

The carbon budget of the managed grasslands of Great Britain - informed by earth observations

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Abstract.

Grasslands cover around two thirds of the agricultural land area of Great Britain (GB) and are important reservoirs of organic carbon (C). Outside a few well-monitored sites the quantification of C dynamics in managed grasslands is limited. Using process models to extrapolate site data is made complex by the spatio-temporal variability of climate, soils, and of grazing and cutting patterns. However, new earth observations (EO) provide sub-field resolution proxy data on the state of grassland canopies to support upscaling. Here, we show the potential of model-data fusion (MDF) to provide robust near-real time C analyses of managed grasslands across GB. We combine EO data and biogeochemical modelling to estimate grassland C balance and to infer the role of management and environment. We implement a MDF algorithm to (1) infer grassland cutting and grazing from data on vegetation volume (Proba-V), (2) optimise model parameters by assimilating leaf area index (LAI) times series data (Sentinel-2) and (3) simulate livestock grazing, grass cutting, and C allocation and C exchanges with the atmosphere. The MDF algorithm was applied for 2017 and 2018 to generate probabilistic C estimates at 1855 fields sampled from across GB. The algorithm was able to effectively assimilate the Sentinel-2 based LAI time-series (overlap=80%, RMSE=1.1 m⁻²m⁻², bias=0.35 m²m⁻²) and predict livestock densities per area that correspond with independent agricultural census-based data ($r=0.68$, RMSE=0.45 LU ha⁻¹, bias=-0.06 LU ha⁻¹). The mean total removed biomass across all simulated fields was 6 (±1.8) tDMha⁻¹y⁻¹. The simulated grassland ecosystems were on average C sinks in 2017 and 2018; the net biome exchange (NBE) was -191±81 (2017) and -49±69 gCm⁻²y⁻¹ (2018). Our results show that the 2018 European summer drought reduced the strength of C sinks in UK grasslands and led to a 9-fold increase in the number fields that were annual C sources (NBE>0) in 2018 (18% of fields) compared to 2017 (2% of fields). The field-scale analysis showed that management in the form of timing, intensity and type of defoliation were key determinants of the C balance of managed grasslands, with cut fields acting as weaker C sinks compared to grazed fields. Nevertheless, extreme weather, such as prolonged droughts, can convert grassland C sinks to sources.

Abbreviations

	GPP: Gross Primary Productivity		NPP: Net Primary Production ($NPP = GPP - R_a$)
	R_a : Autotrophic Respiration	35	LAI: Leaf Area Index
25	R_h : Heterotrophic Respiration		CI: Confidence Interval
	B_g : Grazed Biomass		RCR: Relative Confidence Range ($100 \times CI \div \text{mean}$)
	B_c : Cut Biomass		SD: Standard Deviation
	GCD: $B_g - B_c$		SOC: Soil Organic Carbon
	M: Manure produced by grazing livestock	40	Δ_{SOC} : Change in SOC pool size
30	Reco: Ecosystem Respiration ($Reco = R_a + R_h$)		AGB: Aboveground Biomass
	NEE: Net Ecosystem Exchange ($NEE = Reco - GPP$)		LU: Livestock Units
	NBE: Net Biome Exchange ($NBE = NEE + B_c + B_g - M$)		VPD: Vapour Pressure Deficit (Pa)

1 Introduction

45 Grasslands, natural and managed, are important biomes globally, with large soil carbon (C) pools and an important role in the cycling of water and nutrients (?). In Great Britain (GB), approximately two thirds of the agricultural land is grassland, managed at varying intensities as part of livestock farming systems (?). According to their biomass productivity and management intensity GB grasslands are grouped into rough grazing (low productivity), permanent (medium productivity) and temporary (high productivity) grasslands (?). The environmental impacts of grassland management increase with its intensity.

50 Impacts range from local-scale air and water pollution, due to manure production and nutrient loss, to emissions of all three major global warming-causing greenhouse gases (GHG) i.e. CO_2 , CH_4 and N_2O (??). Quantifying how C travels through the coupled system of the atmosphere, grass, livestock and soil is challenging, due to their dynamic management (grazing, cutting, re-seeding, fertiliser application) (????). However, quantifying C cycling in grasslands is a prerequisite for shaping, implementing and monitoring policies for reducing the climate impact of managed grasslands in GB and across the world (??).

55 Grasses fix C through photosynthesis (gross primary production, GPP), and allocate a fraction of this C to grow stems, leaves and roots. Plant senescence results in transfers of biomass C to litter and dead organic matter in the soil which undergo decomposition. Defoliation, through grazing and cutting, is a major disturbance to C cycling (??). Grass cutting abruptly removes most of the aboveground C from the ecosystem, forcing the grass to rebuild the leaf area necessary for photosynthesis and growth. In contrast, livestock grazing causes frequent but less intense removals of aboveground biomass C. A fraction of

60 the grazed C accumulates in livestock biomass but most of it exits the animal's body as manure, respiration- CO_2 and digestion-

CH₄. The amount of grazing-based manure C that is added to the soil's dead organic matter pool varies significantly depending on farm-level manure management decisions (?).

The potential of managed grasslands in GB, and beyond, to act as C sinks (?????) is premised on achieving a negative C balance at the ecosystem scale. Net ecosystem exchange (NEE) quantifies the C balance at the ecosystem scale based purely on gas fluxes and is equal to the difference between ecosystem respiration ($\text{Reco} = R_h + R_a$) and GPP. Net biome exchange (NBE) quantifies the C balance including lateral flows connected to cutting and animal management. NBE is equal to NEE after accounting for removals (grazing, cutting) and inflows (manure deposition) of C to the ecosystem. Animal-based C fluxes to the atmosphere (respiration CO₂, digestion CH₄) and other ecosystem-scale C losses (leached C, manure-induced CH₄) are sometimes included in the calculation of NBE (?). NEE makes up the bulk of NBE and is measured at field-scale using closed chambers and eddy covariance towers with both techniques having contrasting strengths and weaknesses, and requiring expert knowledge to deploy (?). NBE calculation requires measurements of the lateral flows on which human management plays a major role (?).

Quantitative understanding of the dynamics of C pools and fluxes in grasslands is gained through field and lab-based experiments. This understanding is incorporated into models of ecosystem C biogeochemistry, which are conceptually-coherent structures of mathematical equations that track the fluxes of C in the atmosphere-plant-soil-livestock system (?????). Biogeochemical models can upscale knowledge on ecosystem C dynamics across large areas and over time. Model-based upscaling represents a robust way for diagnosing the role of climate and management on C exchanges, and exploring C sensitivity of future climate and alternate management scenarios. Models require information on environmental conditions as inputs. Providing these inputs across space introduces uncertainty (input uncertainty) to model predictions because the relevant data come from spatial extrapolations of point measurements (i.e. soil surveys, weather stations). Another key source of input uncertainty is the lack of accurate spatial data on grassland management i.e. harvest and grazing patterns and manure and fertiliser use, which must therefore be inferred by some means (???????). Model credibility can be supported by effective calibration with ground data and validating predictions using independent data. Providing uncertainty estimates on model outputs provides robust contexts for model interpretation (?).

Advances in satellite-based remote sensing methods, i.e. Earth Observation (EO), over the past decade have increased the volume and resolution of spatial data on grassland states (e.g. sward biomass, chlorophyll content) and soil factors (e.g. soil moisture and temperature) (?). There is an opportunity to use EO data in model-based studies to perform upscaling with reduced input and parametric uncertainty and with constrained predictive uncertainty and model bias. In this context, high resolution (<100 m), frequently-retrieved (~weekly) EO data on the state of grassland vegetation can be assimilated and used to validate relevant model predictions and to calibrate model parameters at the scale of individual grassland fields (?????). In addition, time-series of EO-based vegetation indices can be used to monitor vegetation volume change and identify the timing of the relevant management i.e. grass harvesting and livestock grazing (????). Leaf area index (LAI) conveys information on vegetation structure and volume, and can be estimated from multispectral optical EO data (?). The volume of EO-derived LAI data is, however, dependant on the frequency of satellite overpasses and the level of cloudiness.

95 In previous analyses at two grassland eddy flux sites in GB we have shown that calibrating biogeochemical model parameters with ground-based LAI observations allowed robust diagnoses of the effects of grazing and cutting on independently measured net C exchanges (?). In a follow-up study at another grassland research farm in GB we demonstrated that model calibration with satellite-based LAI observations was effective for monitoring biomass removals and quantifying management impacts on field-scale C balance (?). Here, we build on this earlier work to demonstrate how EO data and biogeochemical modelling can be
100 combined to (1) detect vegetation-related management operations (i.e. grass cutting and grazing intensity) and (2) to estimate the variation in C dynamics over a large domain (GB) and at fine resolution (sub-field scale). We use a parsimonious process-based biogeochemical model of grassland C dynamics (DALEC-Grass) that is integrated into a probabilistic model-data fusion (MDF) algorithm (CARDAMOM). DALEC-Grass is driven by weather data and field-specific EO-based data on weekly change in vegetation volume. CARDAMOM performs field-specific calibrations of DALEC-Grass parameters by assimilating local EO
105 LAI time-series. The MDF algorithm is implemented for 2017-2018 on a large sample of 1855 managed grassland fields in GB (England, Wales and Scotland). We obtain a sample representative of the different grassland ecosystems and management types by randomly selecting 1 field per 25 km² across GB from the UK's Land Cover Map (vector land parcels). Grazing intensity, cutting timing and yields and C pools and fluxes are predicted by DALEC-Grass for every simulated field. In order to evaluate our MDF analysis, we compare predictions of annual grass yields (grazed and cut biomass) to biomass utilisation data from
110 the relevant literature and to livestock density data from the most recent GB agricultural census data. In 2018, GB was affected by a summer heat and drought wave (summer 2018 was $\approx 1^{\circ}\text{C}$ warmer than summer 2017) allowing us to examine the impact of climate anomalies on grassland C balance (??) The aim of this study is to answer four key questions:

1. Can we detect realistic variations in grassland vegetation management over national domains at field scale by assimilating EO information on LAI?
- 115 2. What is the C balance of managed grasslands and how does it vary across GB?
3. Which factors control the predicted C balance and biomass removals?
4. How large is the analytical uncertainty on C cycling and which factors affect it?

