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Synergizing grassland and soil system model expertise by coupling GRASSMIND (v2.0) and BODIUM (v1.2)

Matthes Kantzenbach[a,b], Sara König[c], Thomas Reitz[d,e], Martin Schädler[f,g], and Franziska Taubert[a]

[a]Department of Ecological Modelling, Helmholtz Centre for Environmental Research – UFZ, Permoserstr. 15, 04318 Leipzig, Germany
[b]Faculty of Environment and Natural Sciences, Brandenburg University of Technology (BTU) Cottbus-Senftenberg, 03046 Cottbus, Germany
[c]Department of Soil System Science, Helmholtz Centre for Environmental Research – UFZ, Theodor-Lieser-Str. 4, 06120 Halle (Saale), Germany
[d]Institute of Agricultural and Nutritional Sciences, Martin Luther University Halle-Wittenberg (MLU), Julius-Kühn-Straße 23, 06112 Halle, Germany
[e]Ecology of Agroecosystems, Helmholtz Centre for Environmental Research – UFZ, Theodor-Lieser-Str. 4, 06120 Halle (Saale), Germany
[f]Department Community Ecology , Helmholtz Centre for Environmental Research – UFZ, Theodor-Lieser-Str. 4, 06120 Halle (Saale), Germany
[g]German Center of Integrative Biodiversity Research (iDiv), Puschstraße 4, 04103 Leipzig, Germany

Correspondence: Matthes Kantzenbach (matthes.kantzenbach@ufz.de)

Abstract. Ecological models often have a specific focus, simplifying other system components. In the context of landscapes under climate change, it is increasingly important to include all relevant components and their interactions in detail in the models. Grassland models, advising management strategies for this important vegetation type of European landscapes, often lack detailed and reliable hydrological and soil resource dynamics that influence plant growth in grasslands. This study investigates the potential to overcome this issue by coupling an existing grassland with a soil system model, making use of their expertise in a specialized area. Here, the individual- and process-based grassland model GRASSMIND is coupled to the systemic soil model BODIUM using the coupling framework FINAM. The influence of soil water on grassland dynamics is shown to be more reliable with the coupled models than with GRASSMIND alone. In addition, the coupling offers the potential to tackle shortcomings in the representation of other plant processes such as root growth. However, the most urgent challenge is to overcome the ambiguity in the parametrization of GRASSMIND itself. Our experience suggests that maintaining the native models as independent components provides flexibility for future improvements but also complicates updating parametrizations in the combined system as the individual models evolve.

1 Introduction

In ecology, process-based models have long been developed to understand the dynamics of environmental systems and to predict future states for deriving recommendations for decision-making. There are many ecological models that simulate the environmental landscape, such as the long-term dynamics of forests, forest-fire interactions (Xi et al., 2009) or the replication

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of plant architecture in grasslands, impact of management or climate change on grasslands (Taubert et al., 2012). Depending on the focus, certain system components are often simplified, with the dynamics being reduced to simple relationships. This bears the risk of inaccuracy in the interaction of the components, for example, due to missing feedback on the simplified component. Especially under climate change, altering the dynamics in the individual model system components, it is important to incorporate the dynamics of the involved components in detail to be able to observe changes in the interaction of the components. For example, with an increasing recurrence of drought events due to climate change, the abundances of species in grasslands change (Müller et al., 2025). On the other hand, species composition as well as management strategy affect the response to drought events (Korell et al., 2024; Bazzichetto et al., 2024). To capture such interactions, the expertise of different models needs to be synergized. Looking at grassland models, the integration of a more detailed hydrological model is a crucial step to overcome certain inaccuracies that grassland models are struggling with (Piseddu et al., 2022). On the other hand, the agroecological soil models which include grassland such as LandscapeDNDC (Petersen et al., 2021) or APSIM (Sándor et al., 2018) often do not account for species composition or competition.

In this work, the soil modeling expertise of BODIUM (König et al., 2023) is combined with the plant modeling expertise of GRASSMIND (Taubert et al., 2020). Instead of creating a further new model, the idea is to synergize the existing expertise by coupling the models. GRASSMIND is an individual and process-based grassland model designed to simulate the daily growth dynamics of species-rich managed temperate grasslands. The growth dynamic is based on the carbon balance, mainly affected by photosynthesis activity and limitations due to water and nitrogen deficiency. It considers the competition between individual plants for light, space, soil water and nitrogen. It allows for the parametrization of multiple species or plant functional types. The climatic conditions and the management actions mowing, irrigation, and fertilization are applied according to input files. The soil dynamics are based on the concepts of CENTURY 4.0 (Parton et al., 2005), using a standard parametrization of a C3 grassland. GRASSMIND has already been used to assess the relevance of different plant functional types for grassland modeling (Schmid et al., 2021; Hetzer et al., 2021) and to evaluate the impact of mowing frequency and air temperature on grassland productivity (Schmid et al., 2022). However, the soil module does not account for changes in soil structure during simulation and has a rather simplified hydrological model. Therefore, it is not well suited to assess the impacts of different soil types on grassland dynamics.

BODIUM is a systemic soil model developed to evaluate the impact of management measures on soil functions such as food production, nutrients storage, and recycling. It represents and connects soil processes such as water dynamics, carbon turnover, and microbiological dynamics according to the current state of knowledge. The soil structure is represented by different pore-size classes and reflects the influence of roots and earthworms on it. The water flow is calculated on the basis of the water potential and the hydraulic conductivity of these pore-size classes. The generic plant growth module is designed for agricultural crops such as wheat or potatoes. Although it can simulate crop rotations, it does not account for competition between individual plants and is thus not suited to simulate grassland communities.

There are different approaches to couple process-based models, from one-way data transfer to a fully integrated modeling framework (Brandmeyer and Karimi, 2000). As we want to capture the dynamic feedback between both models, we need a two-way data exchange between the models during the simulation. On the other hand, we deal with existing models that have

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an independent code structure. As we want to keep the changes to the models minimal, they shall not be fully integrated within a model framework. This is primarily important, as both models are still permanently developing, and the coupling should be flexible to these improvements. For this task, the model coupling framework FINAM (Müller et al., 2025) offers a promising concept. It allows one to wrap existing models into technical components that are used by the coupler, keeping the native models independent and providing a consistent interface. With this, the models run in parallel, performing each time step on their own but then exchanging data between the time steps.

We therefore aim to synergize existing model expertise by coupling a grassland vegetation model with a detailed soil system model, rather than developing a new model from scratch. Specifically, we couple the individual-based grassland model GRASSMIND with the systemic soil model BODIUM. We compare the coupled model system to the standalone native grassland model regarding the interplay of the model processes in drought and non-drought situation using observations of a multi-year field experiment.

2 Methods: model coupling

Following the concept of FINAM, both models are wrapped into technical components to be used by the coupler, and interface variables are defined along which information is exchanged between the models. The case of BODIUM and GRASSMIND is somehow unusual, as both models basically consist of the same main model system components: a plant and a soil component, which are explicitly modeled, while the weather and management are given as an input file. The purpose of the coupling is to combine the specialized plant component of GRASSMIND with the specialized soil component of BODIUM, while the simplified internal soil component of GRASSMIND and the simplified internal plant component of BODIUM are deactivated, as shown in Figure 1(a). Thus, the main task of the interfaces between the models is to replace the former interaction of the specialized and simplified internal components of each model.

To do so, the first step before the actual coupling is to prepare the native models; details of the preparation of the two models are described below. The general process involves identifying the unused component in the model code, deactivating it, and replacing its input to the remaining component by input from new variables that will later be assigned with output from the other model. This replacement of internal calculations by external input shall have no impact on the remaining model components. To ensure this, a self-coupling test is implemented as depicted in Figure 1(b) exemplary for BODIUM, where two instances of the same model are run together. One instance of the native model runs "standalone" with both model system components (specialized and simplified) activated, while information is extracted from the simplified component serving as input for the other model instance running in "coupling mode" (with the simplified model component deactivated). Some exemplary output variables are compared between the instances with the goal of being identical. When extracting the information from the first instance and applying it to the second, it is relevant which variables are used, but also the time within the process order of the time step, when they are read out and the time when they are applied. With the self-coupling test, it can be ensured that all information of the deactivated model component that is relevant for the remaining component is identified.

Technically, this is done by implementing two new model modes that can be activated via a switch. In the first one, the "stan-

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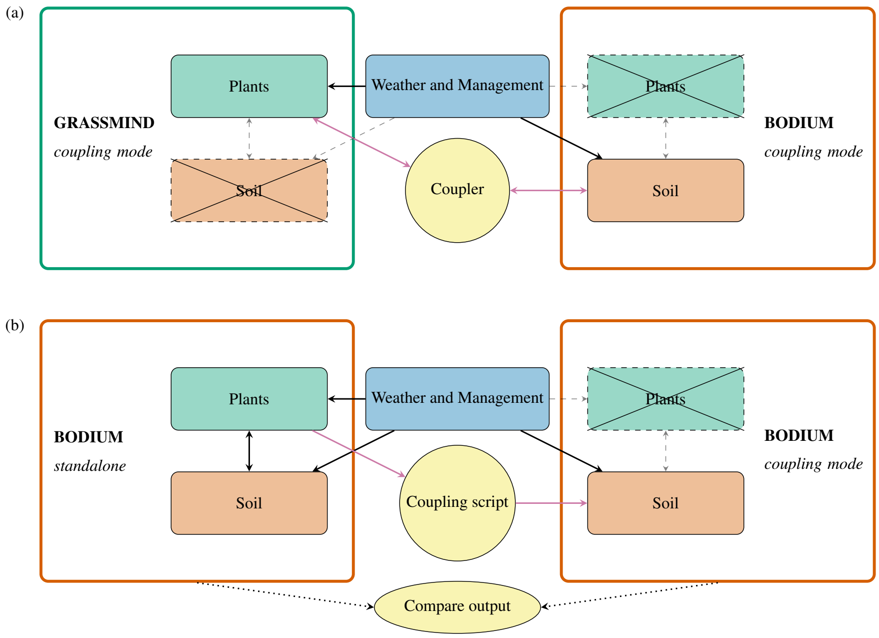

Figure 1. (a) General coupling idea: GRASSMIND and BODIUM run on their own, but the soil respectively the plant component is deactivated and replaced by input from the coupler that is extracted from the other model (indicated by red arrows). The input of weather and management data is harmonized. (b) Self-coupling test (exemplary for BODIUM): information of an standalone running model instance is extracted and used as input for an instance in coupling mode to replace the deactivated component. By ensuring, that the results of both models are the same, the correct identification of the interface variables (shown as red arrows) is verified.

dalone" mode, the model runs as normal, but information is stored in some interface variables at certain points in the process order. In the second one, the "coupling mode", the relevant processes are deactivated, but the input from those interface variables is applied. These interface variables are additional variables that are added to the source code of both models to apply information to, respectively, copy it from the original model variable at a particular place in the code. This indirect access is necessary to have full control over the time schedule within the time step. Otherwise, only the values of a variable at the beginning respectively the end of a time step would be available. The functions to initialize and run the model are made available to a Python interface by developing Python bindings using Cython (Behnel et al., 2011). New functions are implemented to obtain and set the interface variables from a Python script. With this, the self-coupling can be realized in a Python script running both model instances step by step and transferring the values along the interface variables from the "standalone" running model instance to the model instance in "coupling mode" (with the deactivated component). Some further model variables are also made available to Python to evaluate whether both instances produce the same results.

In the second step, the knowledge from the self-coupling, where in the process order the interface variables need to be taken from, is used to find similar points in the process order of the other model to extract the information needed. In this way, the ac-

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tual coupling interfaces are defined. Both models run on daily time steps. While BODIUM is one-dimensional, GRASSMIND considers a parcel of one square meter. However, the positions of the plants are not explicit and all properties are considered horizontally homogeneous within this parcel, so the data are one-dimensional as well. Both models consider a given number of distinct soil layers, which can be parameterized to match. So, the spatial and temporal dimensions of the data are already equal. However, one must keep in mind that the process order of the models within one timestep might differ. As the coupling is bidirectional, it must be decided which model runs every time step first with only information from the last time step and which one second with access to the others model output of the current time step, keeping the inaccuracy of the variable exchange minimal. The information is extracted in the same way as for the self-coupling test. With the bindings, the models can already be coupled directly in a Python script. FINAM components that apply the functions of the Python bindings and automate the data processing are written for the models. Operating the coupled models via the FINAM framework can become handy, when simulations should be run on larger spatial grids with heterogeneous environmental conditions. However, for the calibration and model coupling evaluation, direct coupling scripts are used, as only one parcel with homogeneous conditions is simulated and the FINAM data handling is not needed but would complicate the data flow. Especially for calibration, it is useful to obtain the models output directly as NumPy array and not having it saved as NetCDF file by the automatized data handling. So, it can be directly evaluated without writing it to a file and reading it back in for each iteration.

2.1 Preparation of BODIUM

In BODIUM, the plant component of the model can be identified in the source code as a "Plantstand" object with a set of variables and processes being a member of the central "bodiumrunner" object and a "Root" object, as well as a "RootGrowth" object being members of "SoilNode" objects representing each soil layer. This structure is depicted in more detail in Figure A1. The configuration of the "Plantstand" object is deactivated as well as the use of its variables and functions. In addition, the initialization of the "RootGrowth" object and execution of its functions are deactivated. The "Root" object needs to be initialized, as the use of its variables in the code cannot be replaced by interface variables without completely restructuring the code. So in this case the strategy is to keep the "Root" object, deactivate the internal alteration of its variables, but update them based on interface variables.

In the process of getting identical results in the self-coupling test, described in Section 2, the required interface variables are identified, as listed in Table 1. More details on the realization of the self-coupling test are in the Appendix D.

2.2 Preparation of GRASSMIND

In GRASSMIND, the code is much less structured into different objects. The soil component consists of several variables and functions, or just lines of code inside a more general function belonging to central objects. So, the soil processes are deactivated just at the place in the code where the individual functions are called or lines of code executed. This includes the functions of soil initialization, soil water dynamics, including top-layer evaporation, and carbon-nitrogen dynamics. To ensure that no lines of code that use soil properties are executed in the coupling, soil parameters are not loaded, and the soil water vector is assigned with NaN's. To cope with the deactivation of the processes, GRASSMIND needs the following interface variables as

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input to get identical results in the self-coupling test: Soil water per layer, nitrogen content per layer.

In addition, field capacity, permanent wilting point, and another parameter for the water uptake reduction function are required for each soil layer. In GRASSMIND, these parameters have fixed values, assuming that the soil structure is static. More details on the realization of the self-coupling test are in the Appendix D.

