4. Simulation of winter cover crops in autumn

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4.1 Introduction

Cover crops are non-productive crops that allow to avoid bare soil periods, thus improving soil quality and fostering cash crop production. Cover crop cultivation entails several agro-ecological benefits such as soil organic matter accumulation, nitrate leaching and soil erosion reduction, soil structure stability improvement and weed control. The impact of cover crop cultivation on soil organic matter accumulation and nitrate leaching depends on the interactions between cover crop management (species, sowing and termination date), soil characteristics (soil texture and soil mineral nitrogen content) and weather dynamics (rainfall amount and air temperature ranges during fall cultivation). A practical choice to simulate cover crop effects on soil mineral nitrogen and organic matter, is to represent the soil-plant-atmosphere system dynamics with dynamic simulation models.

Dynamic crop simulation models can assess the convenience of crop management options for a wide range of weather and soil conditions, while the field trial assessments require large resource investments. The simulation of cover crop growth and development, with the associated consequences on water, carbon and nitrogen cycles, supports an informed choice of sowing and termination dates, as well as to evaluate their agronomic and environmental effects. The evaluation of the effects of cover crop cultivation helps to analyse the consequence of the different management practises and can drive the implementation of public policies.

White mustard (*Sinapis alba* L.) and black oat (*Avena strigosa* L.) are two of the most widespread cover crops in Northern Italy. The former, when sowed in optimal conditions, is characterized by a rapid fall growth and biomass accumulation (up to 4.5 t DM ha^{-1}, Haramoto and Gallandt, 2004; Mancinelli et al., 2015; Tadiello et al., 2022) thus allowing to quickly obtain high soil cover levels. On the other hand, even if black oat growth is more limited (up to 3.1 t DM ha^{-1}, Dial, 2014; Schappert et al., 2019; Tadiello et al., 2022), this species is widely adopted due to its fasciculated root system that retaines nitrogen thus reducing leaching losses. Both species also are characterized by high nitrogen uptake levels (20-135 kg N ha^{-1}, Mancinelli et al., 2015;

Richards et al., 1996; Tadiello et al., 2022; Thorup-Kristensen et al., 2003) and are able to effectively control weed species. A dynamic crop model, calibrated to simulate white mustard and black oat cover crops, will allow to evaluate the effects of the interaction between different sowing dates and nitrogen availability on their biomass accumulation, nitrogen uptake and soil cover. Furthermore, it will also provide estimates of soil mineral nitrogen content reduction due to their cultivation, thus allowing to assess the overall effect of cover crop on the protection of deep water bodies. In comparison with field trials, the evaluation performed through the use of a simulation model enbles to test a wider range of sowing date and nitrogen availability combinations, as well as to consider soil and weather variability within the region of interest.

Furthermore, need of calibrating a dynamic crop model to simulate white mustard and black oat has arisen from the need of supporting cover crop management decision within the area of interest, that is characterised by high nitrogen surpluses (Bechini and Castoldi, 2009; Fumagalli et al., 2011).

Few simulation models already simulate white mustard and black oat, among which the most widely used is STICS (Brisson et al., 2008), while HERMES (Kersebaum, 2010) is less commonly used. STICS was calibrated and validated using several experimental databases (Constantin et al., 2015), including crop rotations with mustard, annual ryegrass (*Lolium multiflorum* L.) and common vetch (*Vicia sativa* L.). Then the model was applied in different climatic conditions in France, to evaluate the effect of sowing and termination date on nitrate leaching. The considered sowing date and termination date time frames were limited (respectively from August 2 to September 19 and from November 10 to January 25). Only a few more models address cover crop simulation (Chirinda et al., 2010; Doltra et al., 2019; Leuthold et al., 2021; McClelland et al., 2021b; Melkonian et al., 2017; Olesen et al., 2000), but white mustard and black oat are not parameterized yet, as shown below. The FASSET model was used (Doltra et al., 2019) to evaluate soil fertility management practices (including cover crop cultivation) and their effect on cash crop yield and soil nitrogen dynamics with a focus on N_2O emissions. The simulated cover crop datasets included perennial ryegrass (*Lolium perenne* L.) and a mixture of ryegrass and four leguminous species (hop medic, *Medicago lupulina* L.; trefoil, *Lotus corniculatus* L.; serradella, *Ornithopus sativus* Brot.*;* and subterranean clover, *Trifolium subterraneum* L.) (Chirinda et al., 2010; Olesen et al., 2000). The DSSAT v4.7.0.001 simulation model was applied to address maize (*Zea mays* L.) yield decrease caused by cereal rye (*Secale cereale* L.) cultivation, as autumn-winter cover crop, in sloping

sites (Leuthold et al., 2021). The DayCent model, implemented in the decision support tool COMET-Farm, was employed to assay differences between cover crop and bare soil systems in terms of N_2O emissions and soil organic matter accumulation (McClelland et al., 2021b). This study used published cover crop data, summarized by a meta-analysis (McClelland et al., 2021a), regarding annual ryegrass, cereal rye and hairy vetch (*Vicia villosa* Roth.). The PNM (precision nitrogen management) model (Melkonian et al., 2017) was calibrated to simulate cereal rye and hairy vetch residue mineralisation after termination. Thus, despite their interest in conservation agriculture, cover crops are not frequently simulated with cropping system models, and the two species of interest in this work (white mustard and black oat) are considered rarely.

ARMOSA (Perego et al., 2013) is a dynamic cropping system model, that simulates, at a daily time-step at field scale, crop development and growth, and water and nitrogen dynamics in the soil-plant-atmosphere system. It has a modular structure that involves a micrometeorological model, a crop development and growth model, a soil water balance model and a soil N and carbon balance model. The crop module employs the following calculated variables: evapotranspiration, soil water content, soil nitrogen and carbon contents. The crop growth module is based on gross assimilation of carbon dioxide (CO_2), and estimates maintenance and growth respiration to obtain the final net carbon assimilation as implemented in SUCROS (van Keulen et al., 1982) and WOFOST models (van Keulen and Wolf, 1986). ARMOSA simulates already a variety of cash crops among which grain and silage maize, winter wheat (*Triticum aestivum* L.) and annual ryegrass. However, ARMOSA was never applied to cover crops.

Therefore, the objective of this study is to calibrate and validate the ARMOSA model to simulate the fall growth and development of white mustard and black oat cover crops.

4.2 Materials and methods

4.2.1 Calibration and validation datasets

The model was calibrated and validated using measured data collected over five years in five sites in Lombardia plain (Northern Italy) during field trials involving white mustard and black oat. The sites, reported in Table 1, were the following: Ghedi (GHE, province of Brescia, 45° 23’ N, 10° 17’ E), Landriano (LAN, province of Pavia, 45° 32’ N, 9° 26’ E), Orzinuovi (ORZ, province of Brescia, 45° 23’ N, 9° 54’ E), Sant’Angelo Lodigiano (SAN, province of Lodi, 45° 13’ N, 9° 25’ E) and Sesto ed Uniti (SES, province of Cremona, 45° 17’ N, 9° 91’ E).

The calibration dataset comprised data deriving from the combination of five sites (GHE, LAN, ORZ, SAN and SES) and five years. Cover crop sowing dates ranged between August 30 and September 29; cover crop organic nitrogen fertilisation ranged between no slurry application and cattle slurry application (40 m^3 ha^{-1}) a few days before planting, while pre-planting mineral nitrogen fertilisation was either 0 or 50 kg N ha^{-1}. Emergency irrigation was applied in Sant'Angelo Lodigiano during the season 2017/2018, and the total amount of water distributed one month after cover crop sowing was 25 mm. The validation dataset includes measured data collected over two years in four sites of the Lombardia plain (LAN, ORZ, SAN and SES). In the validation dataset, cover crop sowing dates ranged between September 5 and 25. The cultivated white mustard variety was Architect in all the site*year combinations of the calibration and validation datasets, except for Ghedi 2019 (var. Octopus), Ghedi 2020 and Ghedi 2021 (both var. Architect and var. Octopus were tested). The cultivated black oat variety was Saia 6 in all the site*year combinations of the calibration and validation datasets, except for the site Ghedi (var. Iapar 61).

