PROBABILISTIC CALIBRATION OF A COUPLED ECOSYSTEM AND FIRE MODEL USING OPTICAL AND THERMAL SATELLITE DATA

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1. ABSTRACT

Dynamic global vegetation models (DGVMs) usually use a simplistic approach to model fire disturbance, and usually, fire effects are just prescribed by the user. A better approach, and this is the one take in this work, is to couple a process-based fire model to the DGVM (see, for example, [1]). The DGVM simulates vegetation (and hence, fuel load and type) and will feed it into the fire model, which then simulates fire occurrence, as well as the impact of fire in vegetation (due to complete combustion or cambial kill), which is then fed back into the DGVM. Unfortunately, fire is a complex phenomenon, and as such, its modelling is often difficult. Mechanistic models (either for vegetation or fire) do often have large numbers of parameters, which are often either very difficult to determine. The present work details how some of these parameters can be determined by using a calibration procedure. In this context, calibration implies model parameter selection so that the model produces more realistic simulations of some observed variables. Often this is done by simulating the observations and minimising the difference with the observations. This methodology is limited by the difficulty of integrating prior knowledge, measurement uncertainty, and due to the fact that many sets of very different input parameters can minimise the error function. Another way is to use probabilistic calibration, which is the approach taken in this work.

Probabilistic calibration is based on Bayes' rule:

$$p(\theta|y) = \frac{p(\theta) \cdot p(y|\theta)}{p(y)}, \tag{1}$$

where θ are the model parameters to be calibrated, y are the observations, $p(\theta|y)$ is the *a posteriori* probability density distribution of the model parameters, subject to a set of observations, $p(\theta)$ is the *a priori* probability density distribution of the model parameters (which can include expert knowledge, rough estimates...), $p(y|\theta)$ is the *likelihood* (how well does the model fit the observations?). $p(y)$ is the marginal likelihood, which can be considered a constant so that the posterior distribution adds up to unity, and can be ignored. Probabilistic calibration produces distributions of parameters that produce model results that mimic the observations, taking into account any prior knowledge, observational uncertainty, inter parameter correlations, etc.

We choose the LPJ[2] DGVM coupled with the SPITFIRE[3] fire model. The model is run for Southern Africa, and it is calibrated with respect to burnt area derived from the MODIS burned area product and with daily temporal dynamics derived from Fire Radiative Power data from the SEVIRI instrument on board the Meteosat Second Generation satellite. The parameters that are calibrated are to do with daily ignitions, limits on rate of spread, and assumptions about fire dynamics. For each grid cell over the region of interst, the LPJ+SPITFIRE model is run within a Markov Chain Monte Carlo (MCMC) procedure, and posterior distributions for the calibrated parameters are estimated.

Initial results show that the calibrated LPJ+SPITFIRE system simulates more reaslistic burned areas, both in extent and temporal dynamics. We explore the role of uncertainty in the calibration data sets, and other areas where remote sensing data may be used to improve simulations.

2. REFERENCES

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