2.2.1 Water and nitrogen uptake

In GRASSMIND, water uptake is calculated from the current soil water content in each layer in relation to the field capacity and permanent wilting point of each layer expressed in water content. The field capacity represents the amount of water after drainage and the permanent wilting point the amount of water below which plants start to wilt. They are estimated as the water content that remains in the soil after a certain pressure is applied (Kirkham, 2014). In GRASSMIND, they are assumed to be static. In BODIUM, the water dynamics is calculated directly in terms of the water potential. The calculation of the water uptake compares the current water potential in each layer with parameters that state the ability of plants to extract water in terms of pressure. The water potential of a certain layer is the result of the water flow calculated for different pore-size classes. The volume fraction of these pore-size classes can change over time, representing a dynamic soil structure. So, the water potential is affected by the structure of the soil and its change over time. The soil information that is statically included in the GRASSMIND parameters is contained in the water potential in BODIUM and is flexible to modifications of the soil structure. To use the full potential of BODIUM, its formulations for the water uptake calculation are used in the coupling instead of GRASSMIND's.

The calculation of plant nitrogen uptake is taken from BODIUM as well, as it is again more accurate. There, it is calculated as the sum of nitrogen transported with the uptaken water plus nitrogen transported by diffusion towards the root surface, while in GRASSMIND, simply all nitrogen is available for uptake.

As the implementation in BODIUM does not carry out the calculations of the water and nitrogen uptake for the individual plants (differing in rooting depth and demand), but only for the entity of them, and to avoid unnecessary data transfer between the models, the formulations of BODIUM are implemented in GRASSMIND, where they can be applied for each plant individually. So when GRASSMIND is run in the coupling mode, these formulations replace the internal one. As the newly implemented functions are applied in the same place of the code and have an impact on the same GRASSMIND variables, the self-coupling test remains valid, ensuring the structural functioning of GRASSMIND in the coupling. Only the required input changes from the water and nitrogen content of each soil layer to the water potential and the concentration of NH_4 and NO_3 in each layer, as listed in Table 1. The additional parameters for the water uptake reduction functions in the newly implemented function are set to the same fixed values as in BODIUM.

2.3 Connection

Upon selecting suitable outputs in GRASSMIND to transfer to the interface variables which BODIUM requires in "coupling mode", water and nitrogen uptake can be taken directly from the newly implemented functions in GRASSMIND (which perform the calculations based on the soil water and nitrogen input from BODIUM). There, differentiation between ammonium

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Table 1. Interface variables as determined in self-coupling tests of the models plus additional inputs.

Model	Input Variables	Time of extraction in self-coupling	Required or additional input
BODIUM	Water uptake by plants	single value[a]	required
	NH4 & NO3 uptake by plants	single values[a]	required
	Plant litter amount & C:N ratio	single values[a]	additional
	Root litter amount & C:N ratio	single value[a] (summed over time step)	required
	Exudates amount & C:N ratio	single values[a]	required
	Plant root mass	end of time step	required
	Plant root volume	after management	required
		after plant growth	required
		end of time step	required
	Rain seeping into soil[b]	single value	additional
	Reduced potential evapotranspiration[c]	single value	additional
	Growth season	after plant growth	required
	Nitrogen fixation rate	after plant growth	required[d]
GRASSMIND	Water potential per soil layer	after soil water & nitrogen dynamic	required[e]
	NH4 & NO3 concentration per soil layer	after soil water & nitrogen dynamic	required[e]

[a] unique values per time step, thus can be extracted anywhere after been calculated
[b] precipitation minus interception by plants
[c] potential evapotranspiration minus rain interception by plants (assuming the intercepted water to evaporate on the same day)
[d] in GRASSMIND nitrogen fixation is directly allocated to plant, therefore a constant value of zero is committed
[e] by the native mode, soil water and nitrogen content per soil layer is required, but since adaptions in GRASSMIND to BODIUM, they can be replaced by given variables

(NH4) and nitrate (NO3) is also taken into account, while in the standalone GRASSMIND model version only total soil mineral nitrogen is considered.

BODIUM requires information on root litter for each soil layer separately, while GRASSMIND is only tracking the total value so far. Therefore, a new function is implemented in GRASSMIND, which divides the total input value equally among the rooting layers of the individual plant, whenever a plant contributes to the root litter. So, it is summed for each layer separately over the time step, and the carbon-to-nitrogen (C:N) ratio is calculated from the individual inputs. The aboveground litter fall (mass and C:N ratio) is provided to BODIUM as well by an additional interface. It is added to the same organic matter pool as the root litter in the topmost soil layer.

As the root mass in BODIUM is only updated once at the end of the time step, applying the changes accumulated over the time step, it is taken from GRASSMIND from the end of the time step as well. More complicated is the situation for root volume. In the self-coupling test, there are three processes within one time step of BODIUM identified where the root volume is updated, and the model instance in "coupling mode" requires input from the model instance running "standalone". So, the root volume must be extracted at three points in the process order, and consequently, three interface variables are defined. The first point in

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the process order is after the root volume might change from management operations such as cutting or tillage, the second after it might change from harvest or frost damage, and the third after the change from root growth, decay, and emergence of new plants. In GRASSMIND, there is no consideration of tillage and harvest (other than cutting). In addition, cutting does not have an effect on roots, and there is no frost damage in GRASSMIND. So, in the coupling the root volume is only updated at the last of these three points in the process order, assigning to the corresponding interface the root volume value of GRASSMIND from the end of the time step. For the first two interfaces, the value of the previous time step is transferred.

The growth season has again no counterpart in GRASSMIND. As there is no harvest and reseeding, the growth season can be considered true from the emergence of the first plants. In the coupling, 'True' is passed whenever the leaf area index is larger than zero.

The nitrogen fixation rate is an interface in BODIUM because nitrogen that is fixed from plant symbiosis with bacteria is added to the soil layers of the rooting zone in the model. In GRASSMIND, nitrogen from nitrogen fixation is added directly to the nitrogen pool of the plants. So, in the coupling, a constant value of zero is passed from GRASSMIND to BODIUM. Anyway, in the examined scenario, there are no legumes and, therefore, no nitrogen fixation.

As there was no root exudation in GRASSMIND so far, but it is important for BODIUM, this process is added to the model as discussed in the Appendix B1. It is again a singular value per time step.

GRASSMIND, on the other hand, accounts for the interception of rain, while BODIUM does not, subtracting it from the precipitation and the potential evapotranspiration. So in BODIUM an interface is added for the rainwater that infiltrates the soil, replacing the former input of precipitation from the weather input file and another interface for the reduced potential evapotranspiration.

According to its self-coupling, GRASSMIND needs the water and nitrogen information of the soil layers after the soil and nitrogen dynamics of the current time step have been processed. However, it is not possible for both models to use the information of the other model from the current time step because one of both models needs to run each time step first. It was chosen to run GRASSMIND first, as BODIUM is more dependent on information from the current time step of GRASSMIND. So, the water potential and nitrogen concentration per soil layer from the end of the last time step is passed from BODIUM to GRASSMIND, where it is used for the calculation of the plant water uptake in the next time step. This effectively changes the order of the processes regarding GRASSMINDs former schedule. Now, the uptake of water and nitrogen by plants on a day is calculated first and then the dynamics in the soil. In BODIUM, the schedule was already in this order in the native model.

The schedule of output and input of the interface variables is summarized in Figure 2.

3 Methods: model coupling evaluation

3.1 Data base

For the evaluation of the modeling approaches, data from experimental intensively managed grasslands growing under ambient climate as part of the Global Change Experimental Facility (GCEF) are used (Schädler et al., 2019; Helmholtz Centre for Environmental Research). The site is located in Bad Lauchstädt, Saxony Anhalt, Germany (51° 23′ 30 N, 11° 52′ 49 E,

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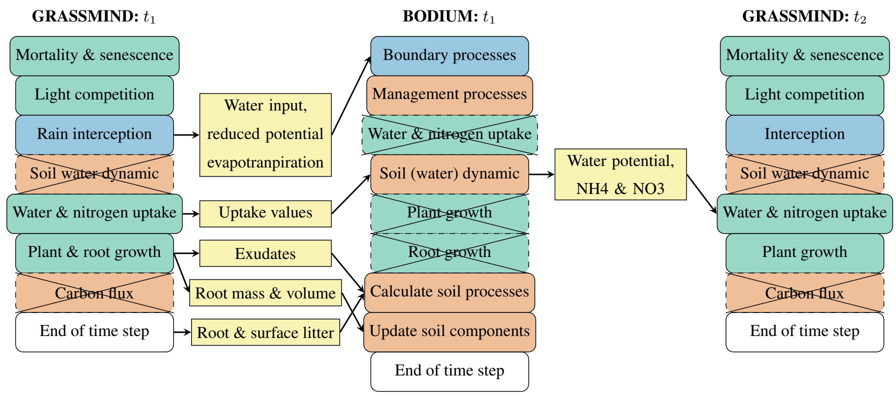

Figure 2. Schematic view of output and input of the interface variables (displayed in square boxed) during process schedule. Processes (displayed in rounded boxes) are ordered from top to bottom in the order of calculation. The simulation of the single time steps is ordered from left to right: first GRASSMIND simulates time step t_1, then BODIUM simulated time step t_1 and then GRASSMIND simulates the next time step t_2.

116 m a.s.l., mean annual precipitation of 525 mm (1993–2013), mean temperature of 9.7 °C (1993–2013)). There, four grass species (*Festulolium*, *Lolium perenne*, *Poa pratensis*, and *Dactylis glomerata*) were seeded in September 2013 in five parcels. Although only those four species have been anticipated for the intensive meadow, other plant species (grasses and forbs) have invaded over time. The composition was chosen based on the official recommendations of the State Research Centre for Agriculture and Horticulture of the federal state Saxony-Anhalt for temporary drier sites managed by mowing. The meadow was regularly mowed to 10 cm height and regularly fertilized with nitrogen (on average 20 g N m^{-2} per year). The yield (of the cut at 10 cm) of an area of 9 × 1.6 m is collected. Additionally, before every mowing event, the meadow is clipped by hand in four 50 × 20 cm areas at 3 cm height to obtain a better estimate of standing biomass. Both collections were dried for 48 h at 70 °C and weighted. The sum of the living and dead masses of the plant species is used. The proportions of forbs are considerably low(i.e. 0.07% to 0.51% in 2015–2018; except for 2019 with 13.2% and 2020 with 41.23%). In addition, soil moisture was measured once a year at three different depths (0–15 cm, 15–30 cm, 30–50 cm) using a fully automatic moisture analyzer (Kern DBS60–3 from Kern & Sohn GmbH, Germany). Before the actual experiment, oat was seeded in April 2013 and harvested in July 2013. As this is not included in the simulation, the soil moisture measurements of August 2013 were excluded from the data set. In 2020, the grassland was plowed and the soil was prepared in September for reseeding of the four grass species on 01 October, as there has been extensive drought damage. Between 2014 and that event, there was no tillage. The time period includes the years of soil moisture drought 2018–2020 (Rakovec et al., 2022). For the period after the second seeding, the biomass measurements are available until 2022 and the yield measurements until 2025. For this period 2020–2025, a second series of soil moisture measurements is available. Permanently installed sensors (SMT100 RS485 Digital Sensor, Truebner GmbH, Germany) measure hourly values for three different depths (0–15 cm, 7.5–22.5 cm, 15–30 cm) on each parcel. The mean daily values up to the end of the year 2025 are used. One sensor reports moisture values greater than 70% (per fresh

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volume) from 5 May 2022 on. Because these values are greater than the pore space, they are excluded.

Mineral soil nitrogen was measured yearly by extracting soil ammonium (NH4) and nitrate (NO3) from 10 g of fresh soil using 1 M KCl at a soil-to-solution ratio of 1:4 (w/v). The samples were shaken horizontally for 1.5 h to facilitate extraction. Subsequently, the suspensions were filtered (Whatman Schleicher and Schuell 595 1/5, Ø 270 mm). NH4 and NO3 concentrations in the filtrates were determined using a flow injection analyzer (FIAstar 5000, Foss GmbH, Rellingen, Germany) (Kuka et al., 2025).

The soil at the experimental site is classified as Haplic Chernozem (Altermann et al., 2005). The composition and the physical characteristics were examined in 2005 for six horizons up to a depth of 190 cm.

The weather data used for model input are made up of different sources. Precipitation and temperature were measured directly on the experimental site (Schädler et al., 2019; Schädler et al., 2025). For data gaps where the sensors failed, a gap-filling method was applied. Shorter gaps in the time-series of precipitation and temperature measurements of each parcel were filled by moving median, some longer gaps (more than 30 days, e.g. in the temperature data) were filled by linear interpolation. In addition, one temperature outlier of about 80 °C was removed and replaced by gap filling as well. The radiation was prepared with the python package "general-copernicus-weather-data" (Banitz et al., 2025), for the coordinates: latitude = 51.391900, longitude = 11.878700. The daylength and potential evapotranspiration were also calculated with the help of the python package (daylength: "get_day_length" in utils.py, potential evapotranspiration: "get_pet_thornthwaite" in convert_weather_data.py), using the temperature measurements from the GCEF site. After gap-filling in precipitation and temperature data, and data acquisition of radiation and day length, the arithmetic mean across the five parcels of each day was calculated and used as weather input for the model for 2015–2025. For the years 2013 and 2014, precipitation and temperature data from a weather station located at the study site are used (Gründling et al., 2022).

3.2 Parametrization of GRASSMIND

To represent the vegetation of the GCEF experiment in GRASSMIND, an average grass species is modeled. This keeps the focus on the plant-soil interaction rather than the interaction between different species and is reasonable for an intensively managed meadow which is dominated by grass species only. GRASSMIND requires 25 plant-specific parameters. Most of them are set to a fixed value based on previous GRASSMIND parametrizations for that site (Hetzer et al., 2021) and literature values, as shown in Table C1. Seven parameters remain as calibration parameters: the overlap factor, which regulates the competition in space between plants; the root parameters, since there are limited data on the rooting pattern of single grass plants, especially not on its dynamics; initial slope of the light response curve & the maximal gross leaf photosynthesis rate, which lies in a wide range depending on the climatic and soil conditions as well as the method of determination (Gilmanov et al., 2007; Fariaszewska et al., 2017, 2020; Peri et al., 2005); the water use efficiency, which depends on the climatic conditions (Fariaszewska et al., 2020; Huang et al., 2017); the height-width ratio of single plants, which was determined in some pot experiments (Hetzer et al., 2021), but not inside a community and under mowing conditions. It is not GRASSMINDs expertise to model quantitative heights, but when calibrating biomass (above 3 cm) and yield (above 10 cm) together, the plant heights are relevant for calibration. To avoid inaccuracy of the heights in the model being compensated by other parameters in the

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calibration, the height-width ratio is chosen to be calibrated as well.

For the standalone runs of GRASSMIND, it requires also a parametrization of soil (for the coupled runs, only the soil parametrization of BODIUM is used). The soil in GRASSMIND is divided into horizontal layers of 10 cm. These layers are parameterized by field capacity, permanent wilting point, porosity, and saturated conductivity. Silt, clay, and sand contents are required as single values for the entire soil (used as parameters for carbon dynamics and nitrogen leaching).

The layer wise values are taken according to the horizon, they are in, using the data from Altermann et al. (2005), given in Table C2. As marked in the table, some horizons are offset, respectively, heightened or shortened by 5 cm in order to match the boundaries of the soil layers in the model. For the sand, silt, and clay content, the values of the six horizons are averaged, weighted according to the proportion of their extent without gravel. This results in 59% silt, 13% clay, and 28% sand.

