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DAVE-Grass: a process-based model for herbaceous vegetation dynamics

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Abstract

Process-based vegetation models are invaluable tools for understanding and predicting vegetation responses to changes in climate and land management. However, many existing models were developed decades ago and do not incorporate our latest knowledge of plant and ecosystem functioning. Here we present DAVE-Grass, a new dynamic and process-based model of herbaceous vegetation function with a focus on Australian grasslands. The model integrates our latest empirical and theoretical understanding of processes considered to be critical for predicting rangeland responses to changes in climate and management: photosynthesis, growth, carbon allocation, phenology, establishment, persistence, water and nutrient dynamics as well as fire behaviour. It represents C_3 and C_4 plants as well as annual and perennial growth forms which compete for resources such as light and water. The model has been evaluated against data from manipulative experiments, land-atmosphere fluxes, biomass, as well as phenology from phenocams and satellites. In this presentation, we showcase early applications of the model with a focus on the current and projected distribution of C_3 and C_4 vegetation across Australia under different climate change scenarios. The process-based nature of the DAVE-Grass model provides insights into the mechanisms underlying observed changes in vegetation cover and composition. By combining these features with its applicability from site to continental scales, the model promises to be a critical tool for guiding effective management and adaptation efforts in rangelands.

Introduction

Grasslands, including managed pastures, rangelands, and savannas, cover approximately 40% of the global ice-free land surface, act as significant C storage, and fulfil a wide range of ecosystem services (Petermann & Buzhdygan, 2021; White et al., 2000). However, many grasslands are at risk from climate change and intensifying land use and land management globally large areas of grasslands have been identified as degraded to some extent (Bardgett et al., 2021). The increasing pressure on grasslands highlights the need for reliable tools to predict their responses to changes in climate and to identify sustainable management options.

Process-based vegetation models are primary tools to understand ecosystem processes and to predict their functioning under a changing climate (Fisher & Koven, 2020). However, existing process-based models are not well suited to investigate many real-world applications. Dynamic vegetation models often oversimplify crucial processes such as phenology, senescence, and plant persistence (De Kauwe et al., 2017). In addition, these types of models often ignore management routines.

Pasture and grass growth models do account for many management activities, but often oversimplify plant physiological processes. In addition, these types of models were often developed for a specific pasture type and are not applicable across larger spatial scales (Ma et al., 2019).

Here, we present the grassland model DAVE-Grass, a newly developed model that aims to overcome these critical limitations of existing models. We give a short overview of key processes represented in the model and showcase its ability at a grassland site in southern NSW.

Methods

Model description

DAVE-Grass is a dynamic, process-based vegetation model that incorporates key physiological, phenological, and plant demographic processes of herbaceous vegetation. Management routines including grazing, mowing, and irrigation, are currently under development. The model is embedded into the widely used LPJ-GUESS dynamic vegetation model (Smith et al., 2014).

The key processes represented in the model are illustrated in Fig. 1. The model uses absorbed radiation by the canopy to calculate photosynthesis in different canopy layers using the Farquhar et al. (1980) model for C_3 vegetation and the von Caemmerer (2000) model for C_4 vegetation. Plant respiration is calculated as in LPJ-GUESS. The resulting net primary productivity (NPP) is used for either growth or kept as storage in the form of non-structural carbohydrates. The carbon (C) used for growth is allocated to different plant components depending on environmental conditions and plant growth stage. Similar processes govern the plant turnover (senescence) rates. These processes are modulated by competition between plant types, disturbances such as fire, as well as nutrient and water availability. Long-term plant survival and dynamics are represented in the form of mortality and establishment processes.