Table 1. Characteristics of calibration and validation data sets: cover crop species (black oat, O; white mustard, M), site, years, and treatment. The treatments are organic or mineral fertilisation (no fertilisation, N_0; slurry or mineral fertilizer applied, N_1), sowing dates (early sowing date, S_1; late sowing date, S_2).

Species	Site	Calibration Year	Validation Year	Treatment	Number of data points per year	Reference
O and M	GHE	2019, 2020 and 2021	-	-	from 1 to 4	This thesis
O	LAN	2018	2017	organic N_0 and N_1	1	Tadiello et al. 2022
O	ORZ	2017	-	S_1 and S_2	1	Cavalli et al. 2019
M	ORZ	2017	2018	S_1 and S_2	1	Cavalli et al. 2019
O and M	ORZ	2018	2017	organic N_0 and N_1	1	Tadiello et al. 2022
O and M	SAN	2017	2018	mineral N_0 and N_1 * S_1 and S_2	1	Cavalli et al. 2019
O and M	SES	2018	2017	-	1	Tadiello et al. 2022

Measurements of aboveground biomass (AGB), nitrogen content in AGB (AGB-N) and soil mineral nitrogen (SMN) were carried out from one to 4 times during the cover crop fall growing season for each site x year combination. For one site (GHE), measured daily soil water content and temperature (at 10, 20 and 30 cm depth) were also available (recorded through Drill and Drop probes, Sentek, Stepney SA, AU).

4.2.2 Soil parameterisation and weather variables

The soil of the five sites, according to the USDA soil texture classification, were sandy-loam (GHE and ORZ) and loam (LAN, SAN and SES). Soil profiles were parameterised using measurements from the upper soil layer (0-30 cm depth), combined with information from the pedological map for deeper layers (Ersal, 1993; Ersal and Provincia di Cremona, 1997; Ersal and Regione Lombardia, Direzione Generale Presidenza, 2000; Giampaolo Dell'Acqua, 2002-2003). Daily weather variables (air temperature, humidity, wind speed, rain and global solar radiation) were obtained, for each site except for GHE, from the nearest weather station belonging to the regional agency for the environment protection (ARPA), located at a distance of 1-12 km from the experimental sites. For GHE weather variables were recorded from an on-site weather station (Vantage Pro2 Gro-Weather, Davis Instruments, Hayward, CA).

4.2.3 Crop parameter calibration and validation

The range of variation of crop parameters was derived from literature regarding black oat and white mustard or similar crops (Table 2). Literature values for KDF coefficient refer to the global radiation, not to the photosynthetically active radiation.

Following a detailed sensitivity analysis of ARMOSA (Perego and Acutis, personal communication), it resulted that biomass accumulation is most sensitive to these parameters: AssimilationRateCO_2, PhotoperiodCriticalThreshold and aCrit.

Table 2. Range of variation of the ARMOSA model parameters that were subject to calibration, and their sources.

			Black oat			White mustard		
Parameter	**Unit**	**Definition**	**Min**	**Max**	**Source**	**Min**	**Max**	**Source**
Tbase	°C	Minimum temperature under which no GDD (Growing Degree Days) are cumulated	4.0	4.8	Tribouillois et al. 2016 Brisson et al. 2008 Mantai et al. 2017	1.0	3.3	Tribouillois et al. 2016 Brisson et al. 2008 van Schothorst 2015 Gill et al. 2007 Kersebaum 2010
Topt_min	°C	Minimum temperature above which the GDD cumulation is optimal	22.0	27.8		20.0	29.6	
Topt_max	°C	Maximum temperature under which the GDD cumulation is optimal	22.0	27.9		20.0	29.6	
Tcutoff	°C	Maximum temperature above which no GDD are cumulated	30.0	35.8		40.0	40.4	
CumulatedGDD	°C d	Cumulated Growing Degrees Day necessary to reach flowering stage from emergence	550	700		502	524	van Schothorst 2015 Kersebaum 2010
VernDays	d	Number of days at optimal vernalization temperature, needed for a full vernalization	0	0	Sampson and Burrows 1972 Brisson et al. 2008	0	0	Brisson et al. 2008 van Schothorst 2015 Bernier and Périlleux 2005 D'Aloia et al. 2008
Photoperiod CriticalThreshold	h	Photoperiod below which development rate is halted	8.0	8.0	Sampson and Burrows 1972 Brisson et al. 2008	9.0	10.5	Brisson et al., 2008 Kinet, 1972 van Schothorst 2015 García et al. 2017
Photoperiod OptimalThreshold	h	Photoperiod above which development rate is not limited by daylight hours	18.0	20.0		16.0	20.0	
$TbaseCO_2$	°C	Minimum temperature under which no CO_2 is assimilated	3.8		Brisson et al. 2008	3.3		Brisson et al. 2008
$Topt\_minCO_2$	°C	Minimum temperature above which CO_2 assimilation is optimal	26.0			12.0		
$Topt\_maxCO_2$	°C	Maximum temperature under which the CO_2 assimilation is optimal	31.6			20.0		
$TcutoffCO_2$	°C	Maximum temperature above which no CO_2 is assimilated	35.8			38.0		
AssimilationRate CO_2	g CO_2 m^{-2} leaf	Maximum CO_2 assimilation rate at light saturation	0.0010	0.0011	de Wit et al. 2020	0.0014	0.0015	de Wit et al. 2020

KDF	unitless	Photosynthetically Active Radiation extinction coefficient	0.4	0.6	Brisson et al. 2008	0.4	0.5	Brisson et al. 2008
SLA	m^2 leaf g^{-1}	LAI to green leaves biomass ratio	0.030	0.050	Brisson et al. 2008 Ramos Junior et al. 2013	0.045	0.045	Brisson et al. 2008
aMin	kg N kg^{-1} DM	Nitrogen dilution curve minimum concentration coefficient	0.015		Colnenne et al. 1998	0.020		Colnenne et al. 1998
aCrit	kg N kg^{-1} DM	Nitrogen dilution curve critical concentration coefficient	0.045			0.040		
aMax	kg N kg^{-1} DM	Nitrogen dilution curve maximum concentration coefficient	0.075			0.050		
B	kg N kg^{-1} DM	Nitrogen dilution curve b coefficient	0.300			0.340		
Cleaves	unitless	Carbon concentration in leaves	0.43		measured	0.38		measured
Cstem	unitless	Carbon concentration in stem	0.43			0.38		
WaterStressCoeff	Unitless	Water stress sensitivity coefficient (it ranges from 7, low sensitivity, to 14, high sensitivity)	7	14	ARMOSA Italian ryegrass (*Lolium multiflorum* L.)	7	14	ARMOSA oilseed rape (*Brassica napus* L.)
RootsMaxDepth	m	Maximum rooting depth	0.3		measured	0.4		measured

Wilting point, field capacity and water content at saturation were calibrated for the site GHE, where they assumed the following values: 23%, 39% and 45%, while in the other sites they were estimated based on soil texture using ARMOSA's pedotransfer functions. For the site GHE, initial values of soil water content were set based on measurements, while for the other sites they were derived by simulating the ordinary agronomic management of the year preceding cover crop. Soil mineral nitrogen content at the beginning of the simulation was adjusted on the basis of the first measurement, when available.