The calibration is done using the optimizer Py-BOBYQA (Cartis et al., 2019, 2022) with the observed field data until the plowing in September 2020. The data points in 2014 are also skipped in the calibration, as GRASSMIND seems not to work well for the initial grow up phase. The mean measurement values of the five parcels for yield, biomass, and soil moisture are calculated for each measurement date. From the simulation results, the values at these dates are extracted. For each iteration, five model instances are run in parallel with different seeds for the random number generator considered for stochastic processes of plant death, and their results are averaged. The resulting values are compared to the mean measurement values and the sum of the absolute differences divided by the mean of the measurement values is calculated. Py-BOBYQA finds the values for the calibration parameters that minimize this sum. As a derivative-free algorithm, it can take care of the stochasticity of the model. We tested two different calibration scenarios: one scenario that only includes measured biomass and yield, and another scenario that includes measured biomass, yield, and soil moisture jointly.

3.3 Parametrization BODIUM

BODIUMs parametrization consists of a configuration file for the soil processes stating, for example, the turnover rates of the different organic matter pools and a parameter file for the soil properties divided into horizontal layers. For parametrization of soil processes, the default configuration is used. As GRASSMIND uses layers of 10 cm depth each, the same extent is chosen in BODIUM for the soil parametrization. Again, data from the soil profile at Bad Lauchstädt (Altermann et al., 2005) are used with the same projection of the horizons on the modeled soil layers. As BODIUM uses for its calculations van Genuchten parameters, a water retention curve is fitted to the field capacity, water content, and permanent wilting point (which states the water content regarding a certain water potential) of each horizon (see Appendix C).

3.4 Evaluation of model performance

Overall, four calibration scenarios are performed: setup 1a: GRASSMIND standalone, calibrated without soil moisture; setup 1b: GRASSMIND standalone, calibrated with soil moisture included; setup 2a: GRASSMIND-BODIUM, calibrated without soil moisture; setup 2b: GRASSMIND-BODIUM, calibrated with soil moisture included. For the evaluation of the uniqueness of the calibration results, the calibration is run twice per setup. With the parameters obtained from the calibrations, the model setups are run 100 times for each calibration result. The mean results and standard deviation over the 100 runs of the output

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variables are calculated. The results are compared between GRASSMIND and GRASSMIND-BODIUM, and it is evaluated whether there is any benefit in using soil moisture in the calibration as well. GRASSMIND standalone and GRASSMIND-BODIUM are compared in terms of how well they can reproduce the biomass, yield, and soil water dynamics of the GCEF site.

The models are run until 2025 (GRASSMIND is restarted with the new seeding, BODIUM is kept running through simulating the tillage event in 2020). The simulation results are compared with the GCEF yield and soil moisture in the second period from 2020 until 2025, which was not part of the calibration.

4 Results

The calibration results differ in the resulting calibration parameters between the two repetitions of the calibration for each setup. However, the results of yield, biomass, and soil moisture show pretty similar patterns. In the following, the results of the better calibration (lower sum of the relative differences) for the particular setup are used. The results of the other calibrations are presented in Appendix E.

4.1 Biomass and Yield

The results of the calibrations are compared with the field measurements of biomass in Figure 3 and for yield in Figure 4. The results of the GRASSMIND calibration without the use of the soil moisture data (setup 1a) show that the model can match the biomass and yield dynamics of the experimental site well for the years 2015–2021. The mean deviation of the simulation mean from the measured values is $0.087\,\mathrm{kg\,m^{-2}}$ for biomass and $0.058\,\mathrm{kg\,m^{-2}}$ for yield in these years. In the first year after seeding, the model underestimates growth. In 2014, where average yields of $0.56\,\mathrm{kg\,m^{-2}}$, $0.42\,\mathrm{kg\,m^{-2}}$ and $0.34\,\mathrm{kg\,m^{-2}}$ are measured, the model only produces yields of $0.0289\,\mathrm{kg\,m^{-2}}$, $0.105\,\mathrm{kg\,m^{-2}}$ and $0.188\,\mathrm{kg\,m^{-2}}$ on average.

Using the soil moisture data in the calibration of GRASSMIND (setup 1b) worsens the match with the measured data. The mean deviation of the simulation mean from the measured values is $0.096\,\mathrm{kg\,m^{-2}}$ for biomass and $0.082\,\mathrm{kg\,m^{-2}}$ for yield in the years 2015–2021. In the year 2014 the yields are slightly higher than in setup 1a ($0.081\,\mathrm{kg\,m^{-2}}$, $0.125\,\mathrm{kg\,m^{-2}}$ and $0.209\,\mathrm{kg\,m^{-2}}$).

The results of the GRASSMIND-BODIUM calibration without soil moisture (setup 2a) show a similar match to the biomass and yield measurements as GRASSMIND (setup 1a). The mean deviation of the simulation mean from the measured values for the years 2015–2021 in the setup 2a is slightly lower for biomass ($0.066\,\mathrm{kg\,m^{-2}}$) and slightly higher for yield ($0.065\,\mathrm{kg\,m^{-2}}$). Similarly to the results of GRASSMIND, the yields in 2014 are underestimated ($0.0143\,\mathrm{kg\,m^{-2}}$, $0.088\,\mathrm{kg\,m^{-2}}$, and $0.218\,\mathrm{kg\,m^{-2}}$).

In contrast to GRASSMIND, the inclusion of soil moisture in the calibration (setup 2b) does not significantly worsen the match with the measured data. The mean deviation of the simulation mean from the measured values for the years 2015–2021 is $0.065\,\mathrm{kg\,m^{-2}}$ for biomass and $0.077\,\mathrm{kg\,m^{-2}}$ for yield. In 2014 the yields are $0.0048\,\mathrm{kg\,m^{-2}}$, $0.078\,\mathrm{kg\,m^{-2}}$, and $0.192\,\mathrm{kg\,m^{-2}}$.

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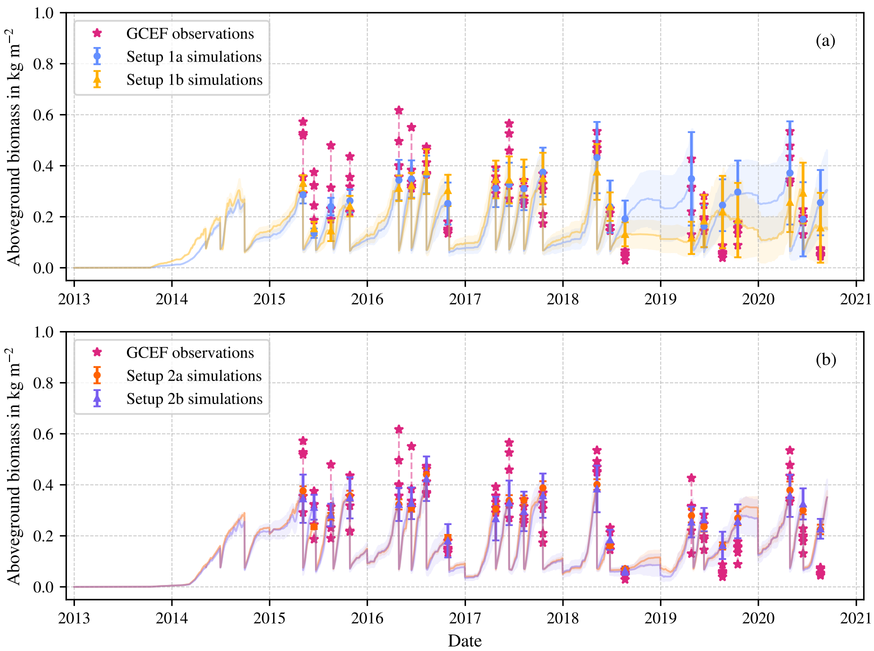

Figure 3. Calibration results of GRASSMIND **(a)** and GRASSMIND-BODIUM **(b)**. Mean biomass and standard deviation of 100 runs using the parametrization from the respective calibration.

A general observation is that the differences between the simulation runs are higher with GRASSMIND than with GRASSMIND-BODIUM. For the yield between 2015 and 2021, the GRASSMIND results have a mean standard deviation of 0.084 $\mathrm{kg\,m^{-2}}$ (setup 1a) respectively 0.068 $\mathrm{kg\,m^{-2}}$ (setup 1b), while the GRASSMIND-BODIUM results have a mean standard deviation of 0.017 $\mathrm{kg\,m^{-2}}$ (setup 2a) respectively 0.065 $\mathrm{kg\,m^{-2}}$ (setup 2b). Especially strong is the standard deviation in GRASSMIND in the drought years, reaching up to 0.192 $\mathrm{kg\,m^{-2}}$.

4.2 Soil moisture and nitrogen

The soil moisture measurements, plotted together with the simulation results of the four setups (Figure 5) show that GRASSMIND standalone calibrated without soil moisture (setup 1a) overestimates soil moisture for all observation dates in all depth layers. It is on average 9.2 percentage points (of soil moisture) above the measurement. The fit to the soil moisture with the setup 1b is better, but still produces mostly to high values of soil moisture. It is on average 5.3 percentage points higher than the observations.

GRASSMIND-BODIUM matches the soil moisture measurements much better than GRASSMIND. The mean deviation of the simulation mean from the measured values is 1.63 percentage points (setup 2a) and 1.65 percentage points (setup 2b). So, even without explicit calibration, the match of the soil moisture is already good, and the inclusion of the soil moisture into the calibration does not further improve the result. In general, the difference between the calibration scenarios is not that strong

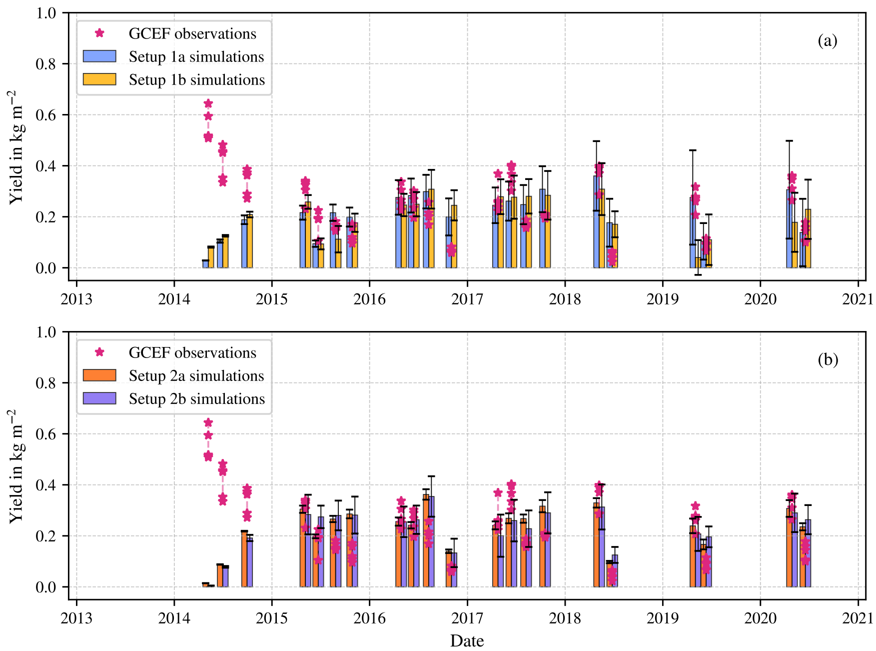

Figure 4. Calibration results of GRASSMIND **(a)** and GRASSMIND-BODIUM **(b)**. Mean yield and standard deviation of 100 runs using the parametrization from the respective calibration.

with GRASSMIND-BODIUM (setups 2a and 2b), as it is with GRASSMIND (setups 1a and 1b). Again, it can be observed that the standard deviation in soil moisture is higher in the simulations with GRASSMIND than with GRASSMIND-BODIUM, especially in the drought years 2018, 2019, 2020.

The mineral nitrogen content in the simulations is compared with the field measurements in Figure 6. The course of the mineral nitrogen in layer D1 is very similar between the runs of all calibration setups and follows the pattern of the measured values quite well. In layer D2, some differences can be seen between GRASSMIND and GRASSMIND-BODIUM in the patterns of the nitrogen course. Over time, the nitrogen values of all modeling approaches are in the same range. However, there is some offset when they increase or decrease between GRASSMIND and GRASSMIND-BODIUM. In layer D2 and in layer D3 the simulated nitrogen values rise faster and are higher in the first years of the simulation with GRASSMIND-BODIUM, than with GRASSMIND.

4.3 Growth limitation factors

Evaluating the proportion of limited access of individual plants to soil water and nitrogen resources (on average in all plants), the mean limitation in water and nitrogen is shown in Figure 7. These variables are the factors with which the potential biomass increment is reduced by the lack of water, respectively nitrogen. As the water limitation is calculated first, the nitrogen

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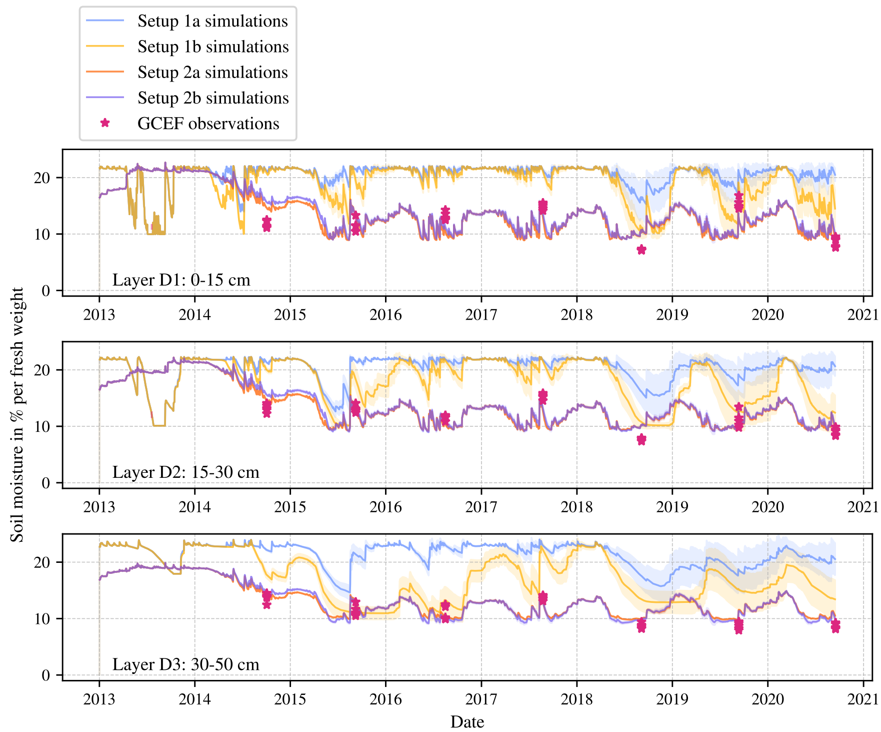

Figure 5. Calibration results of GRASSMIND and GRASSMIND-BODIUM. Mean soil moisture and standard deviation of 100 runs using the parametrization from the respective calibration. The results of the simulations for soil layers with a depth of 10 cm are converted to the soil layers of the measurements by calculating the proportion-weighted mean.

limitation factor applies to the already water limited potential biomass increment. With the calibration of GRASSMIND without soil moisture (setup 1a), it can be seen that there is hardly any water limitation in years without drought. During drought years (2018, 2019, 2020), there is a little water limitation. Minor nitrogen limitation occurs repeatedly throughout the entire period. When soil moisture is used in the calibration (setup 1b), there are distinct peaks of water limitations before drought years and longer phases of water limitations during drought years. The nitrogen limitation is stronger before drought than in the calibration without soil moisture. It decreases with the stronger water limitations from 2018 on.

