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Introducing LPJ-GUESS-SPITFIRE: a coupled global fire-vegetation model

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Abstract

Fire-enabled dynamic global vegetation models (DGVMs) provide modelling frameworks for integrating many drivers of fire regimes and simulating feedbacks between fire and vegetation. They can then be used to investigate fire-vegetation dynamics and project fire activity into future or past scenarios. Here we present the fire-enabled DGVM LPJ-GUESS-SPITFIRE which combines the widely used LPJ-GUESS DGVM with the SPITFIRE global fire model. We also evaluate the model simulation against burnt area and fire speed Earth observation datasets. We find that the model reproduces the global burnt area patterns with reasonable skill and improves on a previous model version. However there are some regions where model performance is lacking, and through the comparison with fire speed we diagnose some possible causes and suggest potential ways to improve model performance. Despite this, we conclude that overall model performance is sufficient for global scale studies.

1. Introduction

Fire activity is determined by both meteorological conditions and fuel availability and flammability (Bradstock, 2010). Thus, to project future fire regimes under global change, methods must capture not only how fire behaviour responds to changing meteorological conditions (direct effects of climate change), but also how they respond to changing fuel properties. These arise from vegetation responses to climate change, which can include alterations to vegetation structure, species composition and overall biomass productivity, and have consequences for fuel availability, flammability and continuity (both horizontally and vertically). Further to this, human-driven factors, both direct (such as changing ignitions patterns and suppression efforts) and indirect (such as land use change and landscape fragmentation), will also affect future fire regimes (Bowman et al., 2011).

One possible means to integrate all these factors is to combine a dynamic global vegetation model (DGVM) with a global fire model. These models are designed to be applied to the full gamut of global vegetation (and so feature rather generalised representations of fire processes) and operate over gridded domains at comparatively coarse scales (typically 50km or larger). In such model frameworks, the DGVM dynamically simulates the ecosystem state using mechanistic representations of many ecosystem and plant physiological processes such as: photosynthesis; autotrophic respiration; biomass allocation; competition for resources; biomass turnover (i.e. litter production); heterotrophic respiration; and nutrient and water cycling (Prentice et al., 2007). DGVMs may also simulate human land use, such as pasture, cropland and managed forest areas. The simulated ecosystem state is used to derive the fuel properties which are used by the global fire model to simulate fire occurrence and behaviour. The fire activity simulated by the fire model then induces biomass combustion and post-fire mortality in the DGVM's vegetation state, thus representing the bidirectional effects and feedbacks between vegetation and fire.

Global fire models vary widely in their complexity, both in terms of the processes represented and calculated fire properties (Hantson et al., 2016; Rabin et al., 2017). The earliest and simplest models only derived burnt area and applied fixed mortality rates and combustion fractions based on vegetation type (e.g. GlobFIRM, Thonicke et al., 2001). However global fire models have become increasingly complex over the last two decades and now include representations of fire properties such as number of successful ignitions, rate of spread, intensity, combustion completeness and size-dependent mortality. Here we present the coupled global fire-vegetation LPJ-GUESS-SPITFIRE, which comprises the LPJ-GUESS DGVM (Smith et al., 2001, 2014) and the SPITFIRE global fire model (Thonicke et al., 2010).

2. Materials and Methods

2.1. The LPJ-GUESS DGVM

LPJ-GUESS builds on the biogeography and biogeochemical cycling of the LPJ DGVM (Sitch et al., 2003) by including a forest gap model of vegetation dynamics through the General Ecosystem Simulator (GUESS) (Smith et al., 2001). In this model, vegetation dynamics are represented through competing cohorts of identical woody individuals over a layer of herbaceous vegetation. In the global version used here, 10 different plant functional types (PFTs) are used to represent the global diversity of tree types (for example "boreal needle-leaved evergreen tree"). For the herbaceous layer two grass types are distinguished, a temperate/boreal type which uses C_3 photosynthesis and tropical grass type which uses C_4 photosynthesis. The dynamics of the woody cohorts are driven by establishment and mortality processes and by generic patch destroying disturbance events, here occurring with a mean return interval of 100 years. These processes are implemented stochastically and so a number of replicate "patches" (typically 15-100, in this study 20) are simulated and averaged to smooth out the resultant stochastic variability.