The agreement between measured and simulated data was assessed using the relative root mean squared error (RRMSE, Loague and Green, 1991), the modelling efficiency (EF, Nash and Sutcliffe, 1970), the coefficient of residual mass (CRM) and the coefficient of correlation (r, Addiscott and Whitmore, 1987). RRMSE (Eq. 1) ranges between 0 (minimum and optimal value) and 100 (maximum value). The optimal value of EF (Eq. 2) is 1; when positive, it indicates that model estimates are better predictors than the mean of the observed values (on the contrary, a negative EF indicates a worse fit than the mean of the observed values).

$$RRMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i - M_i)^2}{n}} \cdot \frac{100}{\bar{M}} \quad [1]$$

$$EF = \frac{\sum_{i=1}^{n}(M_i - \bar{M})^2 - \sum_{i=1}^{n}(M_i - E_i)^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \quad [2]$$

CRM (Eq. 3) optimal value is equal to 0; its negative value indicates that the model overestimates measurements (on the other hand, its positive value indicates underestimation). The coefficient of correlation r (Eq. 4) ranges between 0 (no correlation) and 1 (maximum and optimum value, it indicates perfect correlation).

$$CRM = \frac{\sum_{i=1}^{n} M_i - \sum_{i=1}^{n} E_i}{\sum_{i=1}^{n} M_i} \quad [3]$$

$$r = \frac{\sum_{i=1}^{n}(E_i - \bar{E}) \cdot (M_i - \bar{M})}{\sqrt{\sum_{i=1}^{n}(E_i - \bar{E})^2 \cdot (M_i - \bar{M})^2}} \quad [4]$$

In all the equations, M_i is the i_{th} measured value, while E_i is the simulated i_{th} value. The number of data pairs (measured-simulated) is represented by n, while $\bar{M}$ and $\bar{E}$ are respectively the mean of measured and simulated values. The fitting indices for the measured variables were calculated separately for each site*treatment combination, both for the calibration and the validation datasets. The EF was calculated only for the site (GHE) presenting at least two observed values.

4.3 Results

4.3.1 Simulation of cover crop development (calibration)

The calibrated values of crop development parameters are reported, for black oat and white mustard, in Table 3. ARMOSA correctly simulated crop phenological stage (BBCH) in the site (GHE) for which phenological stage observations were available, with a RRMSE of 25.7%.

Table 3. Calibrated crop development parameters. See Table 2 for a description of each parameter.

Parameter	Measurement units	Black oat	White mustard
Tbase	°C	4.8	3.3
Topt_min	°C	20.0	20.0
Topt_max	°C	30.0	25.0
Tcutoff	°C	35.8	40.0
CumulatedGDD	unitless	540	769
VernDays	d	0	0
PhotoperiodCriticalThreshold	h	8	8
PhotoperiodOptimalThreshold	h	16	11

4.3.2 Simulation of cover crop growth (calibration)

The calibrated values of crop growth parameters are reported, for black oat and white mustard, in Table 4. The calibrated parameters concerned CO_2 assimilation and the nitrogen dilution curve, as well as water deficiency stress sensitivity and root depth.

Table 4. Calibrated crop growth parameters. See Table 2 for a description of each parameter.

Parameter	Measurement units	Black oat	White mustard
$TbaseCO_2$	°C	3.8	3.0
$Topt\_minCO_2$	°C	18.0	16.0
$Topt\_maxCO_2$	°C	25.0	22.0
$TcutoffCO_2$	°C	36.0	38.0
$AssimilationRateCO_2$	g CO_2 m^{-2} leaf	0.0011	0.0015
KDF	unitless	0.6	0.6
SLA	m^2 leaf g^{-1} DM	0.030	0.028
aMin	kg N kg^{-1} DM	0.015	0.020
aCrit	kg N kg^{-1} DM	0.045	0.040
aMax	kg N kg^{-1} DM	0.060	0.050
b	kg N kg^{-1} DM	0.30	0.34
Cleaves	unitless	0.43	0.38
Cstem	unitless	0.43	0.38
WaterStressCoeff	unitless	14	8
RootsMaxDepth	m	0.3	0.4

Overall, the performance was good in the simulation of aboveground biomass (Table 5). The results were less satisfactory for the N concentration of the above ground biomass, and for soil nitrate and ammonium, with RRMSE and CRM not sufficiently close to their optimal values.

Table 5. Average values of evaluation indices of model performance in the five calibration sites. RRMSE (%) is the relative root mean squared error, r (unitless) is the coefficient of determination and CRM (unitless) is the coefficient of residual mass.

	Black oat			**White mustard**		
Variable	**RRMSE**	**r**	**CRM**	**RRMSE**	**r**	**CRM**
Above-ground biomass	27	0.68	0.21	33	0.64	0.19
Above-ground biomass nitrogen concentration	47	0.29	-0.36	25	0.02	-0.04
Nitrate content (0-30 cm depth)	62	0.28	0.37	75	0.48	0.52

As to black oat simulations (Figure 1), AGB was in most cases underestimated: 11 out of 14 simulations reported a positive CRM. Underestimation of AGB was higher for the simulations with late sowing dates (GHE 2021, ORZ S_2, SAN S_2). The agreement between measured and simulated AGB was better (RRMSE < 12%) for the simulations with an organic or mineral fertilisation (LAN N_1, ORZ N_1, SAN S_1*N_1). On the contrary, AGB-N was in most cases overestimated: 10 out of 14 simulations reported a negative CRM value. For the simulation with an organic or mineral fertilisation (LAN N_1, ORZ N_1, SAN S_1*N_1, SAN S_1*N_2) the overestimation was higher (average CRM value of -0.47) than the simulation without fertilisation (average CRM value of -0.32), since the model fit was better for the N_0 simulation (average RRMSE value of 41%) than for the N_1 simulation (average RRMSE value of 62%). NO_3 content in the upper soil layer (0-30 cm) was generally underestimated (in 6 out of 8 cases, CRM was ranging between 0.32 to 0.82).

White mustard AGB simulations (Figure 2) underestimated the measured values in all cases except for GHE 2019 and GHE 2020. The underestimation was higher for N_1 simulations (ORZ N_1, SAN S_1*N_1, SAN S_1*N_2) than for N_0 simulations: the former simulations scored an average CRM value of 0.51, while the CRM average value for the latter was 0.11. Furthermore, the underestimation was higher (average CRM of 0.34) in the early (S_1) than in the late sowing dates (S_2, average CRM of 0.05), with a higher RRMSE in S_1 than in S_2 (39% vs. 28%). The agreement between measured and simulated AGB values of N_0 simulations was higher (average RRMSE equal to 29%) compared to N_1 (average RRMSE of 51%). For AGB-N values a moderate overestimation was prevalent; N_1 simulations obtained a higher agreement between simulated and measured values (average

RRMSE of 10%) than N_0 (average RRMSE of 29%). NO_3 content in the upper soil layer (0-30 cm) was generally underestimated (in 7 out of 8 cases, with CRM ranging from 0.06 to 0.93).