The results of GRASSMIND-BODIUM (setup 2a and 2b) show much more water limitation in the years before drought (mean limitation factors of 0.70 in setup 2a, respectively 0.75 in setup 2b for 2015–2017). In the drought years the water limitation increases on average by 3.7 respectively 5.3 percentage points of limitation in biomass production (mean limitation factors of 0.66 respectively 0.70 for 2018–2020). In the first one and half years after seeding, there are no strong water limitations. Meanwhile, there are strong nitrogen limitations. These disappear almost completely from 2015 on.

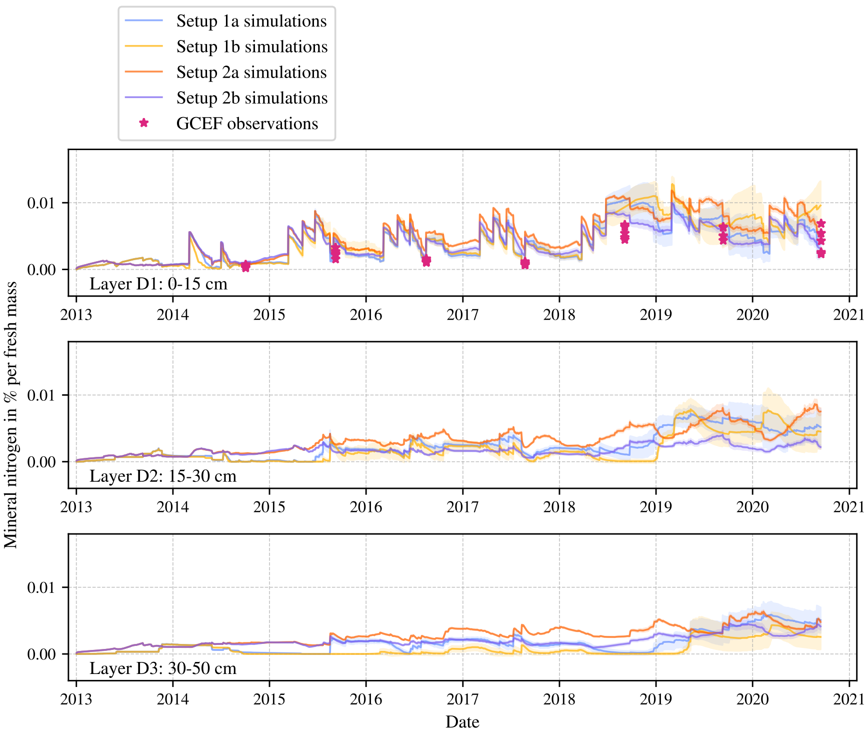

Figure 6. Calibration results of GRASSMIND (setups 1a and 1b) and GRASSMIND-BODIUM (setups 2a and 2b). Mean mineral nitrogen and standard deviation of 100 runs using the parametrization from the respective calibration. The results of the simulations for soil layers with a depth of 10 cm are converted to the soil layers of the measurements by calculating the proportion-weighted mean. Mineral nitrogen was only measured in the layer D1.

4.4 Second seeding period

The simulated yield in the period after the second seeding from 2020 to the end of 2024 do not differ much between GRASSMIND and GRASSMIND-BODIUM, as shown in Figure 8. The mean deviation of the mean results of GRASSMINDs from the measurements is $0.096\,\mathrm{kg\,m^{-2}}$ for the parametrization that was calibrated without soil moisture (setup 1a) and $0.99\,\mathrm{kg\,m^{-2}}$ for the parametrization that was calibrated with soil moisture (setup 1b), excluding the first two values in the first half of 2021. For GRASSMIND-BODIUM, the mean deviation of the mean results are $0.122\,\mathrm{kg\,m^{-2}}$ (setup 2a) respectively $0.118\,\mathrm{kg\,m^{-2}}$ (setup 2b). Again, the representation of the first results after seeding (October 2020) is poor.

The daily soil moisture measurements from GCEF are compared to the simulation results in Figure 9. In all layers, the GRASSMIND simulations result in soil moisture values much higher than the measured values. The simulated values are most of the

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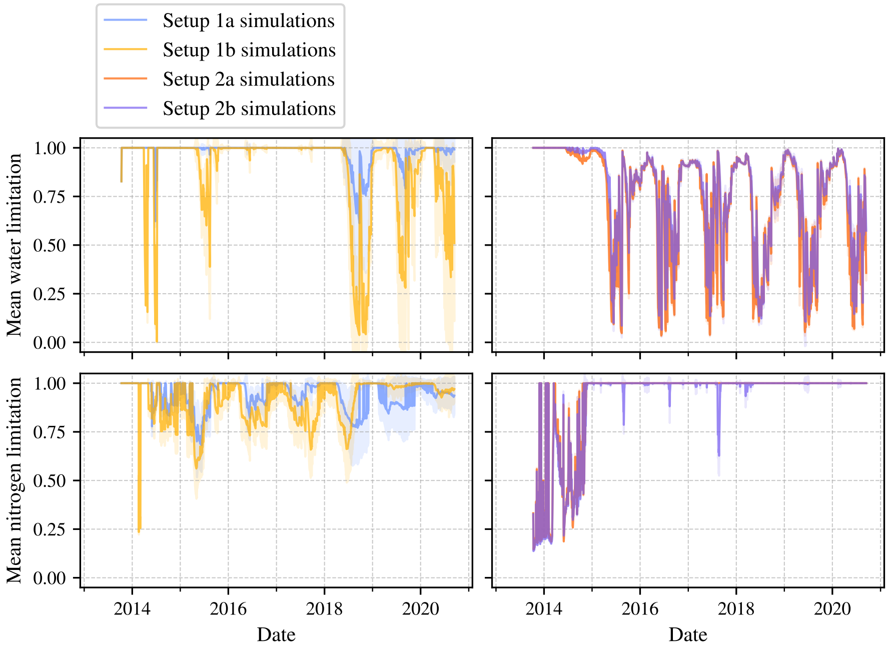

Figure 7. Calibration results of GRASSMIND and GRASSMIND-BODIUM: mean water and nitrogen limitations of all the plants. Mean values and standard deviation of 100 runs using the respective parametrization. A limitation factor of one indicates no limitation by that property at all and a value of zero indicates limitation to no growth at all. Nitrogen limitation is determined after water limitation was applied.

time near the field capacity. The results of setup 1a (calibrated with soil moisture) are slightly better than the results of setup 1b (calibrated without soil moisture). The soil moisture values of setup 1a are on average 19.2, 21.9 and 22.4 percentage points (of soil moisture) higher than the measured values for layers T1, T2 and T3. For setup 1b, they are on average 16.6, 18.4 and 18.8 percentage points higher.

In layer T1 (0–15 cm depth), the results of GRASMIND-BODIUM (setups 2a and 2b) align well with the measurements. Only in the first year after seeding in October 2020 do the simulations result in much higher soil moisture than measured in the field. In addition, in the summer periods in the following years, the simulated moisture is slightly higher than the measured moisture. The soil moisture of setup 2a is on average 4.3 percentage points higher than the measurements and that of setup 2b on average 5.1 percentage points. In layers T2 and T3, the results of GRASSMIND-BODIUM show a pattern similar to the measurements. However, they are offset and on average 7.5 (setup 2a) and 8.3 (setup 2b) percentage points to high in layer T2 and 9.0 (setup 2a) and 9.6 (setup 2b) percentage points to high in layer T3 compared to the measured values. Overall, the differences between setups 2a and 2b are small.

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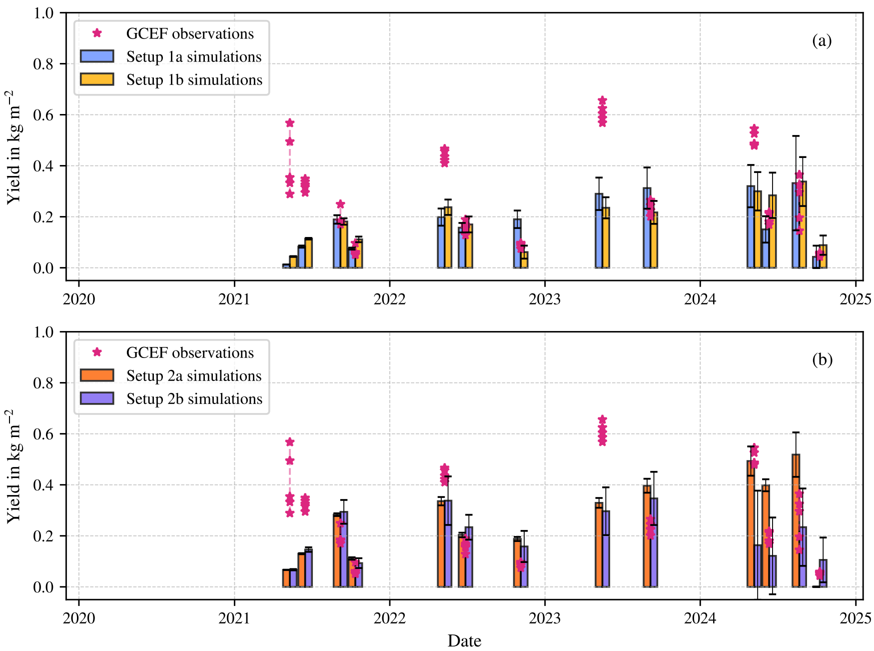

Figure 8. Calibration results of GRASSMIND **(a)** and GRASSMIND-BODIUM **(b)**. Mean yield and standard deviation of 100 runs using the parametrization from the respective calibration for the period after reseeding.

4.5 Calibration parameters

The values of the calibration parameters resulting from the four different setups are listed in Table 2. Here, it is interesting to also present the parameters of the second calibration runs for each setup (Table 3). Clear differences between GRASSMIND and GRASSMIND-BODIUM can be seen for the water use efficiency. The plants in GRASSMIND-BODIUM are calibrated to need more water. The overlap factor is 1.0 or almost 1.0 for all setups in both executions of the calibrations. This is the upper limit for this value in the calibration process. For the other parameters, there are no clear patterns in the comparison between GRASSMIND and GRASSMIND-BODIUM. It can be seen that the values of the rooting parameters and the hight-width ratio are quite ambiguous between the calibration runs. The other calibration parameters are overall more consistent. However, there are some differences in the values of other parameters as well. The initial slope of the light response curve and the water use efficiency is rather consistent for the repetition of the calibration for each setup and in the case of GRASSMIND-BODIUM also between the setups (2a and 2b).

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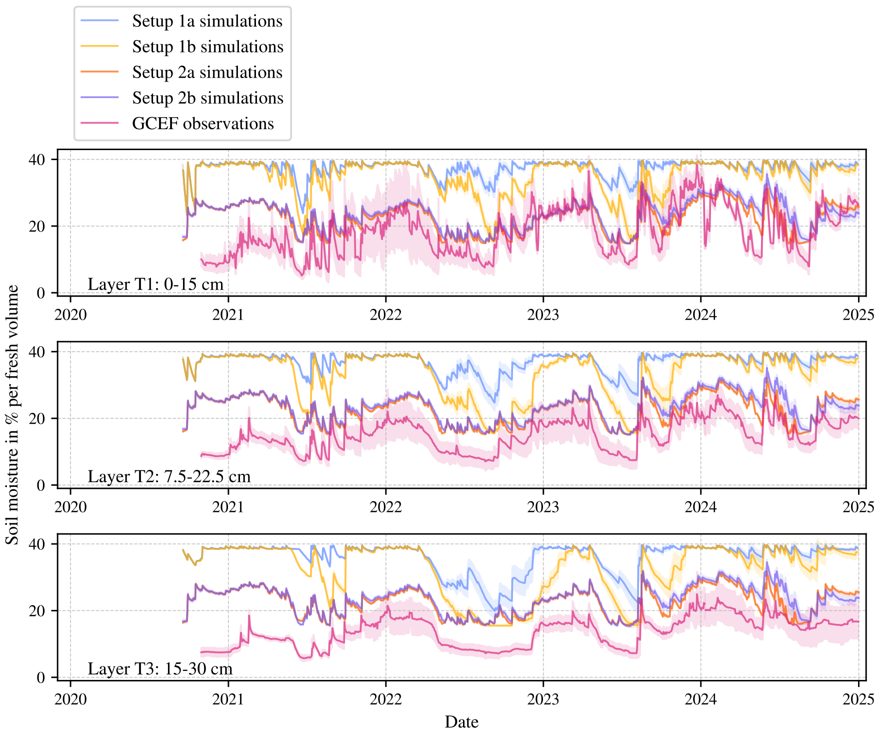

Figure 9. Calibration results of GRASSMIND and GRASSMIND-BODIUM. Mean soil moisture and standard deviation of 100 runs using the parametrization from the respective calibration for the period after reseeding. The results of the simulations for soil layers with a depth of 10 cm are converted to the soil layers of the measurements by calculating the proportion-weighted mean.

5 Discussion

The grassland model GRASSMIND is coupled to the soil system model BODIUM to investigate the benefit that the grassland component can have from a more accurate soil component. The grass specific calibration parameters of GRASSMIND are calibrated to data from an experimental site using GRASSMIND standalone as well as using GRASSMIND-BODIUM. The performance of the modeling approaches to match the measurement data used in calibration and of a second time period is evaluated. The results show that the coupling increases the reliability of the representation of plant water uptake and provides new starting points for future model improvements by offering a meaningful comparability of soil moisture between model and field data.

Both modeling approaches (GRASSMIND and GRASSMIND-BODIUM) can reasonably reproduce the growth pattern of

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Table 2. GRASSMIND calibration parameters for setup 1: GRASSMIND standalone, setup 2: GRASSMIND-BODIUM and a: not using soil moisture in the calibration, b: using soil moisture in the calibration.