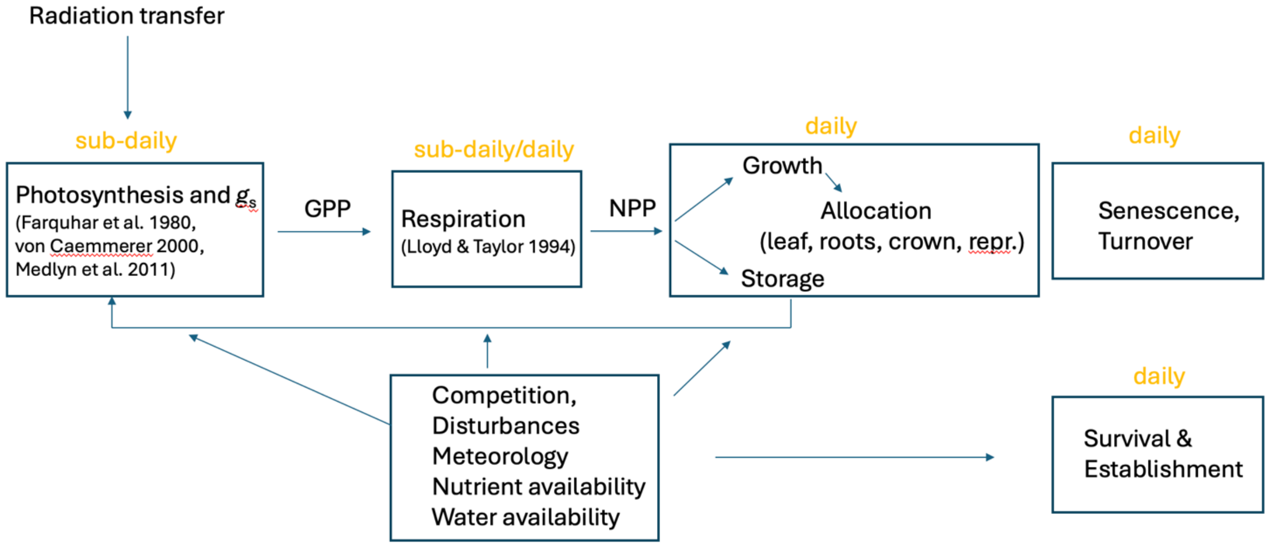

Figure 1: Schematic diagram of the DAVE-Grass model including the most important processes and their interactions.

Site-level application

We present a site-level application of the model at Yanco, an extensively managed, semi-arid grassland site in the western plains of the Murrumbidgee Catchment in southern NSW (latitude: -34.9893, longitude: 146.2907). Mean annual precipitation at the site is ca. 450 mm. More information on the site can be found in Yee et al. (2015). The type or species of grass as well as the grazing intensity are not reported. Meteorology as well as land-atmosphere fluxes of carbon dioxide, water vapour, and heat are measured at the site using an eddy covariance system. Gross primary productivity (GPP) was derived from measured net ecosystem exchange using the SOLO machine learning algorithm.

The model was forced with meteorology measured at the site from 2014 to 2021. In addition to the simulation using measured meteorology (hereafter ‘control’), we performed three factorial experiments to analyse ecosystem responses to the main climate change drivers CO_2 and temperature: 1) elevated CO_2 concentrations of +200 ppm (‘eCO2’), 2) elevated temperatures of 2 °C above ambient, assuming an unchanged constant relative humidity (‘eTair’) and 3) a combination of +200 ppm CO_2 and +2 °C temperature (‘eCO2_Tair’). All experiments started 8 years before the simulation period in 2006 and were implemented as a step change. Prior to that, the model was spun up using recycled meteorology according to standard model procedures.

Results

Observed and simulated GPP

The daily average measured meteorology of the site is shown in Fig. 2a. At the sub-daily time scale, temperature reaches extremes of >40 °C in summer and < 0 °C in winter. Precipitation is distributed relatively evenly throughout the year. The 2018 - 2020 period is characterised by drier-than-average conditions.

Fig. 2b shows the derived GPP from the flux tower in comparison to simulated GPP by the DAVE-Grass model. Observed GPP shows largely irregular temporal dynamics. While peak GPP occurs mostly in spring, productivity is clearly linked to available soil moisture and the ecosystem can be productive in summer if moisture conditions allow. The model reproduces these flux dynamics moderately well ($r^2 = 0.45$). Notable disagreements between simulations and observations occur in summer and autumn 2016, where the model underestimates GPP. Closer examination revealed that biases in available soil moisture are the primary cause for this discrepancy.

The simulations further indicate that the site is C_3-dominated (Fig. 1c). C_4 vegetation is scarcely present and contributes negligibly to GPP in the summer months.

Climate Sensitivity Experiments

The climate sensitivity simulations revealed that elevated CO_2 concentrations had overall positive effects on both C_3 and C_4 vegetation (Figure 2d). C_3 vegetation achieved higher GPP throughout most of the simulation, though not consistently. Periods of high growth and therefore high water use may lead to subsequent phases of reduced water availability compared to the control simulation, limiting productivity in certain time periods.

Elevated air temperatures had positive effects foremost for C_4 vegetation, which contributed a notably higher proportion to overall GPP in a warmer climate (Figure 2e). C_3 vegetation benefited from elevated air temperatures in some periods but showed declined productivity in others.

The combination of elevated air temperatures and elevated CO_2 concentrations (*eCO2_eTair*) had a strong positive effect on C_3 vegetation during most time periods (Fig 2f). However, as in the *eTair* scenario, productivity declined during a few short time periods compared to the control simulation. This is evident in early summer 2018, when drier conditions occurred compared to the control simulation due to increased water use from autumn to spring 2018. In this scenario, C_4 vegetation remains almost unchanged compared to the control run, likely due to strong competition by C_3 plants.