The novelty of this research is to combine EO data and modelling to infer management of grasslands at field-scale across a nation and then to simulate the role of management on grassland C exchanges. The advent of highly-resolved satellite data
120 from Sentinel 2 makes this possible, allowing tracking of \sim weekly changes in LAI at sub-field scales for a national sample of grassland fields. The intermediate complexity model employed means that Bayesian approaches to model calibration can explore the uncertainty of parameters and estimates of C cycling. The key innovation is to combine observations of changes in grassland LAI from space with expected changes in LAI (i.e. grass growth rates) derived from process modelling. The difference between observed and expected change in LAI is used to infer consumption by grazing livestock or removals by
125 grass cutting. The C cycle estimate is then updated based on this estimation.

2 Materials and methods

2.1 Materials

2.1.1 Location of managed grasslands

For the identification of the location and limits of field boundaries for representative grasslands we used the 2018 Land Cover Map plus (LCM), which is updated annually by the Centre of Ecology and Hydrology (CEH) of the UK (www.ceh.ac.uk/crops2015). The LCM includes geo-referenced polygons of improved grassland fields in GB that are identified as such by using a combination of reflectance data. The LCM data are validated against ground observations of land-use type.

2.1.2 DALEC-Grass Model

DALEC-Grass (Fig. 1) is a process-orientated model of intermediate complexity representing the C cycling of grassland ecosystems. DALEC-Grass uses meteorological information to calculate gross primary productivity, autotrophic and heterotrophic respiration, changes in leaf area index (LAI), the C turnover of different plant and soil pools as well as the removal of C via grazing and grass cutting. Photosynthesis is calculated using the Aggregated Canopy Model (ACM) and phenology is calculated using the Growing Season Index (GSI) approach (?). DALEC-Grass uses a dynamic scheme to allocate C to above and below-ground plant tissues, which is based on the assumption that C allocation to roots increases after sufficient leaf area has been developed such that there are diminishing returns on further canopy expansion (?). The model uses a simple scheme to describe C allocation to soil with two pools considered; a more labile litter pool to which dead plant material and manure-C are added, and a more recalcitrant soil organic carbon pool (SOC), which receives C from the litter pool only. At each time-step the volume of simulated grazed biomass-C is converted to animal respiration CO₂-C, digestion CH₄-C and manure-C using generic conversion factors (see Fig. 1) extracted from the relevant literature (????). These generic conversion factors are used because the type, weight and age of animals grazing on individual fields can neither be inferred from EO data nor be reliably estimated from available datasets of livestock spatial distribution (e.g. agricultural census). The conversion factors reflect an averaging of relevant data for beef and dairy cattle and sheep, which are the main types of livestock in the GB. The model's 31 parameters are presented in Table ?? in Appendix A. In this study, DALEC-Grass is implemented at a weekly time-step.

2.1.3 Carbon Data Model Framework (CARDAMOM)

The CARbon DAta MOdel FraMework (CARDAMOM) is a Bayesian MDF framework that is tailored for use in ecosystem biogeochemistry studies (?). By assimilating observational data CARDAMOM updates the distribution of model parameters following the rules of Bayesian inference. A key aspect of CARDAMOM is the use of ecological and dynamic constraints (EDC), which are conditions applied to the parameter sampling process in order to ensure the mathematical, ecological and biogeochemical sensibility (or "common sense") of the simulated system (?). In simple terms, CARDAMOM examines whether the simulated pools and fluxes that result from implementing the model with a sampled parameter vector behave in realistic ways; i.e. do not exceed certain user-defined, widely-accepted and literature-based limits. The EDCs used in CARDAMOM

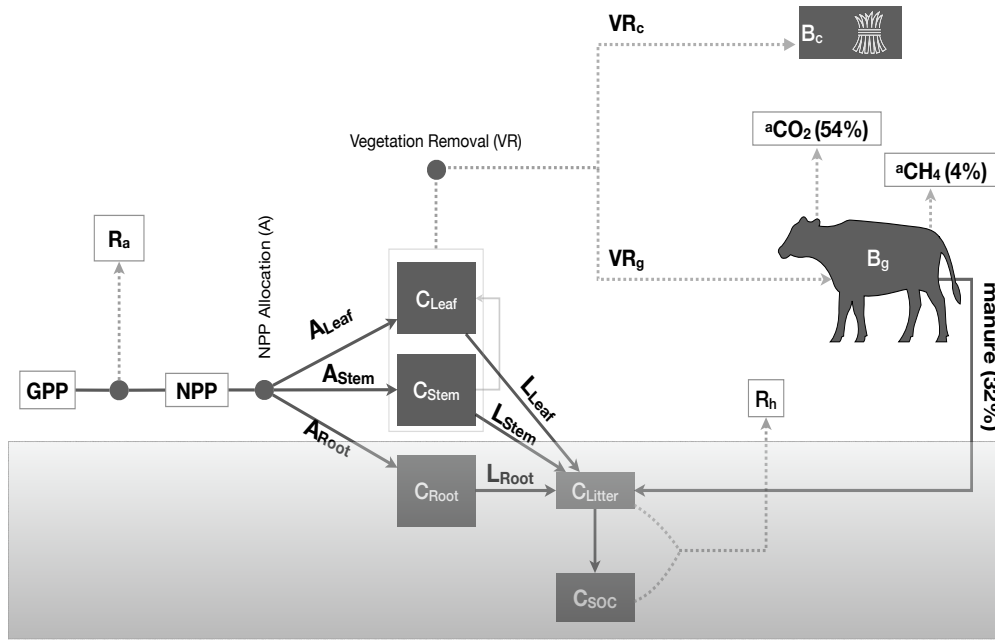


Figure 1. Schematic description of the DALEC-Grass model. DALEC-Grass simulates the dynamics of 5 C pools (C) : leaf, stem, roots, litter and SOC. C is allocated to the 5 C pools via NPP allocation (A) and litter production (L). Vegetation removals (VR) can occur due to grazing or cutting. DALEC-Grass determines whether a vegetation removal is caused by grazing, cutting or neither (see section 2.2.2). When cutting is simulated ($VR_c > 0$) cut biomass (B_c) is removed from the ecosystem. When grazing is simulated ($VR_g > 0$) 32% of grazed biomass (B_g) is converted to manure, 54% of grazed biomass (B_g) is converted to animal respiration (${}^a\text{CO}_2$) and 4% of grazed biomass (B_g) is converted to methane (${}^a\text{CH}_4$). Dotted lines (\cdots) show outward fluxes of C. Solid lines (—) show internal and inward fluxes of C

are presented in Table ?? in Appendix A. A schematic description of how CARDAMOM and DALEC-Grass are connected is provided in Figure ?? in Appendix A.

Bayesian inference is performed in CARDAMOM using the root mean square error (RMSE) between the simulated and the
 160 EO-based LAI time-series to calculate and attribute likelihoods to every sampled parameter vector. In this study, the Simulated Annealing (SA) algorithm is used to implement the probabilistic parameter sampling process (?). After testing the SA algorithm to identify the optimal number of repetitions for achieving acceptable chain convergence the number of parameter proposals was set to 5,000,000. The uncertainty around the assimilated (Sentinel-2) LAI data was set to 15% (relative standard deviation) in this study. However, it should be noted that the uncertainty around remote sensing-based LAI data is poorly determined but
 165 largely underestimated (?).

A uniform distribution was used for each of the 31 DALEC-Grass parameter priors and the range for each parameter prior is presented in Table ?? (Appendix A). In ? DALEC-Grass parameter priors were refined through implementing the model using known vegetation management (cutting dates, livestock density time-series) and by assimilating field-measured LAI and CO₂ flux data (chamber-based and eddy covariance). In ? these model priors have been tested and refined further using EO-based
 170 vegetation reduction time-series (as vegetation management-related model drivers) and by assimilating Sentinel-2 based LAI

time-series. The limits of the uniform parameter distributions used in the present study are based on the results of ? but 4 parameters were allowed to vary more than these results suggested in order to better consider the variability in management factor across GB grasslands (indicated with * in Table ?? in Appendix A). These parameters are the plant photosynthetic N use efficiency (PNUE), the leaf mass C per area (LCA), and the pre-grazing and pre-cutting biomass.

175 2.1.4 Earth observation data

EO-based information of vegetation canopy cover was used to infer vegetation-related management operations (i.e. grazing or cutting). This canopy cover time-series was generated for each simulated field from LAI data from the Copernicus Global Land Service (CGLS) EO database. The CGLS LAI data comprise ~~top-of-atmosphere reflectance processed products from the LAI~~ estimates from on Proba-V satellite ~~, with images that have~~ a spatial resolution of 300m and a temporal resolution of 10 days.