Name	Setup 1a	Setup 1b	Setup 2a	Setup 2b	Unit
Height-width ratio	0.5[a]	0.5[a]	1.03532033	0.5[a]	-
Overlap factor	1.0[b]	1.0[b]	1.0[b]	1.0[b]	-
Root depth parameter r_1	2.0[b]	1.48917845	0.29857211	0.60471778	-[c]
Root depth parameter r_2	0.71276338	0.61994078	0.1[a]	0.1807843	-
Maximal gross leaf photosynthesis rate	28.01871668	28.85572837	29.40831412	27.37948867	$\mu mol\ CO_2\ m^{-2}\ s^{-1}$
Initial slope of light response curve	0.03959705	0.09007844	0.11[b]	0.1071887	$mol\ CO_2\ mol^{-1}$ photons
Water use efficiency (WUE)	17.7542972	21.05575971	10.24599577	11.19306317	g ODM[d] $kg^{-1}\ H_2O$

[a] lower limit in calibration
[b] upper limit in calibration
[c] it is actually only dimensionless if $r_2 = \frac{1}{3}$, otherwise, it has the unit m^{3r_2-1}
[d] Organic Dry Matter

Table 3. GRASSMIND calibration parameters of the repetition of the calibration for setup 1: GRASSMIND standalone, setup 2: GRASSMIND-BODIUM and a: not using soil moisture in the calibration, b: using soil moisture in the calibration.

Name	Setup 1a′	Setup 1b′	Setup 2a′	Setup 2b′	Unit
Height-width ratio	0.51019555	0.73619855	0.5[a]	1.5[b]	-
Overlap factor	0.96353075	1.0[b]	1.0[b]	1.0[b]	-
Root depth parameter r_1	1.50878281	1.34372833	0.25304572	1.43633836	-[c]
Root depth parameter r_2	0.61747711	0.41255602	0.42818415	0.49179805	-
Maximal gross leaf photosynthesis rate	16.25881674	28.88659654	18.47407379	30[b]	$\mu mol\ CO_2\ m^{-2}\ s^{-1}$
Initial slope of light response curve	0.03645097	0.11[b]	0.10084212	0.10265638	$mol\ CO_2\ mol^{-1}$ photons
Water use efficiency (WUE)	17.04105841	23.40269004	10.09217718	9.97928569	g ODM[d] $kg^{-1}\ H_2O$

[a] lower limit in calibration
[b] upper limit in calibration
[c] it is actually only dimensionless if $r_2 = \frac{1}{3}$, otherwise, it has the unit m^{3r_2-1}
[d] Organic Dry Matter

the GCEF site, when calibrated to its data. The most interesting difference is that for GRASSMIND-BODIUM it does not matter whether soil moisture is included in the calibration (next to biomass and yield) or not, while for GRASSMIND standalone, the inclusion of soil moisture worsens the performance in reproducing the growth patterns. The yield of the second period (2020–2024) is also reasonably reproduced with both modeling approaches. The measurement data from this period were not used for the calibration, but are not exactly independent from the calibration data as the conditions are quite identical (same soil, similar weather, similar management). Therefore, reproduction of these data cannot be seen as an argument for a broader applicability of the models. It just confirms the site specific applicability of the models in reproducing the yield under

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the specific conditions.

A general observation in the comparison between the simulated and measured yield is that the simulated yield tends to be slightly lower than the measurements in spring and slightly higher in autumn. One explanation could be that developmental factors accelerate spring growth and restrict growth later in the season (Wingler and Hennessy, 2016), which are not considered in the GRASSMIND plant component.

Although both modeling approaches do not differ much in reproducing the growth pattern, GRASSMIND-BODIUM can match the soil moisture measurements of GCEF much better than GRASSMIND. Not only the yearly measurements of the calibration period, but also the daily dynamics of the second period can be captured much better with GRASSMIND-BODIUM than with GRASSMIND standalone. This was expected as the internal water component of GRASSMIND is very simplified. It is basically a bucket model, where the amount of water that exceeds the field capacity is transferred from its layer to the layer below. GRASSMIND-BODIUM matches the soil moisture measurements not only when they are used for calibration but also in the case of their exclusion (with only biomass and yield measurements used for calibration). This can be seen as an argument that the water uptake formulation in GRASSMIND-BODIUM is realistic, as the water use efficiency that is found to create a water limitation producing a realistic growth pattern simultaneously results in a water consumption that reproduces the soil moisture measurements of GCEF. In GRASSMIND, the use of soil moisture in the calibration affects the resulting model performance. It slightly improves the match with the soil moisture measurements, but meanwhile worsens the match with the biomass and yield measurement. This suggests that we cannot truly compare the soil moisture simulated in GRASSMIND with the soil moisture in the field. It was not designed to realistically represent soil moisture, but rather to represent the limitation in growth by limited soil water. Fulfilling this task such that the growth patterns of GCEF are reproduced does not seem to work with a simulated soil moisture content that is in accordance with the GECF measurements.

However, in the second period, where daily measurements are available, there are also some stronger deviations between GRASSMIND-BODIUM and the measurements. The simulations produce consistently too high soil moisture values in the lower soil layers (7.5–22.5 cm, 15–30 cm) compared to the measurements. In GRASSMIND-BODIUM, soil moisture increases during reseeding and remains high for the first months afterward. This is not the case for the sensor data. This can be explained with weak growth in the first month compared to the data, as the first yields are much too low. Furthermore, it suggests that soil evaporation might be underestimated in the model, which could explain the strong rise of simulated moisture directly after reseeding, in all three layers. This might also be the case during droughts. It can already be seen in the yearly measurements (2013–2020) that the measured soil moisture is lower from 2018 on than in the years before, while there is no such clear decrease in the simulated soil moisture. It is reported that especially for soils with finer texture, the low soil moisture after drought can be carried over into the next years (Groh et al., 2020; Ehrhardt et al., 2025). This seems to be the case for the GCEF site, but is not represented well in the simulations. In 2022 the next drought occurred (A et al., 2022) which could then explain the ongoing deviation between simulation and sensor data. A too low impact of drought on soil moisture in the model could be explained by too low soil evaporation. In BODIUM, a thin layer is simulated at the top of the top layer acting as an evaporation barrier, reflecting hydraulic discontinuity. It could be that this barrier is too strong. It should be tested whether

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an adopted parametrization of the evaporation barrier can improve the results. In addition, it would be interesting to measure the hydraulic parameters of the soil after a drought event again, as they are reported to change under drought towards lower porosity and conductivity (Zhang et al., 2019; Zhu et al., 2024). This could also be an explanation for the lower soil moisture beneath the surface layer. If they change significantly, a hysteresis in the retention curve could be included in the model.

Apart from this, the accuracy of the sensor data should be assessed. The sensors are used with factory calibration, for which a accuracy of ± 3% (volumetric water content) is stated (ICT International, 2025). They state that a medium specific calibration would increase the accuracy up to ± 1% (volumetric water content). It is found by Bogena et al. (2017) that a sensor specific calibration can already strongly increase the accuracy of the SMT100 sensors while being less time consuming than a medium specific calibration. That might be an efficient approach to increase the accuracy of soil moisture measurements at the GCEF and make the variability between the sensors more relatable to the actual differences between the parcels. However, the cited experiment was performed in a sandbox. The soil at the GCEF site has a considerable clay content. This induces shrinkage and crack formation under drying, often resulting in preferential flow (Tang et al., 2011). This could lead to a heterogeneous moisture content in the field and therefore additional measurement inaccuracies, as only one sensor is placed per parcel. Installing multiple sensors per plot could potentially allow for a better assessment of the extent of heterogeneity and the resulting inaccuracy. In addition, shrinkage could cause air pockets around the sensor. If the sensor is not in perfect contact with the medium, this can reduce the measured permittivity and lead to an underestimation of the water content, as Bore et al. (2016) have shown for sensors installed in clay-rock.

Nevertheless, the simulated soil moisture matches the sensor data in the upper layer very well (after the initial period after seeding), and the pattern in the simulated soil moisture course correlates with the pattern in the sensor data overall. This generally strengthens confidence in the modeled plant-water interaction in GRASSMIND-BODIUM. Slightly higher simulated soil moisture values in the upper layer in summer 2022 and 2023 could explain the too high yields in the fall of these years. This might also be improved when the soil evaporation is adjusted. To generally test to what extent the mismatches in yield (or also biomass) can be explained with the deviation in soil moisture, it would be interesting to run the coupled models with direct input of the daily measured soil moisture (translating it into water potential by BODIUM).

The underlying processes of the plant component in GRASSMIND that shape the growth patterns seem to act very differently between the modeling approaches. While in GRASSMIND-BODIUM growth is strongly shaped by the water limitation over all the years, in GRASSMIND standalone, there is much less water limitation in the years before drought. When calibrated without soil moisture, there is hardly any water limitation before drought and even during drought years only very few. So, in this case, the soil water plays very little role in shaping the growth pattern. This difference in the role of the water limitation process is also visible as a shift in the value of the calibration parameter water use efficiency between GRASSMIND and GRASSMIND-BODIUM. As GRASSMIND-BODIUM seems more reliable in the representation of the soil water uptake (simultaneous good representation of yield/biomass and soil moisture), its water limitation can be assumed to be more reliable than GRASSMINDs. However, the exact extent is hard to assess. Being calibrated to match the measurement values, the simulated water limitation might also compensate for other underrepresented limitations (e.g. limitation by nitrogen, phosphorus,

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potassium, or combinations, as highlighted as important for grassland productivity by Fay et al. (2015)).

The differing mean nitrogen limitation patterns between the modeling approaches are also difficult to assess. Wile Cardenas et al. (2019) reports a linear increase in grassland yield with N application rates up to 320 kg N ha^{-1}, Peters et al. (2021) reports no significant difference between nitrogen application rates of 140 and 280 kg N ha^{-1} and highlights the influence of the soil type. So, the average nitrogen fertilization rate of 200 kg N ha^{-1} at the GCEF site is in the range that might be sufficient to not limit plant growth or might also be below. Additionally, the nitrogen limitation is calculated in both modeling approaches, after the water limitation is calculated. So, the factor only becomes less than one if the already water limited production is limited even more by the available nitrogen. This makes the mean nitrogen limitation less informative than the mean water limitation. It also explains the abrupt end of nitrogen limitation after the first one and a half years in GRASSMIND-BODIUM, since from there on strong water limitation occurs. However, despite the lower meaningfulness of the nitrogen limitation factor, the overall picture is communicated: in GRASSMIND-BODIUM, the role of the nitrogen limitation in shaping the growth patterns is negligible next to the water limitation, except in the first one and a half years, where it is dominant, while in GRASSMIND standalone the role of the nitrogen limitation exceeds the role of the water limitation. Almost every time water limitation occurs, nitrogen availability is limiting growth even further. Taking into account the fertilization rate, the division of the roles seems to be more realistic in GRASSMIND-BODIUM, than in GRASSMIND.

Given the similar magnitude of the simulated mineral nitrogen content in the soil, it can be assumed that the differences between the modeling approaches arise mainly from different calculations of nitrogen uptake. In (GRASSMIND-)BODIUM the nitrogen available for uptake is relative to the nitrogen concentration in the soil water. It is calculated as the sum of nitrogen transported with the uptaken water plus nitrogen transported by diffusion towards the root surface (if the demand is not already fulfilled by the nitrogen from convection). In GRASSMIND the nitrogen within one layer is divided by the number of plants rooting in this layer, and each plant is assigned this amount. For each individual plant, the sum of these values over their rooting layers is available for uptake. With that, the number of plants directly impacts the amount of nitrogen available for the other plants. In case of newly emerging seedlings, they might limit the nitrogen access of other plants, without actually using all the nitrogen assigned to them. This could be an explanation for the stronger nitrogen limitation in GRASSMIND. The high nitrogen limitation in the first one and half years in GRASSMIND-BODIUM can be explained by the relatively low simulated mineral nitrogen content and the high soil moisture in this time. In GRASSMIND-BODIUM, where nitrogen uptake is relative to the nitrogen concentration in the water, this is more relevant than in GRASSMIND standalone, where all the mineral nitrogen within a soil layer is available for plant uptake.

The match of the simulated mineral nitrogen content in the soil with the measurements indicates that the assumed carbon to nitrogen ratios of the plant organs (C1) are (at least on average) appropriate.

The differing roles of the growth limitation processes between the modeling approaches reveal that the alignment with the measurement of yield and biomass itself say little about how realistic the underlying processes are represented. Very different occurrences of the limitation processes result in alignments with the yield and biomass data that are equally well. This is caused by the multiple factors in the models that influence growth: the photosynthesis rate, which is calibrated with two parameters;

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the limitation by water, which is calibrated with the water use efficiency parameter and the two rooting parameters affecting the access to soil water; the limitation by nitrogen, which is also affected by the rooting parameters; the crowding mortality, which is influenced by the overlap factor and the height-width ratio; the limitation by temperature, with fixed parameters. So, there are some degrees of freedom to find a combination of these factors to obtain the growth pattern. This is also apparent in the varying calibration parameters between two calibration runs of the same setup. For the further development of grassland models, it is therefore important to find a way to evaluate the individual processes in more detail. This study shows that the inclusion of a more detailed soil water model allows a better examination of the water uptake process. While in GRASSMIND standalone, the simulated soil moisture almost never matches the measured data, in GRASSMIND-BODIUM, the simulated soil moisture generally reproduces the measurements. So, when having accurate (daily) measurement data, it allows for a more detailed investigation. Single mismatches can explain mismatches in other variables and can be used to find flaws in the models and improve them. This is not only helpful for the evaluation of the water uptake process and its parametrization (water use efficiency), but might also be helpful for other related processes, like the modeled root growth.

The rooting depth is calculated in the GRASSMINDs plant component from the two calibrated root depth parameters as a function of the root biomass (linked to the shoot biomass by a given constant ratio). It is assumed that the root mass is evenly distributed over the depth. In field experiments, the rooting patterns of grass species are determined to be much more complex. The maximum rooting depth differs strongly, depending on climatic conditions (Tumber-Dávila et al., 2022) and plant-diversity (Mueller et al., 2013). In addition, management and soil structure affect root growth (Kuka and Joschko, 2024). So, the model strongly simplifies the relations. Nonetheless, the parametrization of the root depth is quite ambiguous. So to systematically analyze the root growth, one should come up with an even more simple relationship (e.g just one parameter for rooting depth) with a more certain parametrization, to be used as a starting point to analyze the mentioned factors. Different rooting strategies other than the equal distribution of root mass over rooting depth should be incorporated, as Nippert and Holdo (2015) have already shown in a simulation study that root distribution can have huge impacts on plant growth and susceptibility to drought. For this, the more accurate soil water representation of GRASSMIND-BODIUM can become handy to compare soil moisture as a result of plant water uptake with field data. From the experimental site, soil data with a higher vertical resolution would be beneficial in order to be able to monitor the water uptake patterns with higher resolution.

