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Calibrating Rothermel's fuel models by genetic algorithms

Ascoli Davide[a], Bovio Giovanni[a], Vacchiano Giorgio[a]

[a] *University of Torino, DISAFA, via Leonardo da Vinci 44, 10095 Grugliasco (TO), Italy*
d.ascoli@unito.it, bovio.giovanni@unito.it, giorgio.vacchiano@unito.it

Abstract

A new method to customize Fire Behaviour Fuel Models was developed by linking Genetic Algorithms (GA) to the Rothermel's equation implemented in the Rothermel package for R. GA randomly generates solutions of fuel model parameters to form an initial population. Each solution is validated against observations of fire rate of spread (ROS) via a goodness-of-fit metric (i.e., RMSE). The population is then selected for its best members, crossed over, and mutated within a range of fuel model parameters space, until fitness is maximized. We tested the performance of GA-optimization against custom fuel models calibrated in two previous studies in grass and shrub fuels. GA was constrained using fuel parameters ranges reported in the selected studies, and was fit against the published ROS measurements. We compared goodness-of-fit (RMSE; R2adj) of fuel models calibrated by GA against that of the original studies. GA improved the fit of Rothermel's model for both studies: RMSE decreased from 5.5 to 4.6 m/min and from 6.9 to 5.4 m/min, respectively for grass and shrub fuel models. R2-adj increased from 0.83 to 0.84, and from 0.73 to 0.83, respectively. We then ran GA-optimization to calibrate a Calluna heaths fuel model against ROS and environmental data measured under experimental conditions. We obtained ranges of fuel model parameters (fuel load; fuel structure) by a field survey in both experimental plots and other Calluna sites of North-West Italy. Ranges of fuel flammability parameters were derived from the literature. We divided fire experiments into a calibration and a validation dataset (20 ROS each) and ran GA-optimization on the calibration dataset to customize the Calluna fuel model. We predicted ROS in the validation dataset by running the Rothermel modelon each of the following fuel models: i) GA-optimized fuel model; ii) the Standard Fuel Model which minimized RMSE against observations; iii) custom fuel models for Calluna heaths, parameterized using modal values from the overall fuel inventory, or inventoried at each experimental plot. Predictions of the Rothermel model reformulation implemented in FCCS, using as input modal values at the vegetation complex or at plot scale, were also evaluated. ROS predictions obtained by GA-optimized fuel model against the calibration dataset had a RMSE of 1.66 m/min and R2-adj of 0.96. When tested against the validation dataset, GA-optimized fuel model produced the lowest prediction error of all the alternative fuel models (RMSE = 1.74 m/min R2-adj = 0.90). FCCS predictions produced RMSE= 3.76 and 2.24 m/min, respectively using modal values from the fuel complex or at the plot scale, and R2-adj= 0.86 in both cases. GA-optimization provided an objective and accurate calibration of custom fuel models. It can be implemented in several fire prediction systems based on the Rothermel model, including the Rothermel package for R. Increasing the range of fuel model parameters beyond the measured values (e.g., +25%, +50%) can further improve GA model performance. However, this raises the question on how far apart from the field truth a fire behaviour fuel model should be stylized.

Keywords*: custom fuel model, optimization, fire rate of spread, prescribed burning, wildfire*

1. Introduction

Rothermel's model (Rothermel 1972) is the primary surface fire spread model of many fire prediction systems (Sullivan 2009; Finney *et al*. 2011; Andrews 2013). In the Rothermel model the forward rate of spread of a surface fire (ROS) is predicted as a function of topography, fire weather and a "fire behaviour fuel model" (hereafter: fuel model) that consists of a number of fuel parameters for a given fuel complex (Albini 1976; Burgan and Rothermel 1984). Standardized fuel models have been developed to facilitate the prediction of ROS (Anderson 1982; Scott and Burgan 2005). However, using standard fuel models can result in poor predictions and this has prompted the need to develop custom fuel models (Cruz and Alexander 2013). Customizing a fuel model is an iterative process of comparing predictions to observed fire rate of spread, and subjectively adjusting the fuel model parameters until a satisfactory result is achieved (Burgan 1987). However, due to complex relationships in Rothermel's model, it is not always easy to guess how changes in fuel parameters will affect the fire behaviour prediction (Burgan and Rothermel 1984).