180 Gaps in the CGLS LAI time-series due to cloud coverage are filled using a machine learning model built with time-series for past years and neighbouring pixels (?). For each simulated field the corresponding time-series has been converted, from their original 10-day time-step, to a weekly time step using linear interpolation. Thereafter, the reduction between subsequent dates in the time-series was calculated. When the change between week n and $n + 1$ was positive the reduction value for week n is 0. Hereafter, we refer to this time-series as the "vegetation reduction" time-series.

185 The EO-based LAI data assimilated in CARDAMOM were calculated from Sentinel-2 images. Atmospherically-corrected images at 20m and 60m resolutions (L2A product) were downloaded from the Amazon Web Services (AWS) Sentinel-2 datapool. The images were processed to remove pixels with cloud and haze and, then, used to calculate LAI (at 20m) using the sen2cor algorithm (?). When available, the field-average Sentinel-2-based LAI value that corresponds to the day closest to the first day of every simulated week is added to the weekly observational LAI time-series that are assimilated through the
190 CARDAMOM MDF framework.

Using two independent EO datasets on LAI provides a more robust and continuous estimate of vegetation dynamics. Due to frequent cloud cover field-specific, high-resolution (20m) and continuous weekly LAI time-series are not available from Sentinel-2 images alone. Hence we use a separate EO-based data product (CGLS LAI) in which observational LAI time-series are gap-filled using techniques that are more robust than simple temporal interpolation. In order to control the impacts of the
195 observational uncertainty of the vegetation reduction data (due to their 300m resolution) we : (1) use relevant mechanisms in DALEC-Grass (see section 2.2.2) and (2) adjust the process of sampling grassland fields (see section 2.2.1) accordingly to match the coarser resolution of vegetation reduction data.

2.1.5 Environmental and management data

Six meteorological drivers are used in DALEC-Grass to drive variations in biogeochemical process: (1) minimum and maximum temperature ($^{\circ}\text{C}$), (2) total short-wave radiation ($\text{MJm}^{-2}\text{d}^{-1}$), (3) atmospheric CO_2 concentration (ppm), (4) 21-day
200 average photoperiod (sec), (5) 21-day average minimum T and (6) 21-day average vapour pressure deficit (Pa). Data were obtained from the ERA5 global atmospheric reanalysis database of the European Centre for Medium-Range Weather Forecasts (ECMWF). Values of soil C (gCm^{-2} at 60cm depth) at 300m resolution were obtained from the the SoilGrids database (?). For

every simulated field the mean and standard deviation (SD) of the corresponding SoilGrids pixels are used to define the range
205 of the model's initial SOC pool size parameter.

Agricultural census-based data on the number of sheep and cattle (beef and dairy) were obtained from the EDINA AgCensus
database (?). They are used in this study to independently evaluate the estimates from the MDF implementation. The AgCensus
data are produced by spatially disaggregating the numbers of cattle and sheep recorded at the level of local administrative units
(for each UK country), into a 5km grid of the UK. The most recently available livestock data for each constituent country of
210 the UK refer to different years; 2010 for England, 2015 for Wales and 2017 for Scotland.

2.2 Methodology

2.2.1 Sampling of grassland fields from the UK land cover map

Implementing the MDF algorithm for the thousands of fields that are classified as improved grassland in the LCM database is
computationally demanding and time consuming. In addition, the resolution of the CGLS (Proba-V-based) vegetation reduction
215 data is 300 m (9 ha). Taking into account that the average managed grassland field is 5-9 ha in area, we set a minimum limit
of 6 ha (and a maximum of 13 ha) when filtering the LCM dataset to obtain the location of fields. Moreover, the number of
EO data points available for each field depends on the time of image capturing and the amount of cloud cover at overpass.
As a consequence, the number of dates of available EO data can vary considerably between fields. We set a limit of having at
least 30 Sentinel-2 data points (during 2017-2018) for a field to be selected for simulation. The fields that met the conditions
220 were allocated to 25km² cells of a 5km grid of GB. One field was randomly selected from each cell, which resulted in a set of
2108 fields (Fig, 2). The CARDAMOM MDF algorithm was implemented for each of the selected fields for 2017 and 2018 by
running DALEC-Grass at a weekly-time step while assimilating the corresponding available EO-based LAI data. We refer to
the outputs of this implementation as "MDF predictions".

2.2.2 Identifying and calibrating grazing and cutting from EO data

225 Field-scale vegetation management activities are inferred from EO-based reduction data. At each time step the vegetation
reduction information is used to infer whether a field has undergone a grass cutting event or a livestock grazing event or
neither. For a vegetation reduction input data point to be simulated as a cutting: (1) the event should occur between April and
October, when cutting tends to occur; (2) the simulated aboveground biomass at the time of cutting should be greater than the
pre-cutting biomass parameter (P28, see Table ??) indicating that there is enough grass for a cut to be worthwhile; and (3)
230 the resulting yield should be $> 80 \text{ g C m}^{-2}$, another economic test for cutting to be likely. If any of these 3 conditions is not
met then a grazing event is indicated and simulated if the simulated aboveground biomass exceeds the pre-grazing biomass
parameter (P27, see Table ??). Otherwise, if neither a cut nor a grazing event can be simulated, no vegetation removal is
simulated.

In addition to this, DALEC-Grass parameters are locally calibrated at every simulated field by assimilating Sentinel-2 based
235 LAI data. This means that the vegetation management-related decisions made by DALEC-Grass during the simulated period

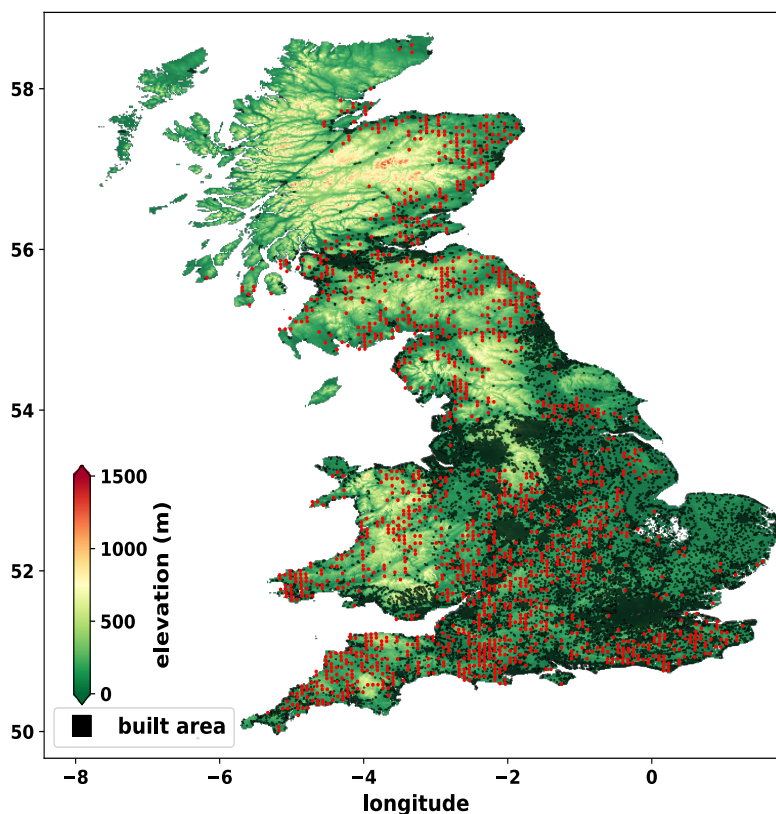


Figure 2. Topographic map of Great Britain (GB) with red symbols showing the locations of sampled fields. Built-up areas are shown in black. Digital elevation model from ?.

are conditioned on observational LAI data also (Fig. 3). Assimilation is performed by implementing DALEC-Grass while sampling from the model's parameter space in order to minimise the error (RMSE) between observational and simulated LAI time-series.

2.2.3 Calculation of presented variables and sign convention

240 The micrometeorological sign convention is used when presenting C balance variables, whereby a positive (+) sign before a NEE and NBE value signifies an addition of C to the atmosphere, and a negative sign (-) signifies a removal of C from the atmosphere. The net change (gCm^{-2}) in the size of the soil organic C (SOC) pool is presented and referred to as Δ_{SOC} . Positive Δ_{SOC} values signify an increase in the SOC pool size and negative values signify a decrease in the SOC pool size. We use the difference between total annually grazed and cut biomass (GCD) to quantify the relative impact of these two vegetation

245 removals methods. A negative (-) GCD value signifies that more biomass was removed from the simulated field via cutting than it was via livestock grazing. A positive (+) GCD value signifies that more biomass was removed via livestock grazing than it was via grass cutting.