Both modeling approaches do not perform well in growth in a certain period after seeding. This might be due to shortcomings in plant competition in GRASSMIND. In the model, all seedlings have exactly the same height when they arise a certain time after the seeding. Therefore, the light competition process assigns every seedling the same irradiance. So, when there is too much shading, all plants do not grow well. This seems to be the case in the model. Plants in the seedling phase that stand in high density undergo strong competition and little differences in height can have a large impact on competitive success (Lambers et al., 1998). As such small height differences are not reflected in the model, all plants suffer from high density. As 2845 seeds are thrown per square meter, simulated a germination rate of 0.68, about 1935 seedlings arise per square meter. Experiments counting tiller densities in grasslands report the number of tillers per square meter of the same magnitude. Bul-

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lock et al. (1994) reports mean tiller densities of 4540 m^{-2} after thinning (*Lolium perenne* and *Agrostis stolonifera*). Lonsdale and Watkinson (1983) reports densities in the range between 1000 and 3000 m^{-2} after thinning (*Lolium perenne* and *Festuca pratensis*). Therefore, too much self thinning is not to be expected at the GCEF. However, the geometry of the modeled plants might differ. The overlap factor is calibrated to 1 or almost 1, which corresponds to (almost) no overlap of individual plants. This seems unrealistic. Together with the fact that the model realizes the measured biomass above ground, it indicates that the modeled geometry of a single plant overestimates the mass above ground per volume. Having less but more heavy plants might not matter for the biomass dynamics once the plants have thinned out, but can explain the growth deficit in the first month under the competition process.

The initial growth phase after seeding in the model might be improved by introducing some diversification of the plants after sowing. Also, reconsidering the mass per shoot volume might help. It was taken from Hetzer et al. (2021), who determined it from individually growing plants. It might differ when measuring plants growing in a community. Furthermore, a revision of the mortality process might have an effect if then the thinning out happens more efficiently. At the moment, plant mortality is only implemented as a consequence of crowding, with the overlap parameter being calibrated to adult plants. The crowding mechanism works to limit the number of plants, but does not consider the current status of the plants. For example, under drought conditions, there is no greater mortality (plants just grow slower or stop growing due to limited resources). It would be generally interesting to revise the mortality mechanism in GRASSMIND taking into account the current supply status of the plants. For the seedling phase, it could be considered that plants are more vulnerable to resource shortage, as reported by Lambers et al. (1998). This might result in a faster thin out after seeding and better growth afterwards in the model. The misperformance in the first growth period after seeding is not likely to be caused by poorly represented initial conditions of the soil, as the pattern is the same after the second seeding, where the soil component is still continuously running from the first period of investigation.

Another limitation of the modeling approaches is that we currently use only one functional type of grass species (although GRASSMIND can simulate multiple functional types). It is parameterized and calibrated to the plant composition at the GCEF site. Thus, the parametrization is not applicable for other plant compositions and cannot express changes in the composition. Furthermore, plant diversity and their effect on ecosystem services cannot be examined. That diversity plays an important role is already apparent from field data (Le Provost et al., 2023). This is of particular importance when moving beyond intensively managed grasslands (dominated by few grass species) to extensively managed grasslands (characterized by multiple plant species). Incorporating multiple species or functional types in the setup brings the challenge of much more parameters that must be assigned according to field measurements or calibrated. Using more calibration parameters means more degrees of freedom, making it even harder to find a unique solution in the calibration. Overall, the uncertainty with which the model is already struggling would rise even further. To deal with this, larger sets of field measurements are required. In the best case, these should include sites of different plant species composition and biomass measurements distinguished by species.

Similar considerations apply to soil structure, management, and climatic conditions. For example, in Germany, the parameterized soil type chernozem only makes up a surface area of about 11,000 km^2 (including chernozem-like soils) and is mainly

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found in Saxony-Anhalt and Thuringia (Altermann et al., 2005). The modeling approaches should be evaluated for various sites with different conditions before the reliability as a predictive model can be assessed. Numerous field experiments are available across Europe (GCEF, eLTER, GrassPlot, Biodiversity Exploratories), offering a large heterogeneity in environmental conditions (weather, soil properties, and management regime). However, except for GCEF, the measurements are rather sparse, measuring, for example, the biomass only once a year. This makes it hardly possible to evaluate the daily growth dynamics of the modeling approaches. A combination with remote sensing data might help solve this issue.

In the calibration, only the mean measurement values of the five parcels at the GCEF site were used. There was quite some variance between the parcels, but it cannot be estimated to what extent this results from the measurement uncertainty or from the actual differences in plant growth between the five parcels. Differences between the parcels might also arise from different initial soil conditions, which were reported to vary at the experimental site (e.g. differences in horizon depths) (Schädler et al., 2019). In the model initialization, such differences were not considered. This makes it difficult to compare the observed variance of the field measurements with the variance of the simulations, which arises only from stochasticity included in the mortality process of plants. To have a somehow similar handling of the variance between the measurement data and the simulation data, the average of five simulation runs was taken for the calculation of the sum of the absolute values of the distances in the calibration process. In the simulation results of biomass and yield, it can be seen that GRASSMIND has a standard deviation in the range of the measurement values in the drought years. Interestingly, this is not the case for GRASSMIND-BODIUM. With the coupled models, the standard deviation between the runs is much lower. Since the only stochasticity included in the models is in the mortality process, it can be concluded that there is some non-linear feedback between the death of plants and the remaining plants in GRASSMIND that is not apparent in GRASSMIND-BODIUM. This different feedback can be explained by differences in the limitation approaches. In GRASSMIND, the available resources of a certain layer (water above the permanent wilting point, nitrogen) are equally divided between all plants rooting into the layer (even if the demand of a plant is lower than this share). So whether a plant is dying or not and whether the dying plant is bigger or smaller (and therefore deeper or more narrow rooting) has a direct impact on the other plants, as they gain more or less resources from certain layers. This feedback is enlarged, when a plant death changes the number of seedlings emerging in the future, as the seedlings get a full share of soil resources from the first layer assigned, which they might not even need. In GRASSMIND-BODIUM, the water that a single plant can receive depends on the water potential, and the nitrogen it can receive depends on the nitrogen concentration. Hence, it is more indirect related to the number of plants. Of course, the number of plants has an impact on the water potential and the nitrogen concentration and thereby on the individual plants, but only for the next timestep, and other processes (like alteration in water flow) might counteract it. So, the feedback of an individual plant on the other plants regarding soil resource allocation is weaker in GRASSMIND-BODIUM than in GRASSMIND.
From the comparison of the standard deviation with the absolute ranges of the measurement values, the variability of GRASSMIND-BODIUM seems much more realistic than that of GRASSMIND, considering that the models do not even include all sources of variability. This advocates for the limitation approaches of GRASSMIND-BODIUM. To further address this, it would be helpful to have a bigger set of measurements (more than five parcels) and an estimation of the measurement error. In addition,

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other sources of variability than in the mortality process could be included in the simulations. For example, soil variability can be a reason for varying yield on the field scale, as discussed by Di Virgilio et al. (2007) for switchgrass.
However, we can already conclude from this that the limitation approaches in GRASSMIND come with a noticeable sensitivity to the number of plants (rooting in a certain layer). This might be critical when we think about uncertainties in the germination or mortality process that can become amplified.

The results emphasize the importance of synergizing model expertise of different components. The coupling via Python bindings comply with the task. Especially under the condition that the native models are permanently under construction, the concept of having independent models that communicate only along defined interfaces is helpful to make use of model improvements in the coupled model system quickly. The formulated self-coupling test is in this context of particular importance to ensure that changes made to the native models do not violate the correct functioning of the model interfaces. The FINAM framework offered no additional value in this setup, as it complicated the workflow and the automatized data handling was not required for coupling models of the same spatial and temporal scale. It might become handy when simulating larger areas with heterogeneous environmental conditions.
The coupling of two mechanistic models also brings challenges and limitations. Splitting a model into two components (in order to use one of both components in the coupling) and identify all relevant interfaces can be quite time consuming. The process order cannot be maintained for both models when they are not equal. Also, the fact that one model needs to run every time step first causes changes in the process order, as the model running first cannot use information from the other model of the current time step. Furthermore, adaptions in the models need to be made in order to be compatible with the other models interfaces. Altogether, there is some modification of the native models in the coupling (in our case primarily in GRASSMIND). Together with the observed change in the role of the individual processes in shaping the growth pattern, this emphasizes that the experience from the models standalone cannot be transferred to the coupled model system, without further considerations. The coupling of two models is not just a technical task, but might require some modeling decisions. In this case, it does not suffice that both models individually are validated, but the coupled model system itself should be validated. It might even be required to repeat the validation when one of the individual models is further developed (and the new versions used in the coupling). Overall, coupling should be seen more as a tool for model development than as a plug-and-play process.
Regarding the design of the native models, it was experienced that a well documented and structured process order supports the finding of appropriate interface variables. To facilitate a potential coupling of a model, it should be well tracked, where and by what process a state variable is updated. An other convenient strategy would be that all updates on state variables are summed up over the time step and applied together to the state variable at the end of a time step, which would make it easier to identify the relevant interfaces and find suitable outputs in the other model that can be used as input to them.

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6 Conclusions

Overall, the results point out the potential that the model coupling of GRASSMIND with BODIUM can have to improve the representation of plant processes in the GRASSMIND, as well as processes in BODIUM (such as soil evaporation). The better representation of soil water in the coupled model system improves the reliability of the water uptake and limitation processes and offers good starting points for future examinations of other plant processes. The water and nitrogen uptake calculations in the coupled model system seem more appropriate to represent their role in limiting the growth. However, the most urgent challenges on the way toward a predictive grassland model that became clear are to eliminate the ambiguity in the parametrization of the plant component in GRASSMIND and to build up a large grassland database of grassland traits, as well as field experimental data. Once these tasks are satisfied, the potential of integrating BODIUMs soil expertise via coupling into the grassland model GRASSMIND can be utilized to improve the representation of plant processes and advance towards a predictive model. The soil model could also benefit from the coupling, receiving more accurate information on water uptake and emissions of organic material from the plants. However, first a more reliable representation of root growth must be realized that includes diverse rooting patterns.

The coupling concept of keeping the models individual and arranging the communication along defined interfaces is beneficial for working with models under permanent development. A self-coupling test is recommended to ensure that the functioning of the interfaces is sustained.

Code and data availability. The code for coupling the GRASSMIND and BODIUM models including all scripts to calibrate and run the models as well as pre- and postprocessing the data is available on Zenodo under https://doi.org/10.5281/zenodo.19204558 (Kantzenbach et al., 2026). The exact version of BODIUM is also included under this link, while the current version is available from the project website https://www.bonares.de/service-portal/models-concepts-evaluations/bodium-modell under the GNU General Public License v3.0 or later.
The GRASSMIND v2.0 model used in this study is integrated into a forest model (FORMIND), underlying its license and publication policy. Hence, the model code is only available on request from the project website https://formind.org/downloads/. An independent code version v3.0 of the GRASSMIND model under EUPL-1.2 license is currently developed, and is available from the project website https://www.ufz.de/index.php?en=48444. Note, however, that this version (GRASSMIND v3.0) has not yet undergone full testing and documentation. The current version of FINAM is available from the project website https://finam.pages.ufz.de/. The version used in this study is archived on Zenodo under https://doi.org/10.5281/zenodo.15268755 (Developers, 2025).

The data of the Global Change Experimental Facility (GCEF) used in the study to parameterize, calibrate and validate the GRASSMIND and GRASSMIND-BODIUM model are available on Zenodo: (1) aboveground biomass: https://doi.org/10.5281/zenodo.19134294 (Auge et al., 2026), (2) management and yield: https://doi.org/10.5281/zenodo.19134131 (Merbach et al., 2026), (3) soil moisture: https://doi.org/10.5281/zenodo.19134016 (Reitz et al., 2026), (4) soil mineral nitrogen: https://doi.org/10.5281/zenodo.19133727 (Schulz et al., 2026).
For the derivation of weather data of the experimental site, partly weather variables are available on PANGEA: (1) precipitation (used from 2015–2024): https://doi.org/10.1594/PANGAEA.968457 (Schädler and Remmler, 2024), (2) precipitation and temperature (used for

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2013 and 2014): https://doi.pangaea.de/10.1594/PANGAEA.949892 (Gründling et al., 2022). Scripts for data preparation and gap-filling are available on Zenodo under https://doi.org/10.5281/zenodo.19129783 (Schädler et al., 2026).

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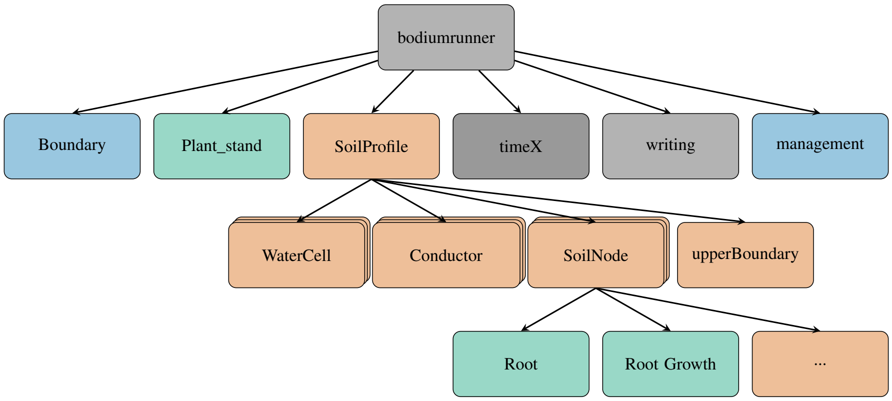

Figure A1. Identifying the plant component in the BODIUM structure. The central "bodiumrunner" class has objects of the classes "Boundary", "Plant_stand", "SoilProfile", "timeX", "writing" and "management" as members. The "SoilProfile" class has an object of the class "upperBoundary" as member as well as as several objects of the classes "WaterCell", "Conductor" and "SoilNode" as member. Each "SoilNode" object representing one soil layer has, next to futher soil objects, objects of the classes "Root" and "RootGrowth" as member. The objects identified as the plant component in BODIUM are colored in green, while soil objects are colored brown, weather and management input objects in blue and technical objects in grey.

Appendix A: BODIUM Structure

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Appendix B: GRASSMIND adaptations

Some adaptations are made compared to the previous GRASSMIND version. Some of them are due to requirements from BODIUM, and some are due to general considerations.

B1 Required from BODIUM

BODIUM requires information on the root exudates of the plants. As there is no exudation in GRASSMIND so far, this must be implemented. It is added by allocating a fixed percentage (in this parametrization ten percent) of the plants production with a fixed C:N ratio to the exudation.

B2 General adaptations

First, the calibration parameter "externalSeedInfluxPerHectar", which states the number of seeds that are invading the simulation area from outside, is eliminated. Originally, this parameter shall account for seeds that reach the simulation area from grasslands adjacent to it. With this parameter and invading process, the complete die-out of one grass species is hindered. However, this parameter has a huge impact on the simulation results. In this study, we set the parameter to zero, as the sum of the inflow and outflow of seeds should be zero on average anyway, assuming that the simulation area is part of a larger grassland similar to it. This change has an effect on the calibration, as parameter sets that result in a low number of plants for some time steps might be discriminated, as the plants might die out in some model runs.