The version of the model used here (v4.1) also includes nitrogen cycling and limitation on photosynthesis (Smith et al., 2014); representation of human land use through croplands, pasture (Lindeskog et al., 2013; Olin et al., 2015) and forest management (Lindeskog et al., 2021); methane emissions from arctic wetlands and permafrost dynamics (Miller & Smith, 2012); emissions of biogenic volatile organic compounds (Arneth, Miller, et al., 2007; Arneth, Niinemets, et al., 2007)**.**

2.2. The SPITFIRE global fire model

SPITFIRE is one of the more complex global fire models. For a full description of the initial implementation see Thonicke et al., 2010, and for details of an earlier version of LPJ-GUESS-SPITFIRE see Rabin et al., 2017. We briefly summarise the main SPITFIRE model structure and logic here. Individual fires are resolved by calculating successful fire starts from potential ignitions from humans and lightning flashes as modified by a flammability index based on fuel moisture. This fuel moisture is based on the Nesterov fire danger index (Nesterov, 1949) and an exponential decay function with smaller coefficients (hence slower fuel drying) for the larger fuel classes. Fire size is modelled as an ellipse with the major axis dependent on rate of spread (which is calculated using the equations of Rothermel 1972) and fire duration (dependent on flammability index with a maximum of 4 hours in the initial formulation). The length-to-breadth ratio of the ellipse is determined by wind speed, and the number of daily fire starts multiplied by the size of each fire gives the daily burned area. Slope is not currently considered in the model as it acts on a landscape scale which is much finer than the coarse continental-to-global spatial scale for which LPJ-GUESS-SPITFIRE is designed.

Combustion completeness, derived from fuel moisture, is used to determine biomass burnt, and trace gas emissions are calculated from biomass burnt using PFT-specific emission factors. Post-fire mortality occurs by two mechanisms, crown scorch and cambial kill. Crown scorch mortality considers the fraction of an individual's crown which is affected by flame height (which is derived from Byram's fire intensity), and a PFT-specific parameter to account for species specific fire resistance. Cambial kill depends on calculated fire residence time (Peterson and Ryan) and bark thickness, with thicker bark providing increased survivorship. Bark thickness is determined based on PFT-specific allometric relationships between bark thickness and diameter at breast height.

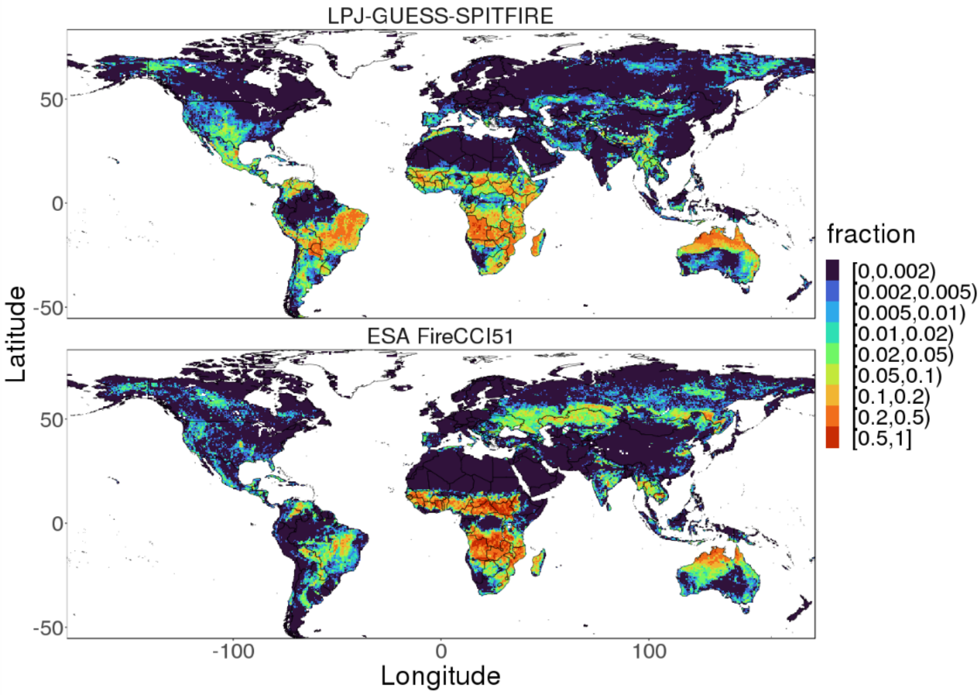
Further to this initial implementation described above, the version of SPITFIRE presented here includes a number of modifications. Whilst the original model did not consider burning in agricultural lands, this implementation burns pastures (with the same formulation as natural area) but not croplands. Further, cropland fraction is used to reduce fire size in *adjacent* areas of natural and pasture lands (i.e. in the same gridcell) to represent the effects of landscape fragmentation on fire size. Fire duration has been modified from a maximum of 4 hours to a maximum of 12 hours, but with an additional reduction factor based on human population density to represent human suppression following Hantson et al. (2015). To integrate SPITFIRE into LPJ-GUESS's replicate patches approach, fire behaviour is calculated separately for each patch and, for the application of post-fire mortality and combustion, burnt area is interpreted probabilistically (ie. each day the patch may burn with probability equal to the daily burnt area) and, if it burns, the combustion effects are applied to the entire patch.