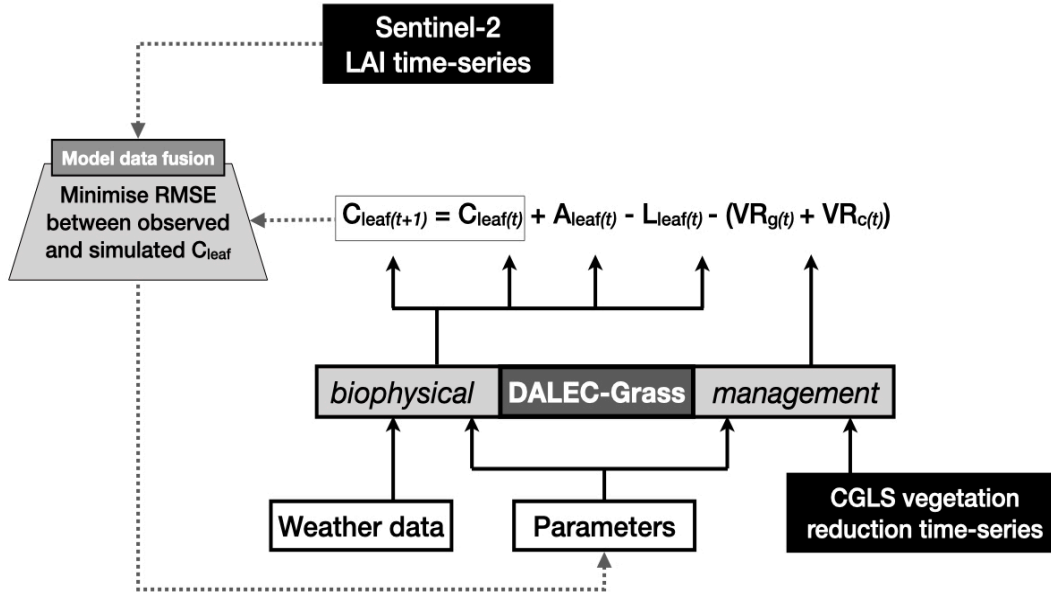


Figure 3. Description of how Sentinel-2 LAI observations, (CGLS) vegetation reduction time-series and DALEC-Grass are used to infer and calculate managed vegetation removals (grazing, cutting). The DALEC-Grass biophysical module simulates weekly leaf growth and senescence driven by weather data. The DALEC-Grass management module simulates weekly vegetation removals driven by the vegetation-reduction data. The CARDAMOM MDF algorithm calibrates the parameters of DALEC-Grass in order to achieve the smallest possible error (RMSE) between Sentinel-2 LAI and simulated LAI time-series. $LAI = C_{leaf} \div P15$ (see table ?? for details on parameter P15). The DALEC-Grass management module determines whether LAI reduction is due to grazing (L_g) or cutting (L_c) or neither. When a grazing reduction is identified ($VR_g > 0$ thus $VR_c = 0$) the livestock C-turnover process (described in 2.1.2) is implemented. When a reduction is identified as produced by cutting ($VR_c > 0$ thus $VR_g = 0$) most leaf biomass is removed; parameters P27, P28, P29, P31 (table ??) play a direct role in cut yield estimation. When neither grazing nor cutting is identified then $VR_c = 0$ and $VR_g = 0$. Boxes in black show EO-based information. C_{leaf} : leaves C pool, A: C allocation, L: litter production, VR_g : vegetation removal due to grazing, VR_c : vegetation removal due to cutting, t: time.

$$NEE = Reco - GPP \quad (1)$$

$$Reco = R_a - R_h \quad Reco = R_a + R_h \quad (2)$$

$$250 \quad NBE = NEE + B_c + B_g - M \quad (3)$$

$$\Delta_{SOC} = C \text{ flux to SOC} - C \text{ losses from SOC} \quad (4)$$

$$GCD = B_g - B_c \quad (5)$$

where NEE: Net Ecosystem Exchange, NBE: Net Biome Exchange, REco: Ecosystem respiration, R_a : Autotrophic respiration, R_h : Heterotrophic respiration, B_c : Cut biomass, B_g : Grazed biomass, M: manure, GCD: grazed - cut biomass, B_g : Grazed biomass, B_c : Cut biomass. Note that C flows into the SOC pool from the litter pool only and C is lost from the SOC pool via

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heterotrophic respiration (Fig. 1). All variables are presented in $\text{gC m}^{-2} \text{t}^{-1}$, where t is the time period over which the results are summed (e.g. 3-months, year).

2.2.4 Assessment and analysis of MDF predictions

To assess the effectiveness of the LAI assimilation process we quantify the level of fit between MDF-predicted and EO-based LAI time-series using (1) the % of overlap between the EO-based data points (field mean) and the corresponding MDF-predicted ranges (95% confidence interval); and (2) the root mean square error (RMSE); and (3) the bias between the simulated and observed time-series. To account for the possibility that some of the simulated fields may not be managed grasslands due to changes in management, but classified as such in the LCM data, we remove from the results any fields for which the estimated overlap is $< 50\%$ (see results for size of post-MDF dataset).

To answer our first science question, the MDF-predicted weekly grazed biomass is converted into livestock units (LU) per ha following the assumptions that : (1) 1 cattle is 1 LU and one sheep is 0.11 LU; (2) 1 LU weighs 650kg; (3) an animal demands $\approx 2.5\%$ of its weight in the form grass dry matter (DM) when grazing; and (4) 47.5% of DM consists of C (?). The MDF-predicted and independent census-based LU ha^{-1} are compared using the correlation coefficient (r) and the RMSE as the assessment metrics. The MDF-based estimates of grass biomass utilisation across GB are assessed against data from the ? study.

To answer our second science question we present and examine the annual and seasonal C balance and the cumulative annual fluxes of the simulated fields. To assess what controls the predicted C balance of the simulated grasslands (our third science question) we quantify the correlation coefficient between meteorological model drivers, management-related model parameters and MDF predictions of C cycling. In order to provide a more quantitative assessment of the factors that control grassland C dynamics we quantify the relative impact of management and climate on the MDF-predicted NBE. We use the model meteorological drivers and the posterior model parameters related to management and climatic controls for every simulated field to train a random forest (RF) model that estimates NBE. 75% of the data are used to train the RF model and 25% to assess its predictive ability (coefficient of determination). Thereafter, we use the Shapley Additive Explanations (SHAP) method to quantify how much each RF-predictor affects the RF-predicted NBE (?). The SHAP method examines the structure of the RF model and provides the weight (SHAP value) that the model gave to each predictor. SHAP values can be seen as the machine learning equivalent of the coefficient of determination (r^2). The estimated SHAP values are normalised (0-1) to be comparable to r^2 . We note that RF is used in this study solely to support MDF data analysis and not for predictive purposes.

For each simulated field and model output the MDF algorithm produces a mean and 95% confidence interval. To answer our fourth science question, we quantify the predictive uncertainty around an output by calculating its relative confidence range (RCR). RCR is equal to the size of the MDF-predicted 95% confidence interval divided by the corresponding mean, and expressed as %. We present and examine the estimated RCRs to identify the key factors that affect uncertainty.

3 Results

3.1 Assimilation of EO-based LAI data

For 12% of the initial dataset of 2108 simulated fields, our analysis failed to generate a simulated-vs-observed LAI overlap
290 > 50%. These fields were removed from the analysis and the final reported dataset includes 1855 fields. Based on the 1855
fields, three performance metrics indicated that CARDAMOM effectively assimilated the provided EO-based LAI time-series
(Fig. ?? in Appendix). Thus, CARDAMOM could identify parameter values for DALEC-grass for each field so that the model
could effectively reproduce the phenological development of the canopy, consistent with meteorological forcing and a realistic
removal of grass by grazing and/or cutting. The overlap between EO-based and simulated LAI was 80 (± 11) %, the RMSE
295 was 1.1 (± 0.22) $\text{m}^{-2}\text{m}^{-2}$ and the bias was 0.35 (± 0.40) $\text{m}^{-2}\text{m}^{-2}$. There were no clear spatial patterns (Fig. ??) in the error
statistics across GB and no obvious geographical biases.

3.2 MDF-predicted livestock density and removed biomass

A comparison of MDF-predictions of livestock density against census-based data (Fig. ??) shows that the MDF-predictions
mirrored the census-based livestock density data well ($r=0.68$, $\text{RMSE}=0.45 \text{ LU ha}^{-1}$). Both datasets show the highest LU
300 concentrated in the SW England with lower values in the Eastern part of England (Fig. 4). Scotland has consistent areas of high
LU in both datasets, in the SW and NE. The GB-average census-based livestock density was $0.76 \pm 47 \text{ LU ha}^{-1}$ and respective
MDF-predicted livestock density was $0.70 \pm 56 \text{ LU ha}^{-1}$. The census-based data (cattle and sheep) for each GB country refer
to different years. Livestock census numbers for England, in particular, were recorded in 2010, since when numbers have
declined (?). This time mismatch with our ~~2018-2018~~ 2017-2018 estimate could explain the small negative bias (-0.06 LU
305 ha^{-1}) between MDF-predicted and census-based LU ha^{-1} .

The analysis suggests that the 1855 simulated fields were managed with varying intensity. The majority of simulated fields
were grazed-only (75%) and no cut-only fields were simulated. Grazed biomass exceeded cut biomass in 85% of the fields
($\text{GCD} > 0$) and cut biomass exceeded grazed biomass in the remaining 15% ($\text{GCD} < 0$). The mean MDF-predicted annual
yield (grazed and cut biomass) was $6 \pm 1.8 \text{ tDMha}^{-1}\text{y}^{-1}$ (5th|25th|75th|95th percentiles : 2.8|4.6|7.3|8.5 $\text{tDMha}^{-1}\text{y}^{-1}$). These
310 results reflect biomass utilisation per grassland management intensity in the UK. Rough grazing grasslands (40% of UK
grassland area) have an annual yield (total removed biomass) of $3.09 \pm 1.56 \text{ tDMha}^{-1}\text{y}^{-1}$, permanent grasslands (50% of UK
grassland area) have an annual yield of $7.41 \pm 2.02 \text{ tDMha}^{-1}\text{y}^{-1}$ and temporary grasslands (10% of UK grassland area) have a
yield of $9.76 \pm 2.03 \text{ tDMha}^{-1}\text{y}^{-1}$ (??).