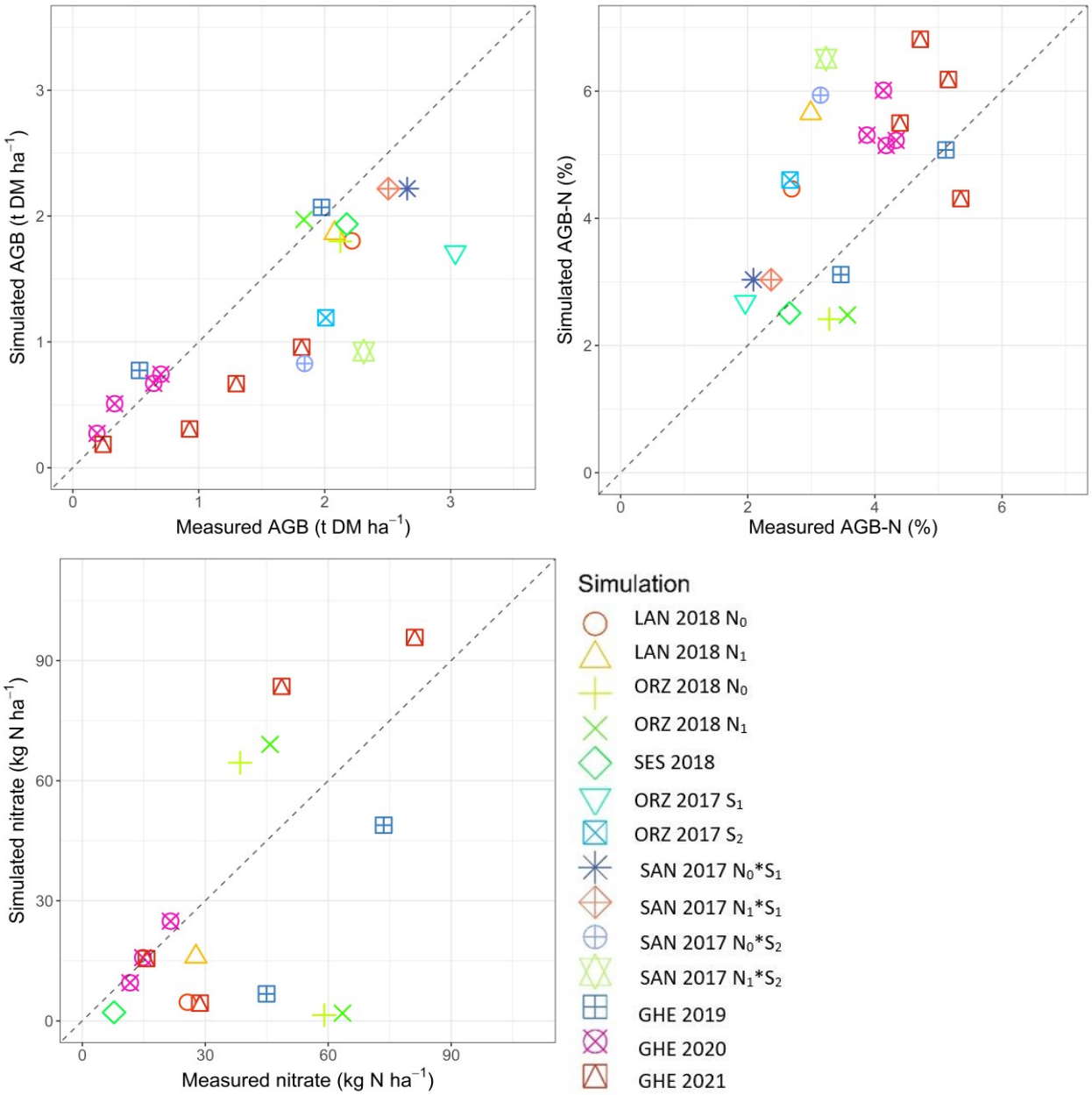

Figure 1: Results of black oat calibration (each site x year combination is represented by a different color x shape combination). The 1:1 line is dashed.

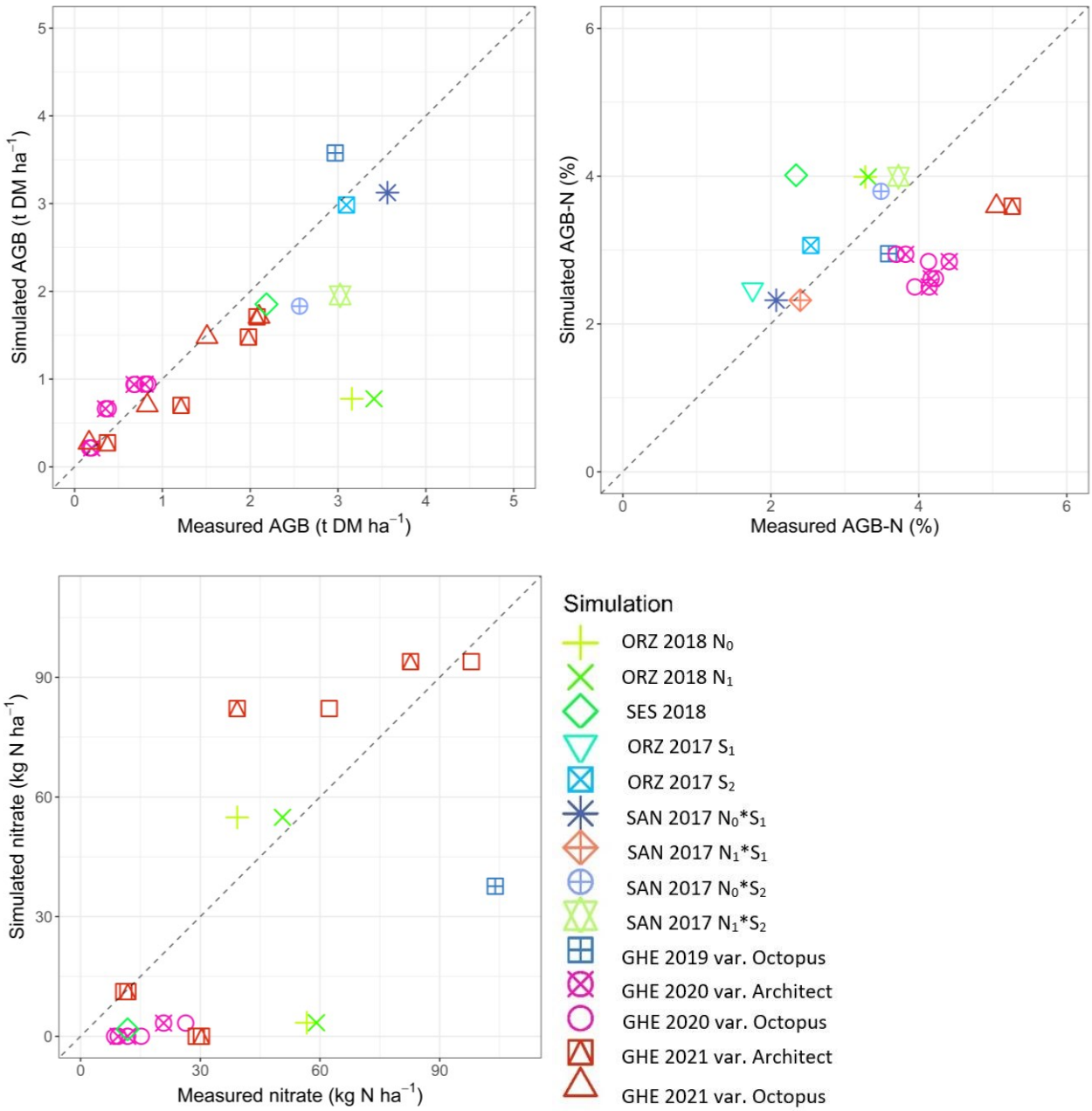

Figure 2: Results of white mustard calibration (each site x year combination is represented by a different color x shape combination). The 1:1 line is dashed.

