Ecological Modelling 266 (2013) 42–57

Contents lists available at SciVerse ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Screening parameters in the Pasture Simulation model using the Morris method

Haythem Ben Touhami[a,b,*], Romain Lardy[a,b], Vincent Barra[b], Gianni Bellocchi[a]

[a] French National Institute for Agricultural Researches, Grassland Ecosystems Research Unit, 5 chemin de Beaulieu, 63039 Clermont-Ferrand, France
[b] Clermont University, Blaise Pascal University, LIMOS - UMR 6158CNRS, 63173 Aubière, France

ARTICLE INFO

Article history:
Received 27 March 2013
Received in revised form 5 July 2013
Accepted 7 July 2013

Keywords:
Grassland
Morris method
Pasture Simulation model (PaSim)
Plasticity
Sensitivity analysis
Vegetation parameters

ABSTRACT

Mechanistic vegetation models with large parameter sets and high temporal resolution are currently used in grassland studies. They need a parsimonious screening method to identify the most influential parameters for the grassland system in specific contexts (weather, soil, management). This is basic to better understand and make use of the outputs from these models. In this study, Morris' method was applied to test the sensitivity of a variety of outputs of the Pasture Simulation model (PaSim) to its parameters in six European multi-year grassland sites (one of them run under both extensive and intensive management regimes). Twenty-eight parameters related to plant physiology and animal digestion were screened and ranked for their sensitivity (under two distributional assumptions of parameter values), with the objective of determining their stability across sites and the minimum requirements for parameter calibration. The sensitivity analysis results proved that PaSim response is fairly stable across European sites, with only a few differences. Key results are that (1) seven influential parameters of vegetation development, aboveground growth and carbon/nitrogen partitioning were globally identified with both uniform and Gaussian distributions of parameter values, (2) two additional parameters (associated with leaf and stem fibre content) were also recognized as relevant for animal CH_4 emissions target output, (3) listing of key parameters differed, but not widely, across sites and targeted outputs, and between distributions (ranking was more plastic), (4) first-order sensitivity rank (strength, μ) was generally similar to (or higher than) higher-order sensitivity (spread, σ), indicating that parameters showing high interaction with other parameters or non-linearities are those with also a high direct effect on output. Overall, Morris' method proved to be an effective and reliable tool to identify key vegetation parameters for the use of PaSim in the European conditions.

1. Introduction

Riedo (1997) and Riedo et al. (1998) developed and described a process-based biogeochemical model for grassland plots, the Pasture Simulation model (PaSim, https://www1.clermont.inra.fr/urep/modeles/pasim.htm), to simulate water, carbon (C) and nitrogen (N) cycling in grassland systems at sub-daily time step. In the basic structure of PaSim, a vegetation module derived from the Hurley Pasture Model (Thornley and Verberne, 1989) is coupled to a soil biology module from CENTURY (Parton et al., 1987). PaSim also incorporates soil physics equations from Campbell (1985) to calculate the water and energy balances. The original model was followed up by improved versions to estimate, for instance, N_2O production (from NO_3–N source) and emissions (Schmid et al., 2001) and the exchange of ammonia with the atmosphere (Riedo et al., 2002).

The most recent improvements of PaSim have been developed at the Grassland Research Unit of the French National Institute of Agricultural Research (INRA-UREP), which has been pursuing research on the C, N and water cycle modelling in parallel to the field observations (Calanca et al., 2007). In particular, Vuichard et al. (2007a,b) improved the simulation of water stress, senescence and the effects of diet quality on the emissions of methane (CH_4) from grazing animals, and introduced optimization capabilities for animal stocking rate and proportion of cut and grazed area on grassland-based, self-sufficient feed production systems. Graux (2011) included options to simulate sown grasslands, introduced optimization options for irrigation and N fertilization, equations for CH_4 emissions from suckler cows and calves, and interactions between functional diversity, climate change and management. A topsoil litter layer was also included to the modelling system (Graux, 2011), and an analytical method of soil organic matter equilibrium implemented to set the

* Corresponding author at: French National Institute for Agricultural Researches, Grassland Ecosystems Research Unit, 5 chemin de Beaulieu, 63039 Clermont-Ferrand, France. Tel.: +33 4 73624866.
E-mail address: hayhtem.ben-touhami@clermont.inra.fr (H.B. Touhami).

0304-3800/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.ecolmodel.2013.07.005

model in steady-state with the climate and management regimes (spin-up run method documented by Lardy et al., 2011).