Most of the MDF-predicted first grass cuts (85%) occurred between the first half of May and the second half of July. For the
315 fields where more than one cut was identified the period between the first and last cut was ≈ 2 months. The MDF-predicted
day-of-year of first cut increased northwards with the mean date of first cut in northern England and Scotland being 3-6 weeks
later than in the southern half of GB. This spatial pattern is likely the combined effect of differences in the onset and duration of
the grass growing season and in related management decisions. Due to the small share of cut-and-grazed fields in the simulated

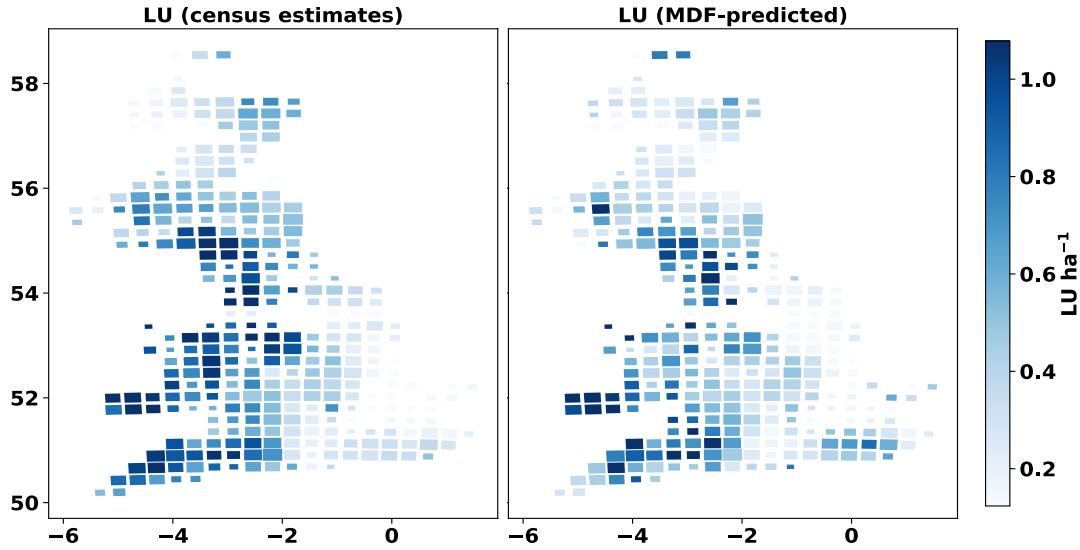


Figure 4. Cartograms of census-based and MDF-predicted livestock density (livestock units, LU ha^{-1}). The size of cells is adjusted according to the number of simulated fields within it.

dataset, and in order to make the spatial pattern more visible, we present the average month of first cut on a regional basis (Fig. 320 ?? in Appendix A).

3.3 Predicted C balance and dynamics

MDF-based C cycle estimates show that management affected the C balance of the simulated grassland ecosystems significantly. The difference between grazed and cut biomass volume (GCD) is used to present the impact that these two biomass removal methods have on C balance. The mean annual GPP across GB fields was 30% higher ($1992 \pm 400 \text{ gCm}^{-2}\text{y}^{-1}$) for 325 fields where most biomass was removed via grazing ($\text{GCD} > 0$) compared to those where cut biomass exceeded grazed biomass ($\text{GCD} < 0$) ($1518 \pm 426 \text{ gCm}^{-2}\text{y}^{-1}$) (Figure 5). Reco was higher for fields dominated by grazing also. The mean NEE across GB was $-232 \pm 94 \text{ gCm}^{-2}\text{y}^{-1}$, the relative role of grazing compared to cutting did not affect NEE significantly, and 95% of the simulated fields were net C sinks at the ecosystem scale. When considering the role of cutting and grazing C removals and returns to the ecosystem, the impact of cutting as a biomass removal method becomes important. The NBE of fields 330 dominated by cutting removals ($\text{GCD} < 0$) was $38 \pm 70 \text{ gCm}^{-2}\text{y}^{-1}$ while fields dominated by grazing removals ($\text{GCD} > 0$) had a NBE of $-126 \pm 95 \text{ gCm}^{-2}\text{y}^{-1}$. On average, 60% more C was removed (grazed and cut) in mostly-cut ($\text{GCD} > 0$) grasslands than in mostly-grazed ($\text{GCD} < 0$) grasslands. The flux of C into the SOC pool was, on average, 66% larger in mostly-grazed ($\text{GCD} < 0$) than mostly-cut ($\text{GCD} > 0$) fields. The annual change in the size of the SOC pool (Δ_{SOC}) for mostly-cut ($\text{GCD} < 0$)

grasslands was $116 \pm 52 \text{ gCm}^{-2}\text{y}^{-1}$ and $36 \pm 40 \text{ gCm}^{-2}\text{y}^{-1}$ for grazing-dominated (GCD>0) fields. The spatial distribution of
 335 MDF-predicted GPP, Reco, NEE, NBE, removed biomass and C flux into SOC is presented in the cartograms of Figure ?? in
 Appendix A.

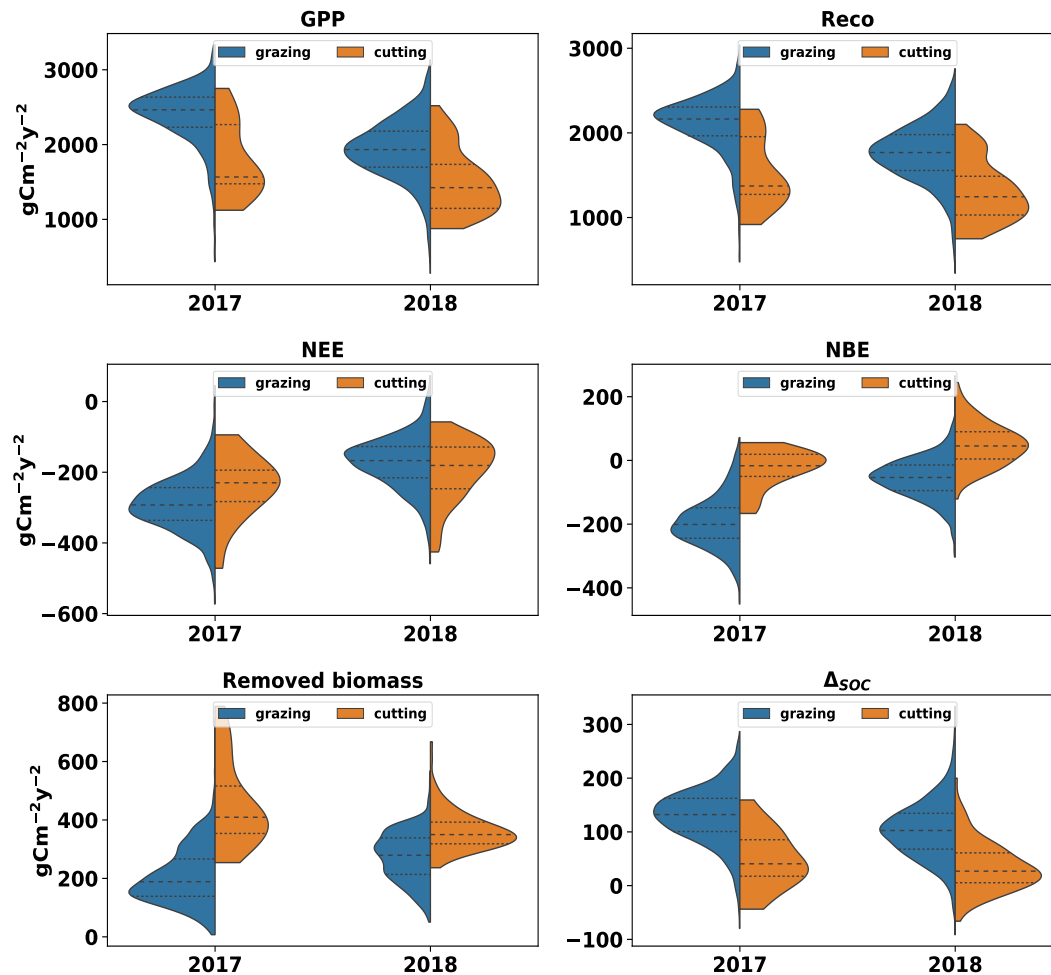


Figure 5. Violin plots of GPP, Reco, removed biomass and C flux from litter to SOC based on MDF-predictions (2017-2018) for all simulated fields. Violin plots are split according to whether grazing or cutting removed most grass biomass. The blue side of each violin-plot shows results for fields in which most biomass was removed via grazing (GCD>0). The orange side shows results for fields in which most biomass was removed via cutting (GCD<0).