For the site GHE, the RRMSE of black oat AGB simulation is respectively equal to 15% (2019), 21% (2020) and 58% (2021), while for AGB-N it is respectively equal to 6%, 33% and 28%. Furthermore, the EF for AGB is equal to 0.93, 0.78 and -0.15, respectively for the three years, while CRM is -0.13, -0.15 and 0.51. AGB-N simulation CRM were respectively equal to 0.05, -0.31 and -0.16. For this site, as reported in Figure 3, AGB trends were correctly reproduced during the first two years, while during the third-year black oat AGB was underestimated from the beginning of November. During 2020 and 2021, AGB-N was instead overestimated from the beginning of November. RRMSE of SMN was on average equal to 80%: soil NH_4 content was

prevalently underestimated during 2020 and 2021. The RRMSE of SWC simulation (Figure 4) was on average equal to 15% (10 cm), 10% (20 cm) and 4% (30 cm), while the RRMSE of ST simulation was respectively 25% (10 cm), 19% (20 cm) and 18% (30 cm).

RRMSE of white mustard AGB (Figure 5) is respectively equal to 20% (2019), 40% (2020) and 16% (2021), while for AGB-N it is respectively equal to 18%, 34% and 30%. Furthermore, the CRM for AGB simulation is equal to -0.21, -0.35 and 0.18 respectively for 2019, 2020 and 2021 while the EF is equal to 0.33 and 0.78 respectively for 2020 and 2021. In this site, AGB accumulation trends were correctly simulated, while AGB-N was generally underestimated during all the three years. RRMSE of SMN was on average equal to 82%, since, as in the case of black oat, soil NH_4 content was prevalently underestimated during the last two years of the trial. The RRMSE of SWC (Figure 6) was on average 11% (10 cm), 7% (20 cm) and 5% (30 cm), while the RRMSE of ST was respectively 38% (10 cm), 28% (20 cm) and 26% (30 cm).

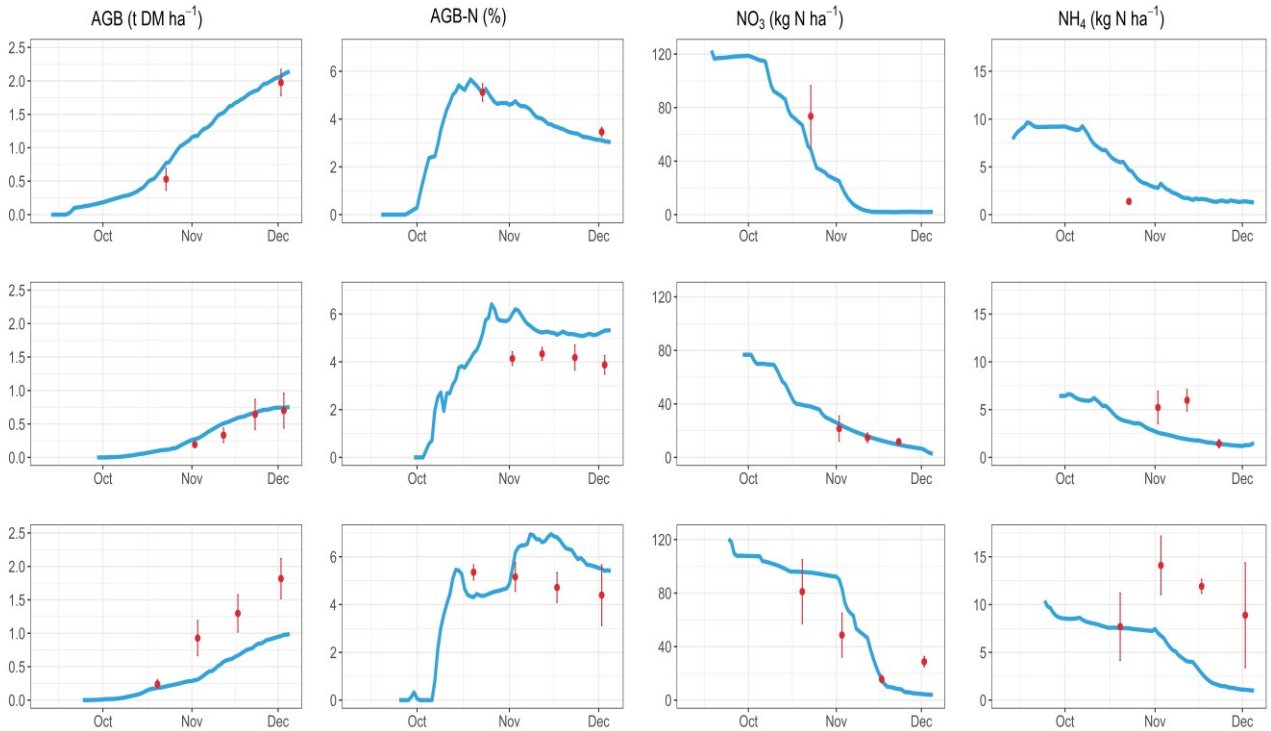

Figure 3: Black oat AGB, AGB-N and SMN (NO_3 and NH_4) at 0-30 cm depth in the site GHE, from the top: 2019 (first row), 2020 (second row) and 2021 (third row). Simulated values are reported by light-blue lines, measured values are reported by red dots. Error bars report standard deviations of measured values.

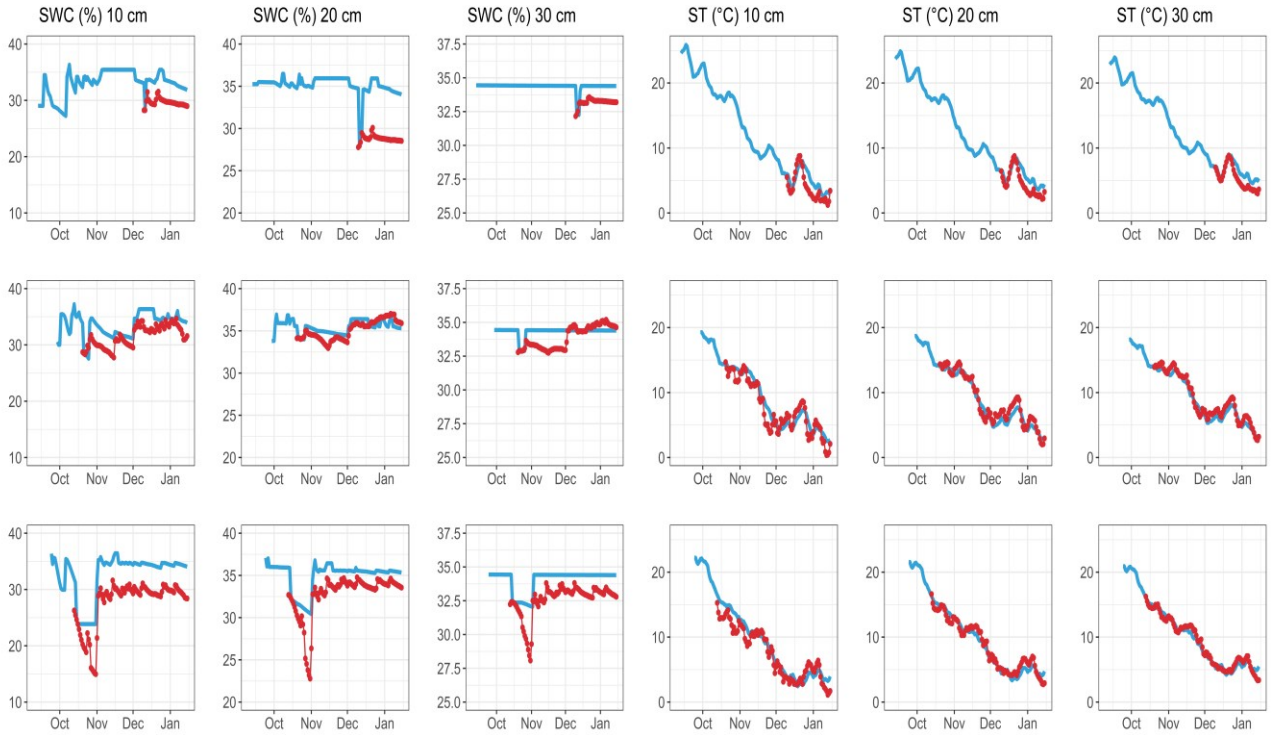

Figure 4: Black oat SWC and ST (at three depths: 10, 20 and 30 cm) in the site GHE, from the top: 2019 (first row), 2020 (second row) and 2021 (third row). Simulated values are reported by light-blue lines, measured values are reported by red dots.