As there were some difficulties in reaching the observed biomass and yield values of the vegetation without external seed influx, the crowding criteria is reconsidered. Plants are assumed to have a uniform cylindrical shape that changes in height and width over time (but with a fixed constant ratio). The aboveground space is, as the soil, separated into distinct layers. In each height layer, the horizontal areas of the plants reaching that layer are summed and multiplied by the overlapping factor (a constant fixed parameter between 0 and 1). If the sum is larger than the simulation area, a reduction factor is assigned to the affected plants. Originally, the maximal reduction factor from all height layers in which a plant grows is taken to assign a mortality probability to the plant. However, since all plants start from the soil surface and grow upward, the height layer of maximal coverage is always the lowest layer at the soil surface, and therefore all plants will be assigned the same mortality probability. Thus, an emerging seedling can possibly kill grown plants (when it triggers crowding mortality, all other plants are killed with the same probability like itself). We included an advantage of larger plants in the crowding process, by taking the reduction factor for a plant from its uppermost height layer. In this context, the shading was also revised. GRASSMIND has been using formulations from FORMIND (Köhler and Huth, 1998) for shading. Each height layer has a certain leaf area index (LAI) over the simulation area, considering the overall amount of plants inside that layer. At the same time, the LAI is calculated for each plant individually over its basal area for each height layer. In FORMIND, the shading of a single plant in the layers above it is calculated from the overall LAI. Below its top, the own LAI is used. This is reasonable for trees which have distinct crowns, but not realistic for grasslands, where the grass leaves overlap with the leafs of different grass plants very strongly. Therefore, the calculations are revised so that the overall LAI is used for the shading calculations at every height of the plant.

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This corresponds to the theoretical situation that the leaves of one plant overlap with the leaves of all plants in the simulation area. This is a generalization as well, but for simulation area of one square meter much more realistic than the generalization of having no overlap of the leaves at all and only shading by higher plants. As in FORMIND, the gross photosynthetic rate of a leaf is calculated as

$$P_{\mathrm{leaf}}(I_{\mathrm{leaf}}) = \frac{\alpha I_{\mathrm{leaf}} p_{\mathrm{max}}}{\alpha I_{\mathrm{leaf}} + p_{\mathrm{max}}}, \tag{B1}$$

where I_{leaf} is the irradiance reaching the leaf, α the quantum efficiency, and p_{max} the maximum gross leaf photosynthesis rate. The irradiance reaching the leaf can be calculated as

$$I_{\mathrm{leaf}} = \frac{k}{1-m} I_{\mathrm{ind}} e^{-kL}, \tag{B2}$$

where k is the light extinction coefficient, m the transmission coefficient, I_{ind} the incoming irradiance on top of the plant, and L the leaf area index of the leaf area that shades the respective leaf (i.e. it is above that leaf). In addition to FORMIND, it is now differentiated between photosynthetic active leaf area and shading leaf area (which includes next to photosynthetic active leaf area the photosynthetic inactive leaf area, e.g. brown leaf area of that plant and the leaf area of other plants). The corresponding photosynthetic active leaf area index and extinction coefficient are L_{ph} and k_{ph}. For shading, they are L_{sh} and k_{sh}. With that, equation B2 becomes

$$I_{\mathrm{leaf}} = \frac{k_{\mathrm{ph}}}{1-m} I_{\mathrm{ind}} e^{-kL_{\mathrm{sh}}}. \tag{B3}$$

To obtain the gross photosynthetic rate of a plant, the gross photosynthetic rate of the individual leaf is integrated over the photosynthetic active leaf area index of the plant.

$$P_{\mathrm{ind}} = \int_0^{L_{\mathrm{ph}}^0} P_{\mathrm{leaf}}(I_{\mathrm{leaf}})\, dL_{\mathrm{ph}}, \tag{B4}$$

with L_{ph}^0 the leaf area index of the entire plant in its area. Assuming the leaf area index to increase linearly over the layer, it applies within a certain layer lay

$$dL_{\mathrm{ph}} = dL_{\mathrm{sh}} \frac{L_{\mathrm{ph}}^{\mathrm{lay}}}{L_{\mathrm{sh}}^{\mathrm{lay}}}, \tag{B5}$$

where $L_{\mathrm{ph}}^{\mathrm{lay}}$ and $L_{\mathrm{ph}}^{\mathrm{lay}}$ are the photosynthetic active and shading leaf area indices of the respective layer. Integrating each layer individually using the incoming radiation at the top of the layer $I_{\mathrm{ind}}^{\mathrm{lay}}$, it applies to the gross photosynthetic rate of the individual plant inside the layer

$$P_{\mathrm{ind}}^{\mathrm{lay}} = \frac{L_{\mathrm{ph}}^{\mathrm{lay}}}{L_{\mathrm{sh}}^{\mathrm{lay}}} \int_0^{L_{\mathrm{sh}}^{\mathrm{lay}}} \frac{\alpha \frac{k_{\mathrm{ph}}}{1-m} I_{\mathrm{ind}}^{\mathrm{lay}} e^{-k_{\mathrm{sh}} L_{\mathrm{sh}}} p_{\mathrm{max}}}{\alpha \frac{k_{\mathrm{ph}}}{1-m} I_{\mathrm{ind}}^{\mathrm{lay}} e^{-k_{\mathrm{sh}} L_{\mathrm{sh}}} + p_{\mathrm{max}}}\, dL_{\mathrm{sh}}. \tag{B6}$$

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Using $\frac{u'(x)}{u(x)} = \frac{d}{dx} ln|u(x)|$ with $u(L_{\mathrm{sh}}) = \alpha \frac{k_{\mathrm{ph}}}{1-m} I^{\mathrm{lay}}_{\mathrm{ind}} e^{-k_{\mathrm{sh}} L_{\mathrm{sh}}} + p_{\max}$, yields

$$P^{\mathrm{lay}}_{\mathrm{ind}} = -\frac{L^{\mathrm{lay}}_{\mathrm{ph}}}{L^{\mathrm{lay}}_{\mathrm{sh}}} p_{\max} [u(x)]_0^{L^{\mathrm{lay}}_{\mathrm{sh}}} \tag{B7}$$

$$= \frac{L^{\mathrm{lay}}_{\mathrm{ph}}}{L^{\mathrm{lay}}_{\mathrm{sh}}} p_{\max}\, ln \left(\frac{\alpha k_{\mathrm{ph}} I^{\mathrm{lay}}_{\mathrm{ind}} + p_{\max}(1-m)}{\alpha k_{\mathrm{ph}} I^{\mathrm{lay}}_{\mathrm{ind}} e^{-k_{\mathrm{sh}} L^{\mathrm{lay}}_{\mathrm{sh}}} + p_{\max}(1-m)} \right). \tag{B8}$$

With this formulation, the gross photosynthetic rate of each plant can be calculated, summing up the contributions of each height layer.

Another revision is made to the allocation rates. GRASSMIND uses a given shoot-root ratio as an input parameter. Originally, the proportion of the net primary production that is allocated to the root and that which is allocated to the shoot was fixed based on the shoot root ratio (and the ratio of the net primary production that goes into growth in the first place). However, as the shoot biomass declines at mowing and the root biomass does not, this leads to a growing violation of the shoot-root ratio in favor of the root biomass. To avoid this, the allocation rates a_{root} and a_{shoot} are adapted based on the current root biomass M_{root} and the shoot biomass M_{shoot}. The biomass increase P_{growth} should be allocated so that the shoot root ratio r_{sr} is restored. The allocation rates shall obey

$$a_{\mathrm{root}} + a_{\mathrm{shoot}} = 1, \tag{B9}$$

$$\frac{M_{\mathrm{shoot}} + a_{\mathrm{shoot}} P_{\mathrm{growth}}}{M_{\mathrm{root}} + a_{\mathrm{root}} P_{\mathrm{growth}}} = r_{\mathrm{sr}}, \tag{B10}$$

which can be resolved to

$$a_{\mathrm{shoot}} = \frac{r_{\mathrm{sr}}(M_{\mathrm{root}} + P_{\mathrm{growth}}) - M_{\mathrm{shoot}}}{(1 + r_{\mathrm{sr}}) P_{\mathrm{growth}}}. \tag{B11}$$

Additionally, the restriction that a_{root} and a_{shoot} must be positive applies. As net primary production is not yet available at the place in the process order, where the allocation rates are calculated, gross primary production P_{gross} is used instead. With that, the violation of the shoot-root ratio is restored a little slower. So, the allocation rates are calculated as

$$a_{\mathrm{shoot}} = \begin{cases} 0 & \text{if } \frac{r_{\mathrm{sr}}(M_{\mathrm{root}}+P_{\mathrm{gross}})-M_{\mathrm{shoot}}}{(1+r_{\mathrm{sr}})P_{\mathrm{gross}}} < 0 \\ 1 & \text{if } \frac{r_{\mathrm{sr}}(M_{\mathrm{root}}+P_{\mathrm{gross}})-M_{\mathrm{shoot}}}{(1+r_{\mathrm{sr}})P_{\mathrm{gross}}} > 1 \\ \frac{r_{\mathrm{sr}}(M_{\mathrm{root}}+P_{\mathrm{gross}})-M_{\mathrm{shoot}}}{(1+r_{\mathrm{sr}})P_{\mathrm{gross}}} & \text{else,} \end{cases} \tag{B12}$$

$$a_{\mathrm{root}} = 1 - a_{\mathrm{shoot}}. \tag{B13}$$

Appendix C: Parametrization

The model parameters of GRASSMIND that are fixed (not calibrated) are given in Table C1. The field capacity and permanent wilting point for each soil layer are used as given in Table C3.

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Table C1. Fixed GRASSMIND model parameters.

Trait group	Name	Value	Unit	Reference
Geometry	Maximal plant size	2	m	Technical parameter
	Seedling height	0.03	m	
	Shoot-root ratio	3.41	-	Hetzer et al. (2021)
	Form factor (mass per shoot cylinder volume)	0.001	$\mathrm{ton\,m^{-3}}$	Hetzer et al. (2021)
	Specific leaf area	8000	$\mathrm{kg\,m^{-2}}$	Estimated[a]
Production	Light extinction coefficient	0.5	-	Zhang et al. (2014)
	Light transmission coefficient	0.1	-	Hetzer et al. (2021)
	Maintenance respiration rate	7.3	$\mathrm{ton\,ODM\,a^{-1}}$	Hetzer et al. (2021)
	Growth respiration fraction	0.25	-	Hetzer et al. (2021)
	Symbiotic nitrogen fixation fraction	0	-	
	Npp allocation to plant growth	0.8	-	Assume 10% into reproduction
	Npp allocation to exudation	0.1	-	Adopted BODIUM parameter
	MSW	0.4	-	Granier et al. (1999)
	h2L	-80000	Pa	Adopted BODIUM parameter
	h2H	-20000	Pa	Adopted BODIUM parameter
	C:N ratio green leaves	15	-	Estimated[b]
	C:N ratio brown leaves	25	-	Estimated[b]
	C:N ratio roots	30	-	Estimated[b]
	C:N ratio seeds	20	-	Estimated[b]
	C:N ratio exudates	40	-	Estimated[b]
Mortality	Background mortality	0.2		Hetzer et al. (2021)
	Leaf life span	43	d	Hetzer et al. (2021)
	Root life span	504	d	Tjoelker et al. (2005)
Reproduction	Seed pulse	2845		Hetzer et al. (2021)
	Sow date	267	d (since 2013)	GCEF
	Seed mass	1.5 e-9	ton	Estimated[c]
	Seed germination rates	0.68	-	Hetzer et al. (2021)
	Seed germination time	17	d	Hetzer et al. (2021)

[a] Estimated based on GCEF measurements of biomass and leaf area index

[b] C:N ratios are estimated based on different values reported in Khan et al. (2016), Wang and Schjoerring (2012), Sanaullah et al. (2010), Wong et al. (2024), Skersiene et al. (2024)

[c] Seed mass is estimated based on values of the different grass species reported in Schädler et al. (2019), Gutmane and Adamovich (2005), Borawska-Jarmułowicz et al. (2017), Obraztsov et al. (2018)

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Table C2. Soil moisture parameters as reported in Altermann et al. (2005).

Layer	Depth	Field Capacity (6.3 kPa)	Water Content (31.6 kPa)	Permanent wilting point (1500 kPa)
1–3	0–30 cm	$0.384\,\mathrm{m^3\,m^{-3}}$	$0.328\,\mathrm{m^3\,m^{-3}}$	$0.155\,\mathrm{m^3\,m^{-3}}$
4–5	30–50[a] cm	$0.385\,\mathrm{m^3\,m^{-3}}$	$0.330\,\mathrm{m^3\,m^{-3}}$	$0.151\,\mathrm{m^3\,m^{-3}}$
6	50[a]–60[a] cm	$0.377\,\mathrm{m^3\,m^{-3}}$	$0.319\,\mathrm{m^3\,m^{-3}}$	$0.150\,\mathrm{m^3\,m^{-3}}$
7–13	60[a]–130[a] cm	$0.382\,\mathrm{m^3\,m^{-3}}$	$0.294\,\mathrm{m^3\,m^{-3}}$	$0.095\,\mathrm{m^3\,m^{-3}}$
14–17	130[a]–170 cm	$0.156\,\mathrm{m^3\,m^{-3}}$	$0.113\,\mathrm{m^3\,m^{-3}}$	$0.070\,\mathrm{m^3\,m^{-3}}$
18–19	170–190 cm	$0.202\,\mathrm{m^3\,m^{-3}}$	$0.142\,\mathrm{m^3\,m^{-3}}$	$0.084\,\mathrm{m^3\,m^{-3}}$

[a] The indicated depth values are shifted by plus 5 cm compared to Altermann et al. (2005) in order to obtain the 10 cm thick layers required by GRASSMIND.

The van Genuchten parameters for the BODIUM configuration are determined from the set of field capacity, water content, and permanent wilting point, reported in Altermann et al. (2005) for each horizon. The values for each layer are summarized in Table C2. The van Genuchten model

$$\theta(\psi) = \theta_\mathrm{r} + \frac{\theta_\mathrm{s} - \theta_\mathrm{r}}{1 + (\alpha + |\psi|^n)^{1-\frac{1}{n}}}, \tag{C1}$$

is used, where θ is the water content, θ_r and θ_s the residual and saturated water content, ψ the water potential, α and n are two model parameters. For each layer, the parameters θ_r, θ_s, α and n are determined by minimizing the sum of the squared residuals at the three data points. The resulting parameters are summarized in Table C4. As we have fitted 4 parameters to three data points, the results are not unique but still a valid representation of the data. The water retention curves intersect the data points, and in between, the ambiguity corresponds to the uncertainty of the dataset in this range of water potential.

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Table C3. Soil parameters as reported in Altermann et al. (2005).