Seasonal NEE varied across GB, with strongest sinks in Spring and Summer, strongest sources in Autumn, and close to neutral net exchanges during Winter (Fig. 6). However, there were clear inter-annual differences between 2017 and 2018 in the analysis. Across the southern third of GB (the Midlands and Southern England) many grasslands became C sources during
 340 the summer of 2018 while remaining areas were weaker sinks than in 2017 6). This pattern was driven by the 2018 European drought and heat wave, which affected GB as a whole and was particularly acute in the southern half of England (?). The

three-week rolling average VPD in summer 2018 across GB was 50% higher than in summer 2017 (Fig. ?? in supplementary material). The GB-average GPP, Reco, H_f , R_h , C flux to soil and soil C sequestration (annual change in SOC size) decreased between 2017 and 2018 (Table 1). The GB-average NEE and NBE increased between 2017 and 2018, indicating a reduction in sink strengths (Fig. 5). While only 2% of the simulated grasslands had a NBE>0 in 2017 this share increased 9-fold to 18% in 2018 (Fig. ?? in Appendix A). The GB-average total removed biomass in the drought-affected 2018 was 27% higher than in 2017. Reductions in cut yields and increases in grazed biomass underlie this increase in GB-average removed biomass (Fig. 5). In this context, the area-mean grazed biomass during the 3 months of spring 2018, in the southern half of GB, and the 3 months of summer 2018, in the northern half, was higher than the respective seasons in 2017 (results not presented).

Table 1. GB-average annual C fluxes and C balance (in $\text{gCm}^{-2}\text{y}^{-1}$) in 2017 and 2018

	2017	2018
GPP	2390±383	1900±402
Reco	2100±332	1725±352
R_h	975±156	831±166
NEE	-289±76	-174±74
NBE	-191±81	-49±69
Removed biomass*	220±98	280±85
C flux into soil Manure**	218±51 43±21	186±55 50±21
Δ_{SOC}	129±50	98±55

* the sum of grazed and cut biomass in a year

** manure is produced by simulated grazing livestock and directly enters the soil litter pool (external manure inputs are not considered)

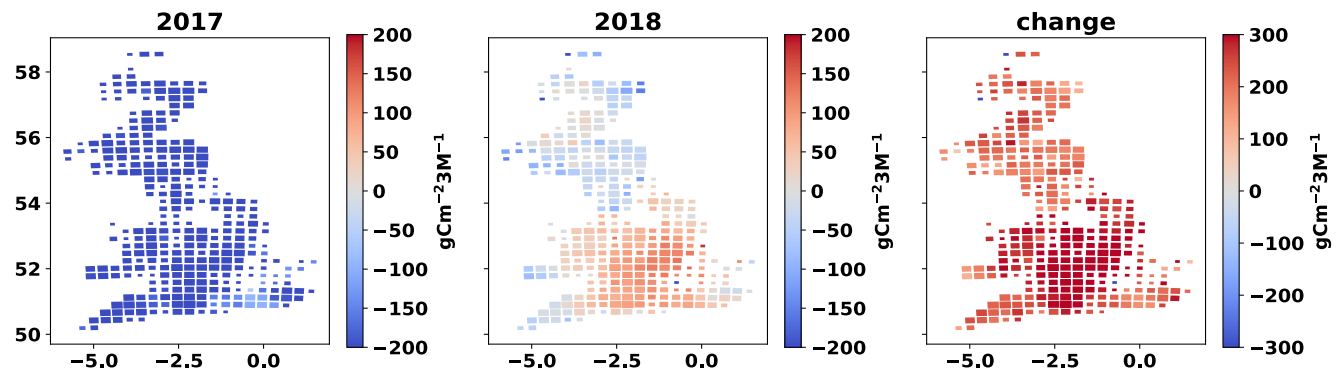


Figure 6. Cartograms of cumulative NEE for summer 2017, summer 2018 and change in summer NEE between 2017 and 2018 (cumulative NEE 2018 - cumulative summer NEE 2017). The mean MDF-predicted seasonal NEE of all fields in each cell is presented. The size of cells is adjusted according to the number of simulated fields within it

350 3.4 Controls on C cycling in UK grasslands

Correlation coefficients (Fig. 7) generated across the 1855 fields show the links between meteorological drivers, key processes (model parameters) and model outputs (C exchanges). There are strong positive correlations between GPP, Reco, C inputs to soil and root:shoot ratio, and these factors are strongly negatively correlated with NBE and NEE. The most productive fields (higher GPP) are associated with high inputs of C to soils and are the strongest C sinks (more negative NEE and NBE).
355 Among modelled processes, the ratio of C allocation to roots relative to stems and leaves (root:shoot ratio) is the most strongly correlated with the net C balance of the simulated fields (Fig. 7). More-frequent and higher-yielding grass cuts reduce root:shoot ratio and, therefore, reduce the flux of C to litter and, subsequently, to the recalcitrant soil C pool (SOC). The predicted flux of C to the SOC pool has a significant but low positive correlation ($r=0.38$) with the size of SOC pool. Despite that, MDF results show that the volume of C transferred to the SOC pool during the simulated period is, on average, equal to $1 (\pm 0.25)$ % of the
360 size of the SOC pool. NBE and NEE are positively correlated to livestock units (LU) and biomass removals, i.e. increases in LU and removals reduce C sinks. Temperature and radiation have relatively weak correlations with NEE and NBE. In contrast, VPD was more strongly related to C fluxes. Higher VPD values correlate with lower GPP and higher NEE and NBE. This positive r for VPD reflects the strong, negative role of the 2018 summer drought.

We expanded on the correlations-based analysis of the MDF results by using (1) the MDF-predicted data on NBE, and (2)
365 the corresponding meteorological drivers and (3) model parameters describing climatic and management controls on grass growth, to train a RF model that estimates NBE. The resulting RF model was able to explain 93% of the variance in MDF-predicted NBE ($r^2=0.93$) using 5 predictors: VPD, mean T, solar radiation, all posterior DALEC-Grass parameters related to climatic effects on grass growth and all posterior parameters related to grassland management. The weight (normalised SHAP) attributed by the RF model to these 5 predictors suggests that management parameters (aggregated weight for all parameters
370 in the group) were the most important factor for grassland NBE over the simulated period (Table 2. The normalised SHAP for management parameters was the highest among the 5 NBE predictors in 2017 (contributed by 34% to NBE) and the second highest (contributed by 38%) in 2018. The 2018 summer heat wave caused the contribution of VPD to NBE to increase from 3% in 2017 to 40% in 2018. Overall, these results reaffirm the conclusions of correlations-based analysis and clarify the importance of grassland management relative to climate and climatic anomalies.

Table 2. Normalised SHAP values for RF-based estimation of annual NBE in 2017 and 2018.

Predictor	2017	2018
Climatic effects (parameters)	0.30	0.19
Management effects (parameters)	0.34	0.38
Mean Air Temperature	0.02	0.02
Vapour Pressure Deficit	0.03	0.40
Solar Radiation	0.31	0.01

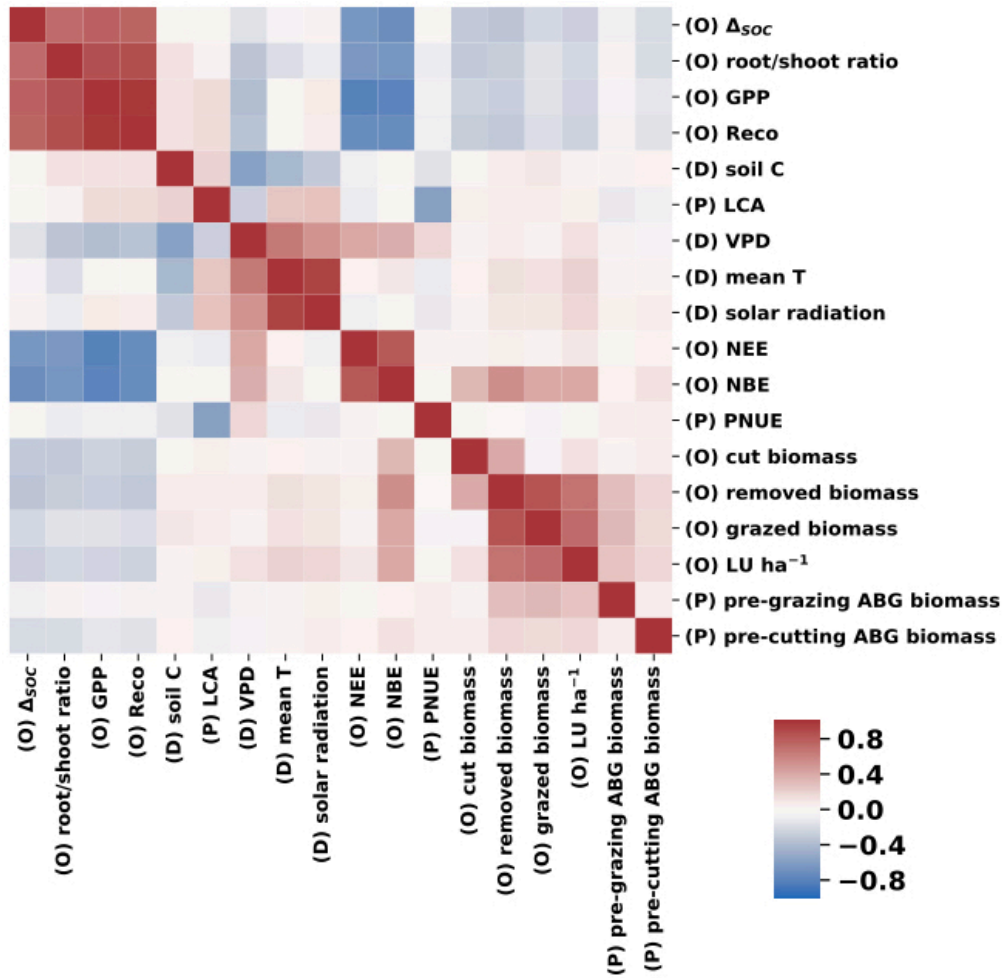


Figure 7. Heatmap of correlation coefficients (r) between annual mean meteorological model drivers (D), selected model parameters (P) and annual mean MDF predictions (O).