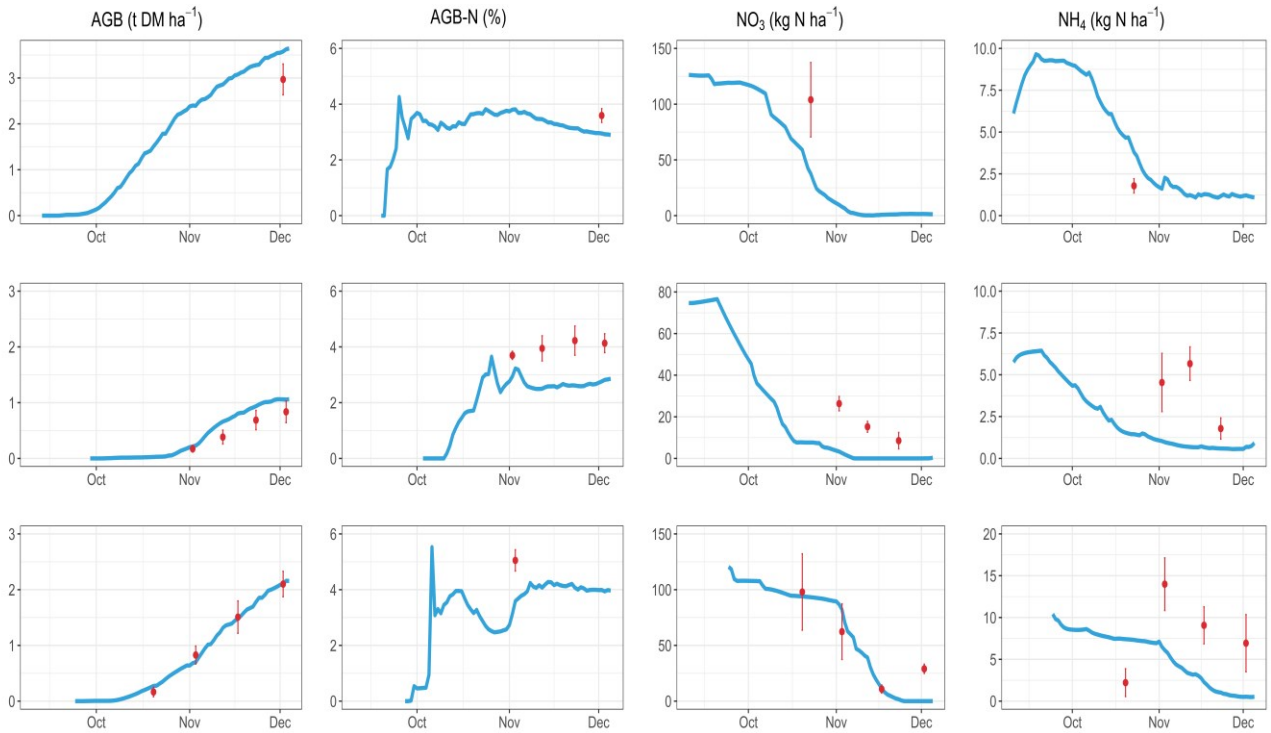

Figure 5: White mustard AGB, AGB-N and SMN (NO_3 and NH_4) in the site GHE, from the top: 2019 (first row), 2020 (second row) and 2021 (third row). Simulated values are reported by light-blue lines, measured values are reported by red dots. Error bars report standard deviations of measured values.

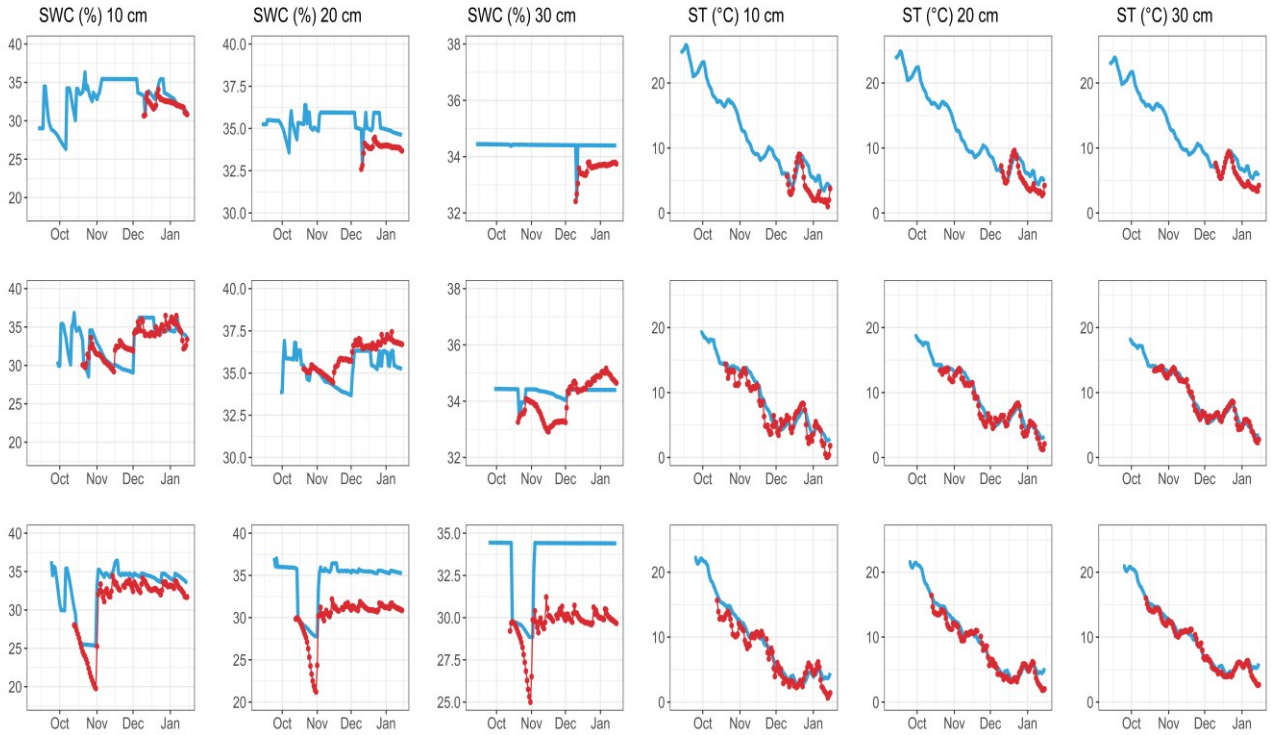

Figure 6: White mustard SWC and ST (at three depths: 10, 20 and 30 cm) in the site GHE, from the top: 2019 (first row), 2020 (second row) and 2021 (third row). Simulated values are reported by light-blue lines, measured values are reported by red dots.