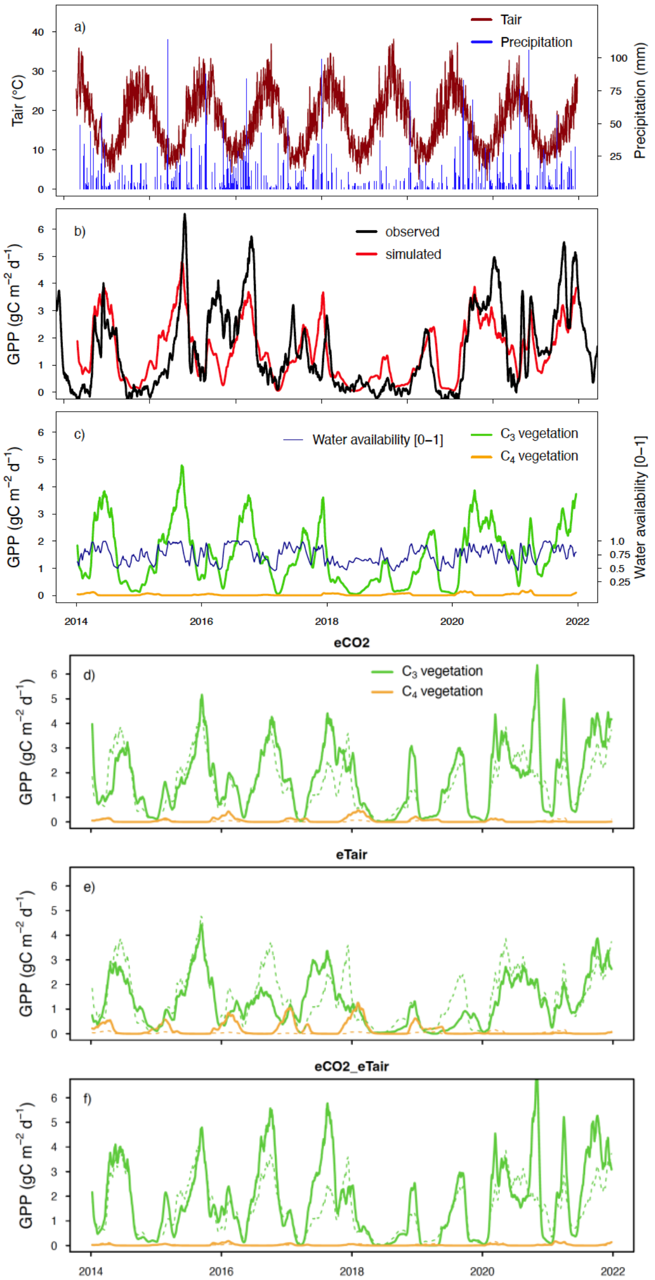

Figure 2 a) Measured average daily air temperature and precipitation at the Yanco site. b) Observed and simulated (control experiment) of gross primary productivity (GPP). c) simulated GPP divided into contributions from C_3 and C_4 vegetation. Shown is also simulated plant available soil water content as a scalar from 0 to 1. Panels d) to f) show the climate sensitivity experiments: d) elevated CO_2

concentrations (+200 ppm), e) elevated air temperatures (+2 °C), and f) a combination of elevated CO_2 concentrations (+200 ppm) and air temperatures (+2 °C). The dashed lines denote the control simulations as shown in panel c.

Discussion

We present a brief overview of the DAVE-Grass model, a newly developed process-based model of herbaceous vegetation functioning. The model includes physiological, phenological, and plant demographic processes that were informed by the latest theory and data and that are commonly ignored or oversimplified in current dynamic vegetation models, especially for herbaceous vegetation (De Kauwe et al., 2017; Wilcox et al., 2023).

The application of the model to the Yanco site, a semi-arid grassland in southern NSW, demonstrates that the current model version can broadly capture the irregular patterns of ecosystem productivity at this location. Nonetheless, further model development is needed to improve the dynamics of vegetation productivity. Improvement should focus on hydrological processes such as soil evaporation and percolation, as well as the sensitivity of vegetation processes like photosynthesis and leaf senescence to water stress.

The climate sensitivity scenarios illustrate that the model predicts beneficial effects of higher CO_2 concentrations for both C_3 and C_4 vegetation. This is likely due to direct CO_2 fertilisation effects for C_3 plants as well as water savings effects due to stomatal closure for both C_3 and C_4 plants (Ainsworth & Rogers, 2007; Morgan et al., 2011). As expected, higher air temperatures benefited C_4 plants (Yamori et al., 2014), whereas a combination of these two factors benefited C_3 plants more than C_4 plants. In all cases, the simulations reveal strong legacy effects, meaning that the past state of vegetation influences its current state.

In summary, this case study offers a foundation for understanding the factors driving vegetation distribution and predicting how these patterns may shift in a future climate.

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