375 3.5 Predictive uncertainty

The size of the uncertainty around MDF estimates is quantified using the RCR (relative confidence range) of MDF outputs. The mean RCR is $42 \pm 9\%$ for LAI, $21 \pm 10\%$ for GPP, $18 \pm 6\%$ for Reco and $26 \pm 16\%$ for grazed biomass (Figure 8). MDF predictive uncertainty is therefore a small fraction of the mean estimate of these scalar variables. The GB-average RCR for LAI, GPP and grazed biomass prediction increased from 44%, 26% and 27% in fields where cut biomass did not exceed grazed biomass ($GCD > 0$) to 54%, 40% and 52% in fields where cut biomass exceeded grazed biomass ($GCD < 0$). The higher RCR (mean and SD) for LAI and grazed biomass is caused by the spatio-temporal uncertainty in the vegetation reduction time-series. This input-related uncertainty leads to the MDF algorithm being less effective in identifying cutting instances in some simulated fields; i.e. sampled parameter vectors produce varying predictions on the timing and intensity of grass cuts.

380

The impact of input data uncertainty on RCR is also reflected on the shape of RCR distributions for GPP and grazed biomass (violin plots in Fig. 8). The assimilated EO LAI time-series condition the simulated LAI, which combined with the simulated removals (grazing/cutting), determine the weekly GPP at each simulated field. Reducing the uncertainty (spatial and temporal) around the vegetation reduction data is expected to lead to less variable predictions of cutting timing and intensity and, thus, to lower predictive uncertainty overall.

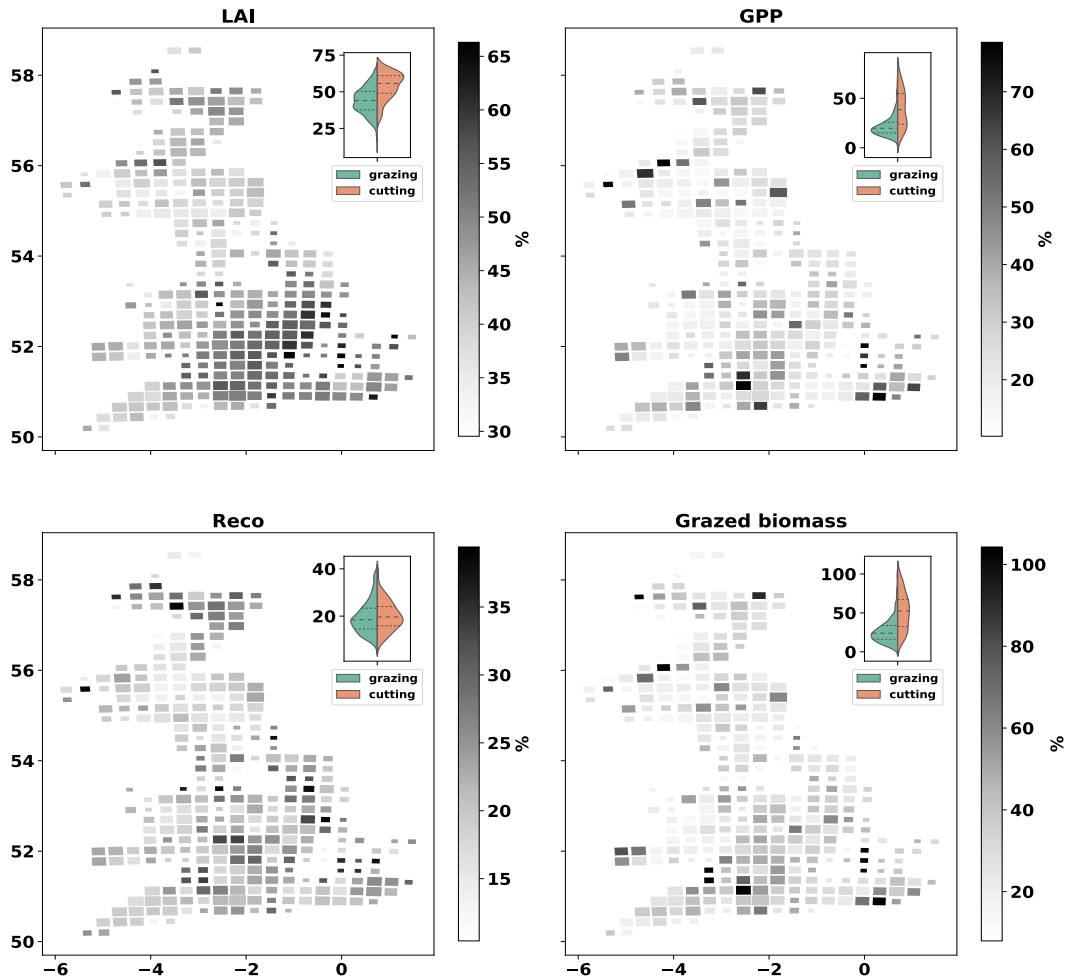


Figure 8. Cartograms of relative confidence range (RCR, $100 \times CI \div \text{mean}$) of MDF-predicted LAI, GPP, Reco and grazed biomass. The mean across all fields in each cell is presented. The size of cells is adjusted according to the number of simulated fields within it. The violin-plot insets present the distribution of MDF estimates grouped according to the relative contribution of grazing and cutting to the total annual biomass removal (GCD). The green side of each violin-plot shows results for fields in which most biomass was removed via grazing (GCD>0). The orange side shows results for fields in which most biomass was removed via cutting (GCD<0).

4 Discussion

390 4.1 Grassland vegetation management across GB

Process modelling combined with earth observation can identify grassland vegetation management effectively over large spatial domains. The distribution of MDF-based livestock densities across GB mirrors the independent determined census-based numbers of cattle and sheep per area; MDF estimated livestock density = $0.7 (\pm 0.56)$ LU ha⁻¹, census based livestock density = $0.76 (\pm 0.46)$ LU ha⁻¹. Considering that grasslands with a corresponding LU ha⁻¹ < ≈ 0.5 are thought as supporting a low
395 livestock density and those with LU ha⁻¹ > ≈ 1 as supporting a high livestock density, the average managed grassland in GB supported an intermediate livestock density in 2017-2018 (?).

The MDF-predicted GB-average pasture dry matter yield (6 ± 1.8 tDMha⁻¹y⁻¹) is within the range for UK permanent pastures (7.41 ± 2.02 tDMha⁻¹y⁻¹) as estimated by ? using statistical extrapolation of field-measured data. Due to the field-size limits (6-13ha) used in sampling for fields across GB, the share of less intensively managed grasslands is likely biased high
400 in the simulated fields' dataset (?). Cut-only grasslands were under-represented in our analysis, as we expected $\approx 10\%$ of field to be in temporary management for cutting. We believe this is an artefact of the noise in the vegetation reduction time-series, which led to cut-only grasslands failing to pass the 50% overlap limit and being excluded from the final dataset. The inclusion of fields that are 6-13ha in size could have led to an under-representation of cut-only fields but we note that no data exist on the percentage of managed grasslands that are grazed-only, cut-and-grazed and cut-only.

405 4.2 The C balance of managed grasslands

The majority of managed grasslands in GB were net C sinks during 2017 (NEE = -289 ± 76 gCm⁻²y⁻¹) and 2018 (NEE = -174 ± 74 gCm⁻²y⁻¹) at the ecosystem level, i.e. based on CO₂ gas exchanges. Numerous flux tower-based studies have concluded that managed temperate grasslands are, on average, C sinks but NEE estimates vary greatly between ≈ -700 gCm⁻²y⁻¹ to almost C-neutrality (??). The scale of NEE increase between 2017 and 2018 is comparable to past field-based estimates
410 under normal and heat-wave conditions (?). When considering C fluxes that also included grazing/cutting removals and manure return to the soil (i.e. NBE), the simulated grasslands were net C sinks during 2017 (NBE = -191 ± 82 gCm⁻²y⁻¹) and close to C neutral in 2018 (NBE = -49 ± 70 gCm⁻²y⁻¹). These NBE estimates are comparable to those in the literature but the inconsistency in the variables included in NBE calculations makes comparisons less than straightforward (?). Based on RF-based analyses of climate drivers and model parameters we argue that the increase in mean annual NEE and NBE between 2017 and
415 2018 was caused by the 2018 summer heatwave. The negative effect of elevated annual temperatures on grassland biomass productivity and NEE has been examined in measurements and model-based studies on European grasslands before (????).
~~The mechanistic understanding~~, An increase in the annual cumulative NEE between 2017 and 2018 was also measured (with eddy covariance) at a managed grassland in the UK (?). While the mechanistic understanding and the model representation ; of how plants respond of plants response to increased VPD is improving ~~but~~, key aspects are still disputed (?).