4.3.3 Model validation

The results of model validation, for both species, are reported in Table 6. Generally, the model showed a moderate to good agreement between measured and simulated crop-related variables (AGB and AGB-N), while model performance for nitrate content of the upper soil layer (0-30 cm) was variable.

Table 6. Average values, for the validation dataset, of evaluation indices of model performance. RRMSE (%) is the relative root mean squared error, r (unitless) is the coefficient of determination and CRM (unitless) is the coefficient of residual mass.

	Black oat			**White mustard**		
Variable	**RRMSE**	**r**	**CRM**	**RRMSE**	**r**	**CRM**
Above-ground biomass	34	0.78	0.34	37	0.05	0.23
Above-ground biomass nitrogen concentration	26	0.73	-0.26	26	0.54	-0.08
Nitrate content (0-30 cm depth)	25	0.93	0.25	58	0.99	0.55

The results of the model validation for black oat are reported in Figure 7. For AGB the agreement between simulated and measured values was higher for N_0 (LAN N_0, ORZ N_0, SAN S_1*N_0, SAN S_2*N_0 and SES N_0) that reported an average RRMSE of 28%. The N_1 simulations (LAN N_1, ORZ N_1, SAN S_1*N_1, SAN S_2*N_1) reported an average RRMSE of 41%. As to AGB-N, both N_1 and N_0 treatments reported a similar agreement. Although the

agreement between simulated and measured values of AGB and AGB-N was sufficient, the simulation of these two variables was characterized respectively by underestimation and overestimation. For AGB simulation, the underestimation was lower for N_0 simulations (average CRM value of 0.28) than for N_1 simulations (average CRM value of 0.41), while the overestimation of AGB-N was equivalent in both types of simulations.

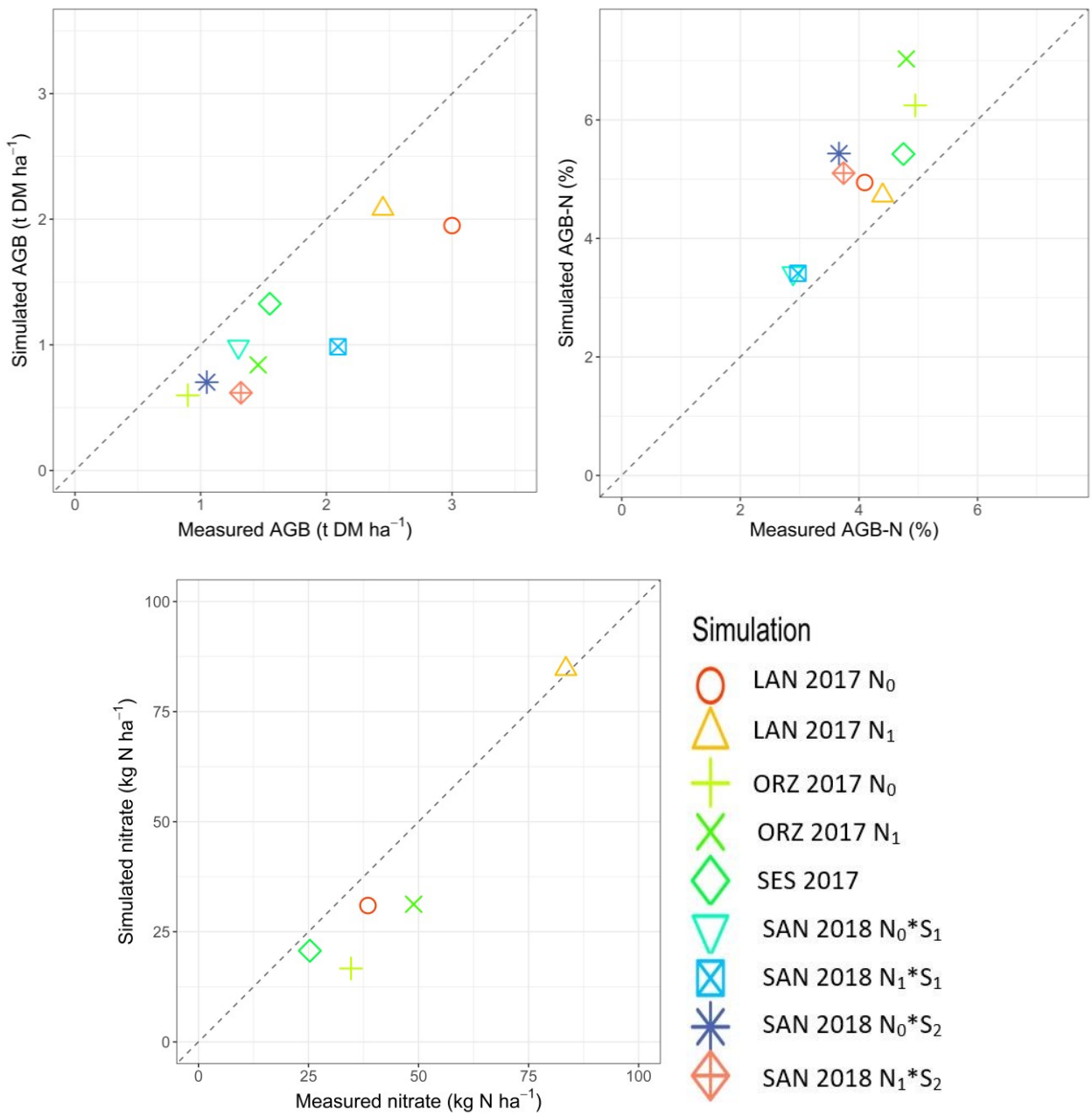

Figure 7: Results of black oat validation (each site x year combination is represented by a different colour x shape combination). The 1:1 line is dashed.

The agreement between simulated and measured NO_3 content in the upper soil layer was higher for N_1 simulations (average RRMSE of 19%) than for N_0 simulations (average RRMSE of 30%). The N_1 simulations

also reported a lower underestimation of this variable (average CRM of 0.18) when compared to N_0 simulations (average CRM of 0.30).

Model validation results for white mustard are reported in Figure 8. As for black oat, the agreement between simulated and measured values was sufficient for AGB and AGB-N, while model fitting of the nitrate content was not sufficiently close to the optimal value.