2.3. Simulation set up

For the simulations used here we applied the standard LPJ-GUESS global settings and parameters (Smith et al., 2014). The input datasets required for LPJ-GUESS (climate, atmospheric CO2 concentration, nitrogen deposition and land use data) followed the TRENDY 2019 protocol (Friedlingstein et al., 2019). The TRENDY project coordinates an ensemble of DGVMs for estimation of the land carbon fluxes used in the Global Carbon Budget[30] on an annual basis and so the TRENDY protocol specifies state-of-the-art DGVM input datasets. To provide SPITFIRE with the additional information required for ignitions, the WGLC (Kaplan & Lau, 2019) lightning flash density and HYDE3.2 population density (Klein Goldewijk et al., 2017) datasets were used. The simulations followed the standard LPJ-GUESS spinup procedure whereby the first 30 years of the climate dataset (1901-1930) are detrended and repeated for 500 years to allow the vegetation and soil carbon pools to reach equilibrium. Following this, the full transient climate time series (1901-2018) was used.

2.4. Comparison data sets

To assess overall model performance, simulated burnt area was compared to the observed ESA FireCCI51 burnt area data set (Lizundia-Loiola et al., 2020). Both the observations and model output were summed to annual totals which were then averaged across the years 2001 to 2018. We also compare the daily simulated fire speed to mean fire speed from the Global Fire Atlas (GFA, Andela et al., 2019). SPITFIRE does not explicitly simulate mean daily fire speed, but it can be derived by dividing the length of the major ellipse in the fire size calculation by the duration of the observation period (in this case one day, matching the GFA units of fire speed and observation interval). This "macroscopic" fire speed depends on rate of spread and fire duration (in this case the duration of fire propagation within one day), and so comparing this to observations allows a first-order check of the combined effects of these two simulated properties. In order to examine fire behaviour at the peak of the fire season where the bulk of burning occurs, we compared the maximum of the mean monthly fire speeds.



[30] https://www.globalcarbonproject.org/

Figure 1- Annual fractional burnt area from the LPJ-GUESS-SPITFIRE simulation and the ESA FireCCI51 dataset (mean 2001-2018).

3. Results

LPJ-GUESS-SPITFIRE reproduced the global patterns of burnt area reasonably well (Fig. 1), with the largest burnt area simulated in the tropical savanna and dry forest regions. It also correctly simulated little or no burning in areas which are too arid (ie too dry to allow sufficient accumulation of fuel), humid or cold to burn and a modest amount of burning in the temperate and boreal zones. There were, however, some sizable regional discrepancies and, in some cases, opposite tendencies can be observed in the same climate zones but different continents. In the dry tropics fire activity was overestimated in South America but underestimated in Africa. Burnt area was overestimated in the continental interior of the US, but underestimated in the interior of Eurasia. The model simulated well the extent of burning in the warm temperate coastal and mediterranean regions (e.g. the Pacific coast and South East in the US, southern Australia, around the Mediterranean and across the Cape region in South Africa) with some small regional mismatches. In the boreal zone a reasonable amount of fire was simulated, but there were significant spatial mismatches between the modelled burnt area and the observed data.