PaSim has evolved over time, increasing in complexity to meet the increasingly complex challenges facing grassland agriculture. This has required the formulation of a large set of equations, which has inevitably increased the number of parameters to be defined. A major problem with the use of complex ecological models is incomplete knowledge of input variables and parameters. This means that model estimates are highly dependent on parameter settings, leading to a large uncertainty due to uncertainties in parameter values and distributions, driving variables (climate, soil and management) and model structure (e.g. Gabrielle et al., 2006). The structure of PaSim is too complex for an easy appreciation of the relationship between input factors and output variables. Such an appreciation, i.e. the understanding of how the model behaves in response to changes in its input parameters, is of fundamental importance to ensure a correct use of models. Parameter estimation, in particular, is a key challenge in ecological model development (Richter and Sondgerath, 1990). A conventional assumption is that the estimated parameter values are temporally invariant, and thus remain constant throughout the entire simulation period. If this simplification can be considered as a useful step in the simulation, biological parameters can vary across ecosystems, but also spatially within a specific ecosystem. One salient factor attributing to the variability is that biological parameters are sensitive to the abiotic and biotic changes that exist in the environment. Because of this susceptibility to the environment, it is difficult to translate biological parameters measured within controlled operating conditions into a numerical framework. Owing to the necessity of modelling a variety of grassland systems and the novelty of some of the modelling approaches developed in PaSim, there is therefore a need to better understand model behaviour under a range of conditions, by examining the sensitivity of multiple model outputs to multiple model parameters. To deal with large complex non-linear models, focus placed in the problem of parameter identifiability is necessary to recognize the parameters that have the most influence on the state variables for which measured data are available, and so in order to reduce the parameterization effort (Jacquez and Perry, 1990; Brun et al., 2001; Haag, 2006). Sensitivity analysis (SA) is the main tool for doing so (after Rabitz, 1989). It assesses the change in the outputs due to changes in the model parameters (the latter generated by sampling from their values' distributional range). As a result, SA provides a valuable method to identify properties and reinforce the understanding of the system under study (Saltelli et al., 2000). The distinction between influential (relevant) and non-influential parameters is generally made based on SA results (Cariboni et al., 2007). By ranking model parameters in order of importance (Cryer and Havens, 1999), SA offers guidance to the design of experimental programs as well as to more efficient model coding or calibration.

SA can be implemented either locally to examine the effect of minor variations of the parameter values on model results, or globally to consider the entire range of parameter values (Xu and Gertner, 2007). The latter is generally based on differential analysis through the use of Taylor series (e.g. Pastres and Ciavatta, 2005) and the Monte Carlo method (e.g. Annan, 2001). To date, sensitivity studies with PaSim have essentially been based on relatively local SA, yet limited to a narrowed range of conditions (climate, management) and few output variables (Graux, 2011). This is why, in this study, we have performed a wide range of sensitivity experiments on PaSim, using an improved version of the Morris (1991) method, known to be computationally cheap, model-independent, and able to discriminate between the least and the most influential parameters and obtain sensitivity information. The aim of this paper is to document the SA results of PaSim, obtained using multiple years of meteorological and management data at sites representative of contrasting conditions in Europe. A wide range of output variables

Table 1
Location and climate of the grassland study sites (available through the European Fluxes Database Cluster, http://www.europe-fluxdata.eu).

Country	Site	ID	Years	Geographical settings			Climate			Sources
				Latitude	Longitude	Elevation (m a.s.l.)	Mean air temperature (°C)	Precipitation total (mm yr^{-1})	Reference evapotranspiration (mm yr^{-1})	
France	Laqueuille	LAQ-1 LAQ-2	2002–2009 2002–2009	45°38′N	02°44′E	1040	7.8	1072	769	Klumpp et al. (2011)
Hungary	Bugac-Puszta	BUG	2003–2008	46°41′N	19°36′E	140	10.2	520	890	Pintér et al. (2008)
Italy	Amplero	AMP	2003–2007	41°52′N	13°38′E	884	9.4	781	927	Wohlfahrt et al. (2008)
Switzerland	Früebüel	FRU	2006–2010	47°06′N	08.32′E	982	7.7	1625	643	Gilgen and Buchmann (2009), Zeeman et al. (2010)
	Oensingen	OEN	2002–2009	47°17′N	07°44′E	450	9.3	1197	736	Ammann et al. (2007)
United Kingdom	Easter Bush	EAB	2002–2008	55°52′N	03°02′W	190	9.0	956	610	Soussana et al. (2007)