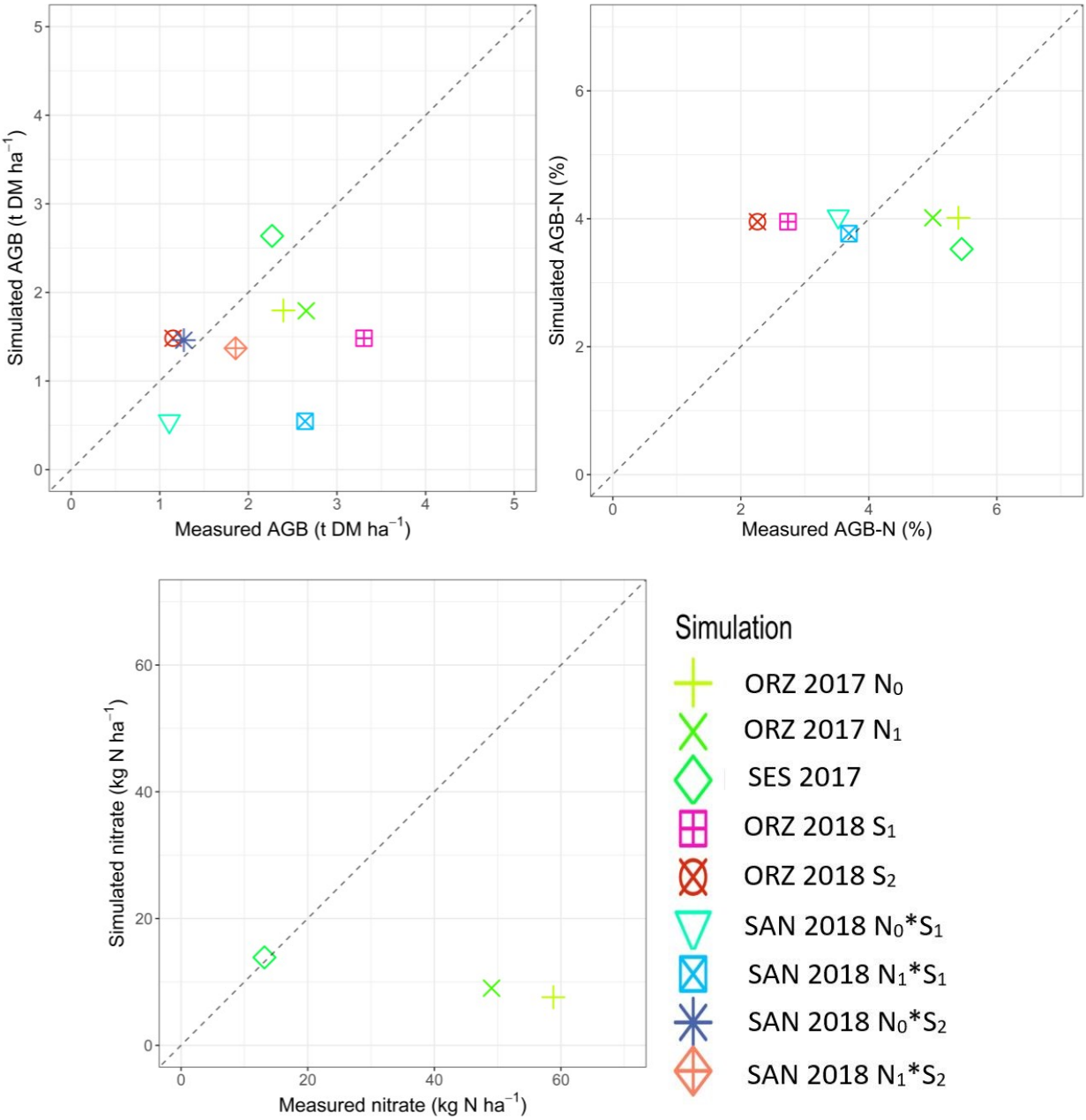

Figure 8: Results of white mustard validation (each site x year combination is represented by a different colour x shape combination). The 1:1 line is dashed.

As in the case of black oat, the N_0 simulations (ORZ S_1, ORZ S_2, ORZ N_0, SAN S_1*N_0, SAN S_2*N_0 and SES N_0) reported a higher agreement between simulated and measured values of AGB (average RRMSE of 32%)

compared to N_1 simulations (ORZ N_1, SAN S_1*N_1, SAN S_2*N_1) that obtained a higher RRMSE (46%). The underestimation of this variable was lower (average CRM of 0.12) in the first cases than in the second ones (average CRM of 0.46). Concerning AGB-N, on the contrary, the agreement was higher for N_1 simulations (average RRMSE of 32%) than for N_0 simulations (average RRMSE of 44%). This variable was overestimated in N_1 simulations (average CRM value of -0.19) and it was underestimated in N_0 simulations (average CRM value of 0.01). NO_3 content simulation was more accurate in N_0 simulations (average RRMSE of 46%) than in N_1 simulations (average RRMSE of 82%).

4.4 Discussion

The calibration site with the highest number of measured variables (BBCH, AGB, AGB-N, C to N ratio of AGB, NO_3 and NH_4 content from the layer 0-30 and 30-45 cm, SWC and ST at 10, 20 and 30 cm depths) was GHE. Furthermore, this site also had the highest number of measured datapoints (up to four for the period sowing date-first half of December) and an on-site weather station (performing hourly measurements). The other calibration sites had less soil and crop information to be employed for calibration, with measurements of AGB, AGB-N, NO_3 and NH_4 content from the layer 0-30 cm, a maximum of two datapoints, and weather variables obtained from the nearest weather station. Overall, the behaviour exhibited both by black oat and white mustard during the field trials belonging to the calibration dataset was rather variable. White mustard above-ground biomass at the end of November/beginning of December ranged from 0.36 to 6.03 t DM ha^{-1}, with an average of 2.87 t DM ha^{-1} (± 1.38 t DM ha^{-1}); the corresponding values for black oat were 0.47 to 4.14 t DM ha^{-1} with an average value of 2.09 t DM ha^{-1} (± 0.67 t DM ha^{-1}). In addition, above-ground biomass nitrogen content was variable within N_0 and N_1 treatments. The variability of crop growth and development patterns is due to the interactions between the experimental and environmental factors (soil properties and interannual weather variability). Weather variability led to water stress in some cases (SAN and ORZ, in 2017 and 2018), while in other cases (GHE 2021) crop productivity was limited by factors that are not represented by the model; this may explain poor model performance in some conditions. Constantin et al. (2015), who applied the STICS model to cover crops, reported an average RRMSE for white mustard of 20% and 22%, respectively for above-ground biomass and its nitrogen content, and of 32.5% and 35.5% for ryegrass. This model performance is similar to what we have obtained with the ARMOSA model. For black oat simulation,

these results show that the agreement between measured and simulated AGB was higher for the simulations with an organic or mineral fertilisation, in contrast with the results obtained with FASSET model for minerally-fertilized ryegrass cover crops (Doltra et al., 2019).

Soil conditions (SWC and ST for the site GHE) were well simulated by the model. Other simulations of soil water content of the whole soil profile, carried out in similar conditions with the STICS model (Constantin et al., 2015), gave the following results: RRMSE equal to 5 and 6%, for white mustard and ryegrass cover crops respectively. These results are comparable with the ones obtained with ARMOSA in GHE. The worst performance was found for simulated SWC at 10 cm depth during 2021 under black oat (Fig. 4), with a consistent overestimation. This probably indicates that the value of field capacity that was representative of soil conditions in 2019 and 2020, was too high in 2021, for reasons that we were not able to understand. It is interesting to observe that AGB was poorly simulated in this same situation (black oat in 2021).

The low accuracy in our simulations of soil nitrate and ammonium is in part explained by the difficulty in the calibration of the nitrogen dilution curve of these species, for which no extensive data sets like those needed for that purpose are available (e.g. Plénet and Lemaire, 2000; Ciampitti et al., 2022). Other reasons to explain the poor performance in simulating soil nitrate may include the lack of measurements six out of 14 simulations, the fact that measured data were in most cases available only for the 0-30 cm soil depth, and the high measurement variability in some cases (as seen in Fig. 3 and Fig. 5).

4.5 Conclusions

These results confirmed the reliability of the model in assessing AGB and AGB-N evolution during time, as well as soil water content and temperature dynamics at different soil depths. ARMOSA model was predominantly able to reproduce the effect of varying crop management treatments (early or late sowing date, mineral/organic fertilisation rate) and of interannual weather variability on black oat and white mustard cover crops in the Po plain of Northern Italy. However, cover crop cultivation effect on soil mineral nitrogen was not adequately reproduced by the model. The restricted availability of soil data for several sites of the calibration dataset influenced model simulation of soil mineral nitrogen content. This highlights the need of further field trials, designed to measure the data needed to improve the simulation of cover crop nitrogen

uptake. Overall, these results will allow the use of ARMOSA to compare cover crop management scenarios, both in conventional and minimum tillage cropping systems of the studied area.

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