**, *122*, 97–106. [[CrossRef](#)]
49. Seidel, S.J.; Palosuo, T.; Thorburn, P.; Wallach, D. Towards improved calibration of crop models—Where are we now and where should we go? *Eur. J. Agron.* **2018**, *94*, 25–35. [[CrossRef](#)]
50. van Ittersum, M.K.; Cassman, K.G.; Grassini, P.; Wolf, J.; Tittonell, P.; Hochman, Z. Yield gap analysis with local to global relevance—A review. *Field Crops Res.* **2013**, *143*, 4–17. [[CrossRef](#)]
51. Rodriguez, D.; Sadras, V.O. The limit to wheat water-use efficiency in eastern Australia. I. Gradients in the radiation environment and atmospheric demand. *Aust. J. Agric. Res.* **2007**, *58*, 287. [[CrossRef](#)]
52. Campbell, J.W.; Aarup, T. Photosynthetically available radiation at high latitudes. *Limnol. Oceanogr.* **1989**, *34*, 1490–1499. [[CrossRef](#)]
53. Zangvil, A.; Aviv, O.E. On the effect of latitude and season on the relation between the diffuse fraction of solar radiation and the ratio of global to extraterrestrial radiation. *Sol. Energy* **1987**, *39*, 321–327. [[CrossRef](#)]
54. Aikman, D.P. Potential Increase in Photosynthetic Efficiency from the Redistribution of Solar Radiation in a Crop. *J. Exp. Bot.* **1989**, *40*, 855–864. [[CrossRef](#)]

55. Gitelson, A.A.; Viña, A.; Arkebauer, T.J.; Rundquist, D.C.; Keydan, G.; Leavitt, B. Remote estimation of leaf area index and green leaf biomass in maize canopies. *Geophys. Res. Lett.* **2003**, *30*. [[CrossRef](#)]
56. Lindquist, J.L.; Arkebauer, T.J.; Walters, D.T.; Cassman, K.G.; Dobermann, A. Maize radiation use efficiency under optimal growth conditions. *Agron. J.* **2005**, *97*, 72–78. [[CrossRef](#)]



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).