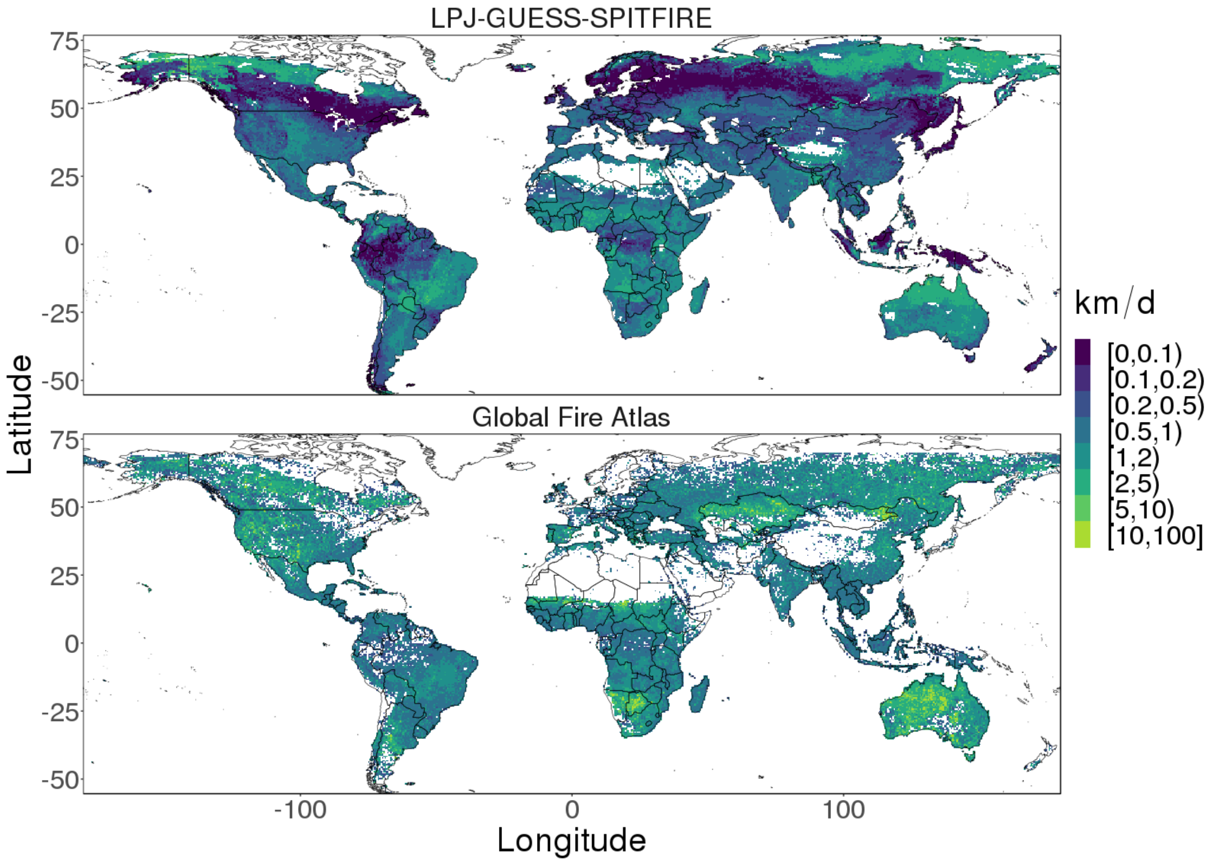


Figure 2 - Maximum of mean monthly fire speed from the LPJ-GUESS-SPITFIRE simulation and Global Fire Atlas dataset (mean 2001-2015).

The comparison of the maximum of mean monthly fire speeds (Fig. 2) gives some indication of what may be driving some of the discrepancies in burnt area. Whilst there was fairly good correspondence in the tropics and much of the temperate zone, there were considerable mismatches elsewhere. In central Eurasia, peak fire speed was underestimated and this corresponds with the region of underestimated burnt area (Fig. 1). Across the boreal forest fire speed was extremely low in LPJ-GUESS-SPITFIRE compared to the GFA observations and at very high latitudes (beyond the simulated tree line) it was very large, even in areas where no fires are observed.

4. Discussion

Compared to a simulation performed by a previous version of LPJ-GUESS-SPITFIRE used in the Fire Model Intercomparison Project (FireMIP, Rabin et al., 2017; Hantson et al., 2020), the simulation presented here showed a tangible improvement, as evidenced by a reduction of normalised mean error (NME, Kelley et al., 2013) from 0.96 (Hantson et al., 2020) to 0.77 (this study). This is similar to the other models from the FireMIP ensemble. However, given the importance of understanding and forecasting fire activity, it is a clear and present priority for the community to reduce this error and improve the skill of global fire models. In the

case of LPJ-GUESS-SPITFIRE, we can identify the boreal and arctic zones as areas for improvement. Our investigation of fire speed indicates that in the arctic region fire speed is too high which can only be a consequence of an over-simulation of fuel load and flammability. A cursory consideration of LPJ-GUESS's global PFTs reveals that there are no tundra shrubs included in the global setup. Instead, the C_3 grass PFT is the only viable vegetation type beyond the tree line, thus an overproduction of highly flammable fuel is simulated.

The underestimation of burnt area in the boreal forest is harder to diagnose. However, corresponding underestimation of fire speed indicates the simulated fuel characteristics are at least partly the issue, giving a definite direction for model improvement.

5. Conclusions

Here we have presented LPJ-GUESS-SPITFIRE, a coupled global fire-vegetation model, and some basic model evaluation. The model shows some regional discrepancies in spatial burnt area patterns, particularly at the higher latitudes, and we suggest some ways forward. However, the model does capture the global distribution of burnt area reasonably well and demonstrates similar model skill to other models in a recent model intercomparison project. We therefore consider it suitable for examining fire and vegetation interactions at global scope.

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