420 Our study shows that biomass removals were key determinants of the C balance of managed grasslands. The role of cutting relative to grazing as a biomass removal method was found to be particularly important. Grasslands in which most biomass

was removed via cutting had a lower GPP and Reco as opposed to grasslands in which grazing was the main biomass removal method (Fig. 5). However, when GPP and Reco are summed the resulting NEE did not vary significantly between mostly grazed and mostly cut grasslands. All of the simulated grasslands were grazed and underwent more or less frequent defoliation during the simulated period. When cutting occurs the leaf area of a grassland is reduced close to zero, which represents a diminution of the grassland's photosynthetic capacity. According to DALEC-Grass, in the post-cutting period the simulated grassland allocates almost all of its C to aboveground tissues (stems,leaves) in order to build up the leaf area necessary to increase photosynthetic activity and sustain growth. This causes a smaller root-to-shoot ratio in grazed and cut grasslands compare to grazed-only ones as well as a reduction of root-based C inputs to the litter pool (lower R_h). Grazing that occurs during the post-cut period maintains the volume of leaves at relatively low levels. This leads to a reduced annual GPP for grasslands that are both grazed and cut and also means lower manure-C returns to the soil, which explains the weaker C sinks (higher NBE) of most grazed-and-cut grasslands compared to grazed-only fields.

4.3 Factors that control managed grassland C dynamics

Management and climate have a combined effect on C dynamics and disentangling their individual impacts is a challenge (?). Here, we used a correlation matrix of model drivers, parameters and outputs to understand how climate and management affect the predicted C fluxes and balance of the simulated grasslands. The correlation matrix revealed a negative effect ($r < 0$) of VPD on GPP and Reco, and a positive effect ($r > 0$) on NEE and NBE. Biomass removals had a similar effect with higher removals corresponding to lower GPP and Reco and more positive NEE and NBE. Moreover, we used the model's climate drivers and all of its management and climate-related parameters to train a RF model that estimates NBE. The analysis of the RF model structure showed that the contribution of VPD as a RF predictor of NBE increased from 3% in 2017 to 40% in 2018, with VPD being the most important determinant of NBE in 2018. This increase is linked to the heat wave and drought conditions during that year. Management-related parameters were the most important determinant of NBE in 2017 and the second most important in 2018.

The conclusions that we draw in regards to which factors have more influence on grassland C dynamics are based on two assumptions. Firstly, we assume that the simulated grasslands are well-optimised for the intended use; i.e. to sustain different types of livestock (e.g. dairy and/or beef cattle and/or sheep). This means that each sward is maintained in good condition and that farmers manage their fields optimally based on their long-term experience. Secondly, the fact that a large share of the simulated fields (especially in the southern half of England) experienced continuous weeks of unusually hot and dry weather conditions during one (2018) of the two simulated years is treated as a climate anomaly; i.e. climate in 2018 is not representative of normal climatic controls on C balance. Based on these assumptions, we argue that the simulated vegetation management, as inferred from the observational data, was adapted to the seasonal weather anomaly. Therefore, significant changes in ecosystem C cycling were beyond the control of human management and can be mostly attributed to the seasonal weather anomaly.

Our findings on the role of management are in agreement with findings in a number of relevant studies, notwithstanding differences in methodologies and eco-climatic conditions. ? found that higher biomass removals increase NBE based on C flux measurements in cut-and-grazed temperate grasslands in the USA. ? used eddy covariance measurements of C fluxes at a

cut-only and a grazed-only field in Hungary and found that the cut field had a more positive NBE (smaller sink) than the grazed field. ? reached the same conclusion as ? using eddy covariance measurements from a cut-only versus grazed-only experiment in France. ? reviewed studies on European managed grassland C balance and found that grazed-only grasslands had the lowest NBE, followed by cut-only grasslands with cut-and-grazed grasslands having the highest NBE (NBE in this study included animal methane-C and C-leaching fluxes). Based on eddy covariance measurements over two years at three grassland sites with varying management intensity in Switzerland ? concluded that management (including biomass removals and manure application) has a strong influence on C fluxes and balance.

In summary, we conclude that management is a key determinant of the C balance of managed grasslands in GB. We note that climatic anomalies, such as heat waves and droughts, can reduce the relative importance of management as a determinant of grassland C balance. In simple terms, human decisions can adjust grassland sink or source strength and this depends mostly on the soil's existing C stock, the sward's composition and condition and the timing and intensity of livestock grazing and grass cutting. Climate change can change this fine C balance substantially and prolonged heat and drought is one way in which this can occur in regions with temperate maritime climate.

4.4 Predictive uncertainty

We use the RCR to quantify the uncertainty around the MDF-predicted variables. RCR shows how wide the 95% confidence intervals (i.e. $2 \times SD$, assuming normality) are relative to the mean value. The assimilated LAI data come from processing Sentinel-2 images and have an uncertainty attached to them. This observational uncertainty is not always examined in relevant studies but a relative SD of 15% is considered as representative (?). This means that the average RCR of the assimilated observational LAI data is 30%. Considering that MDF predictions incorporate model parametric uncertainty as well, the mean analysis LAI RCR of 45% is, as expected, larger than, but of similar magnitude to, the observational uncertainty of 30% (Fig. 8).

The estimated predictive uncertainty for LAI, GPP and grazed biomass was noticeably higher for fields that were mostly cut (GCD<0) (Fig. 8). The MDF algorithm does not infer cutting simply by translating large reductions in vegetation as cuts. The MDF algorithm examines each weekly vegetation reduction input to decide whether to simulate it as cutting, grazing or ignore it depending on the simulated amount of foliar biomass at the time. The simulated amount of foliar biomass is constrained through the assimilation of field-specific EO-based LAI time-series. A weekly vegetation reduction will be simulated as a cut when it is reasonable both biophysically and agronomically based on the EDCs (see section 2.1.2). This higher predictive uncertainty when cutting occurs suggests that the best way to obtain more accurate predictions is to improve the spatial and temporal resolution of the vegetation reduction time-series and/or estimates of LAI. Using radar (e.g. Sentinel-1) to derive LAI in spite of cloud cover would be a valuable advance.

4.5 Limitations

This study uses a MDF algorithm that depends on EO data and process modelling of C dynamics in grasslands. The ProbabV-based vegetation reduction time-series that are used to drive DALEC-Grass have a resolution (9ha) that is coarse when

490 compared to the average size of grassland fields in GB. These noisy data on vegetation reduction cause increased uncertainty in MDF predictions especially in regards to the timing of cutting events. Moreover, most areas of GB are affected by frequent cloudiness, which means that the number of Sentinel 2-based LAI data points per year and simulated field is limited compared to other parts of the world. However, we ensured 30 images per field over two years in our selection process, and this richness of information at field resolution and for national domains is unprecedented in such an analysis.

495 DALEC-Grass was developed and tested under UK conditions, showing high skill in predicting C allocation and CO₂ fluxes under variable management and different soil conditions (?). However, DALEC-Grass can only infer effects on grass growth through the processes it simulates, and so can mis-attribute effects arising from missing processes. For instance, the MDF algorithm can adjust a specific plant growth rate parameter (DALEC parameter P10, photosynthetic N use efficiency) between fields based on observed LAI dynamics and weather. Inferred P10 variation among fields might be linked to spatial patterns in soil fertility. But because there is no direct soil moisture constraint on LAI in DALEC-grass to be adjusted, a real spatial soil 500 moisture limitation on LAI might be mis-interpreted as a restriction on P10. So we should be cautious in interpreting process variation and assigning with certainty to a particular forcing. Also, a single P10 estimate is made for each field covering both 2017 and 2018, so the current analysis does not allow field nutrient supply (and therefore P10) to change between years. The strong differences in sink strengths observed in the 2017 and 2018 analyses are informative. The flux differences cannot arise from parameter differences between years, as these parameters are constant. Instead differences must arise from process 505 changes (e.g. GPP) resulting from changes to the forcing (VPD, Fig. 2) and changes to the assimilated data (LAI) between years. The larger LAI uncertainty in southern GB (Fig. 8) may be related to soil moisture impacts on grass growth that we fail to identify with the current model structure. Finally, DALEC-Grass has been validated against data from grasslands dominated (>90%) by perennial ryegrass (*Lolium perenne*) and its ability to simulate swards with larger shares of herbs and forbs has not been tested.

510 Overall, the ability to use field-specific observed information on key aspects of grassland vegetation and to infer its management (vegetation grazing and cutting) are the key advancements presented in this study. In this context, the majority of grassland-focused model-based estimates at large scales typically rely on uncertain information on grazing and cutting. Also, with few recent exceptions most relevant studies do not include field-specific validation of model predictions, which results in highly uncertain estimates. Despite that, the calculation of lateral flows of C remains an outstanding challenge as it depends on 515 information that cannot be inferred from EO-based time-series. The size, type and age of livestock significantly affect livestock turnover of grazed biomass-C. While we cannot infer this information from EO data, our probabilistic MDF framework allow us to attribute uncertainty to livestock C turnover and, thus, to quantify their impact on predictions. This attribution can be done by treating grazed biomass-C conversion factors (Fig. 1) as model parameters. It is, currently, not possible to detect manure spreading events from EO data. Therefore, we do not consider external manure-C addition to the soil.

520 4.6 Future work

Our overarching aim is to produce a computational ecosystem science framework that is (1) able to utilise the swathes of EO data that are increasingly becoming available while (2) being easy to adapt and incorporate new knowledge gained from