Layer	Depth	Pore space	Saturated conductivity	Bulk density	Organic carbon content	C:N ratio
1–3	0–30 cm	0.462 $m^3 m^{-3}$	60.4 $cm d^{-1}$	1.40 $g cm^{-3}$	2.06 %	11.3
4–5	30–50[a] cm	0.475 $m^3 m^{-3}$	28.0 $cm d^{-1}$	1.38 $g cm^{-3}$	1.12 %	9.9
6	50[a]–60[a] cm	0.508 $m^3 m^{-3}$	27.7 $cm d^{-1}$	1.31 $g cm^{-3}$	0.60 %	8.0
7–13	60[a]–130[a] cm	0.468 $m^3 m^{-3}$	10.8 $cm d^{-1}$	1.42 $g cm^{-3}$	0.11 %	4.2
14–17	130[a]–170 cm	0.320 $m^3 m^{-3}$	124.3 $cm d^{-1}$	1.81 $g cm^{-3}$	0.01 %	0.6
18–19	170–190 cm	0.354 $m^3 m^{-3}$	62.5 $cm d^{-1}$	1.70 $g cm^{-3}$	0.04 %	2.5

[a] The indicated depth values are shifted by plus 5 cm compared to Altermann et al. (2005) in order to obtain the 10 cm thick layers required by GRASSMIND.

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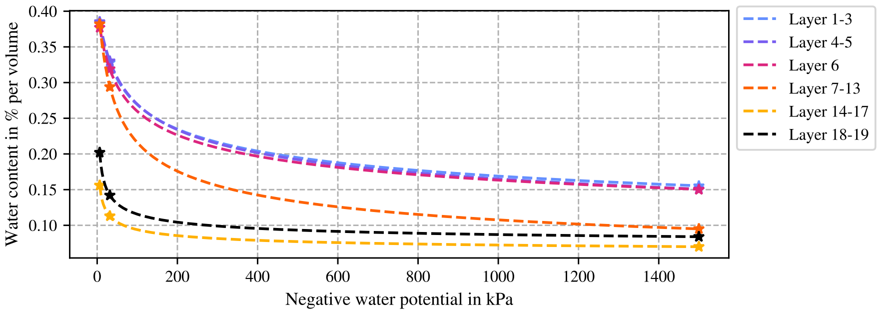

Figure C1. Water retention curves of the soil layers calculated with the van Genuchten model. The parameters were optimized, such that the retention curve insects the three water content values at different pressures measured by Altermann et al. (2005) for each layer.

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Table C4. Van Genuchten parameters of the soil layers used for the parametrization of BODIUM.

Layer	Depth	θ_s	θ_r	α	n
1–3	0–30 cm	0.4025	0.00844	0.000061	1.2181
4–5	30–50 cm	0.4021	0.00088	0.000055	1.2232
6	50–60 cm	0.3983	0.01591	0.000068	1.2256
7–13	60–120 cm	0.4126	0.00151	0.000076	1.3123
14–17	130–170 cm	0.3160	0.05462	0.002410	1.3458
18–19	170–190 cm	0.3486	0.06571	0.001085	1.3703

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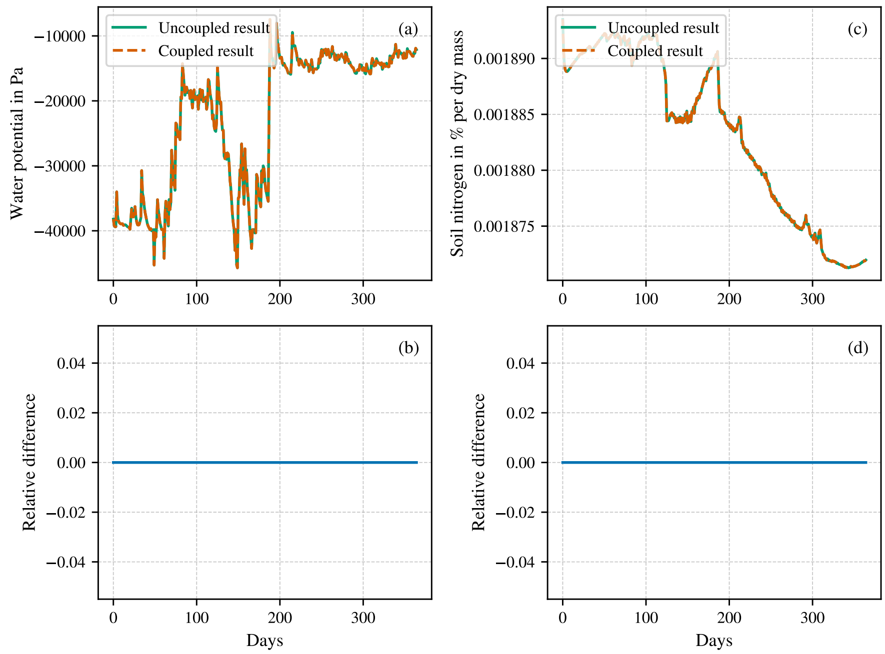

Figure D1. Exemplary results of the self-coupling test of BODIUM for (a),(b) water potential and (c),(d) nitrogen content of soil layer zero. (a) and (c) are showing the absolute results of the uncoupled and the coupled model instance together, (b) and (d) are showing the relative difference between the model instances (relative to the simulation time mean of the uncoupled result).

Appendix D: Self coupling test

As described in Section 2, in the self-coupling test of BODIUM, an instance of BODIUM is run standalone. A second instance is run in coupling mode, but instead using input from GRASSMIND, it uses input extracted from the standalone instance of BODIUM. In both cases, the water potential, the soil water content and the soil nitrogen content are extracted to be compared. The current default configuration is used so that the test can be easily repeated with every update of BODIUM. The simulations are run over a year of simulation time. In the output, it is checked that this includes a vegetation period. THe plot of both outputs together shows that the results of both instances are identical, as shown in Figure D1 exemplary for the water potential and the nitrogen content in the first soil layer.

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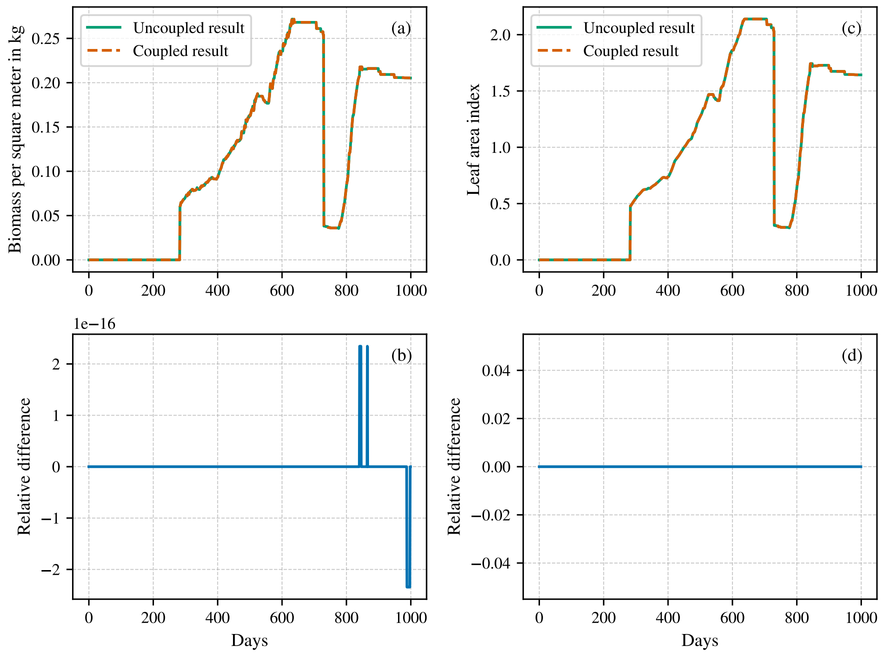

Figure D2. Exemplary results of the self-coupling test of GRASSMIND for (a),(b) biomass per square meter and (c),(d) leaf area index. (a) and (c) are showing the absolute results of the uncoupled and the coupled model instance together, (b) and (d) are showing the relative difference between the model instances (relative to the simulation time mean of the uncoupled result).

The self-coupling test of GRASSMIND was performed in the same way, running a standalone instance and an instance in coupling mode receiving input from the first one. For comparison, leaf area index, biomass and number of plants per square meter are extracted. As shown in Figure D2 exemplary for biomass and leaf area index, the results are identical or the difference is in the range of numerical error.

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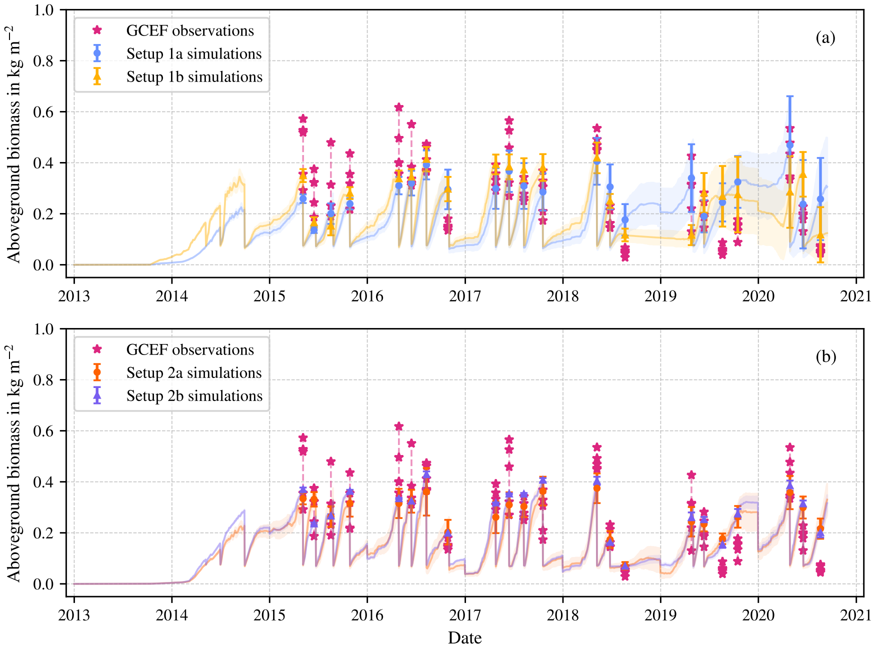

Figure E1. Calibration results of second calibration runs of GRASSMIND **(a)** and GRASSMIND-BODIUM **(b)**. Mean biomass and standard deviation of 100 runs using the parametrization from the respective calibration.

Appendix E: Other calibration results

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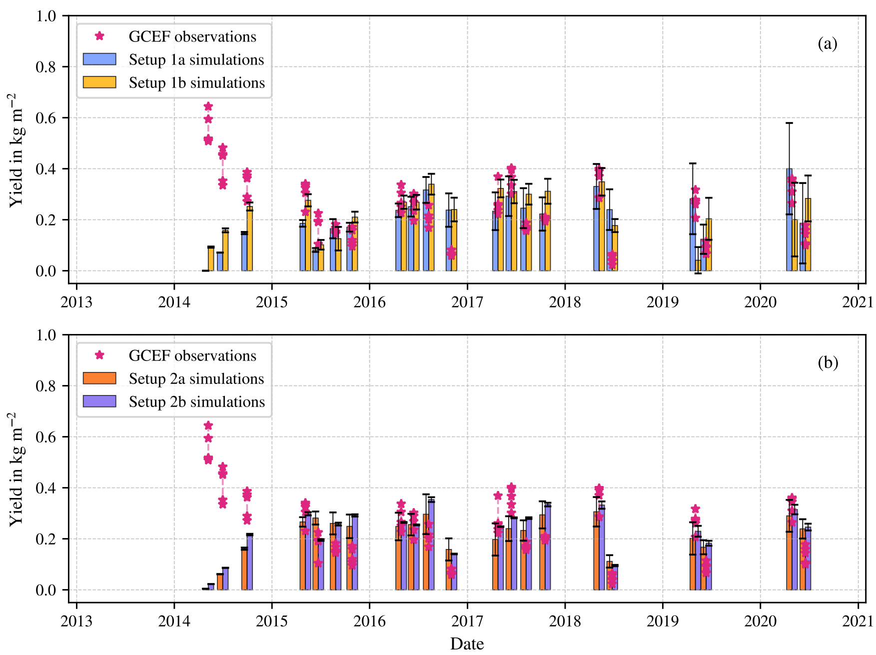

Figure E2. Calibration results of second calibration runs of GRASSMIND **(a)** and GRASSMIND-BODIUM **(b)**. Mean yield and standard deviation of 100 runs using the parametrization from the respective calibration.

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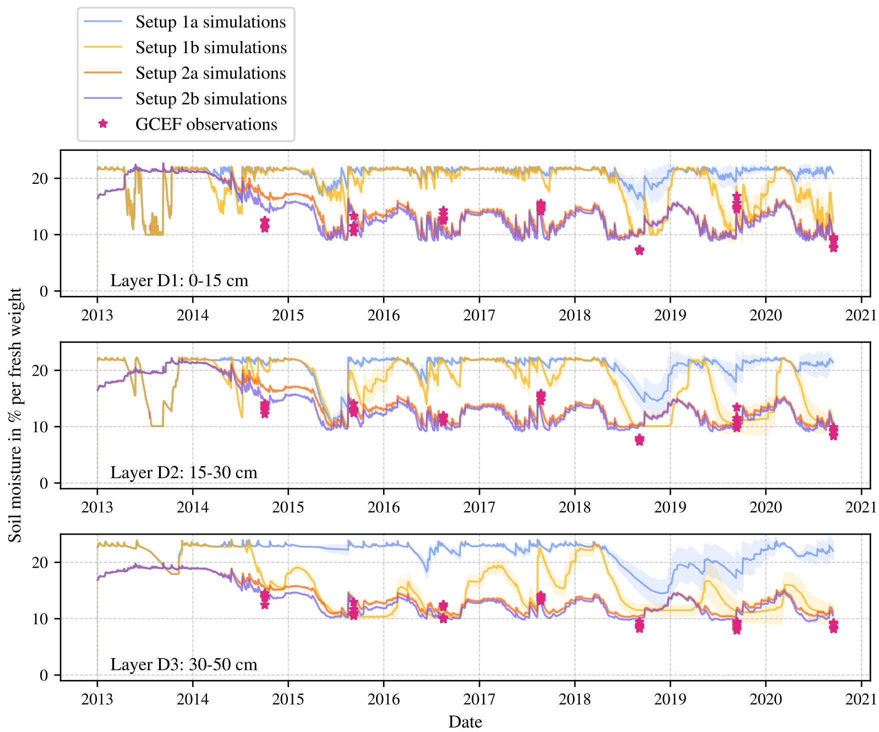

Figure E3. Calibration results of the second calibration runs of GRASSMIND and GRASSMIND-BODIUM. Mean soil moisture and standard deviation of 100 runs using the parametrization from the respective calibration. The results of the simulations for soil layers with a depth of 10 cm are converted to the soil layers of the measurements by calculating the proportion-weighted mean.

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Author contributions. FT and SK developed the idea of the coupling; MK designed and performed the coupling and evaluation, regularly obtaining feedback from FT; FT and SK provided expertise on GRASSMIND respectively BODIUM; TR and MS provided the field data; MK wrote the paper and all authors reviewed the paper and proposed improvements.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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The color palette suggested by Wong (2011) was used for the figures in this article, as well as the color palette by the IBM Design Library as cited by Nichols.

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