Optimization methods, which explore many possible combinations of fuel model parameters, showed the best solution for calibrating custom fuel models in previous studies (Cruz and Fernandes 2008). However, there are no standard methods or published codes for running an automated optimization of a custom fuel model against observed/expected fire rate of spread.

Genetic Algorithms (GA) (Holland 1975) have been used to calibrate models in several fields (e.g., Wang 1991), including fire science (Finney 2004; Lautenberger *et al*. 2006; Wendt *et al*. 2013). However, an optimization of fuel model parameters using GA has not been attempted yet. GA is a search heuristic which generates numeric solutions to an optimization problem using techniques inspired by natural evolution (e.g., mutation). During GA, many solutions are randomly generated to form an initial population. Each solution is validated against the observations via a user-defined metric of goodness-of-fit. The population is then selected for its best members, crossed over, and randomly mutated within a range of parameter space, until fitness is maximized.

The study objectives are: i) to test a fuel model calibration method based on GA; ii) to implement the GA-optimization method to calibrate a fuel model for *Calluna* heath vegetation.

2. Methods

2.1. GA-optimization testing

To predict the forward rate of spread at the head of a surface fire (ROS), we used Rothermel's equation implemented in the *ros ( )* function of the Rothermel package for R[1] (Vacchiano and Ascoli 2014). To test GA-optimization, we searched for studies with the following characteristics: i) a published dataset of observed ROS, including fuel moisture, wind speed and slope steepness associated to each observation; ii) custom fuel model parameters calibrated using the ROS dataset; iii) inventory and laboratory fuel data from which to infer ranges of fuel model parameters to force the GA-optimization (Table 1, columns A-B); iv) ROS predictions using the same equation implemented in the Rothermel package for R (corrections to original the equation as implemented in BehavePlus). Following these criteria, we found suitable data for both grass (Sneeuwjagt and Frandsen 1977) and shrub fuels (Van Wilgen *et al*. 1985).

GA-optimization was carried out using the *GA* package for R (Scrucca 2014). GA were run with 9999 maximum iterations, a mutation probability of 0.1, and elitism of 0.05 (i.e., the 5 best solutions are retained at each simulation). As a fitness metric, we chose the root mean square error (RMSE) of observed vs. predicted ROS. Then, we compared goodness-of-fit (RMSE; R^2adj) of GA-optimized fuel models against the calibration methods used in selected studies, while keeping constant the fire environment (i.e., fuel moisture; wind speed; slope).

[1] http://cran.r-project.org/web/packages/Rothermel/index.html

Table 1. Fuel model parameters range used to force GA-optimization against observed ROS for both the test analysis (column A-B) and the heath fuel model calibration (column C).

Fuel model	A[2]	B[3]	C
Fuel Type	Grass fuels	Shrub fuels	Calluna heath
Load 1-h (t ha^{-1})	0.5 – 4	1.56 – 6.24	0.24 – 2.625
Load 10-h (t ha^{-1})	–	0.4 – 1.2	–
Load 100-h (t ha^{-1})	–	0.06 – 0.18	–
Load Live Herb (t ha^{-1})	0 – 0.9	1 – 6	0.825 – 7
Load Live Woody (t ha^{-1})	–	0.64 – 6.72	2.175 – 13
SA/V 1-h (m^2 m^{-3})	4600 – 14800	4200 – 8000	6640 – 10036
SA/V 10-h (m^2 m^{-3})	–	358	358
SA/V 100-h (m^2 m^{-3})	–	98	98
SA/V Live Herb (m^2 m^{-3})	4600 – 14800	4200 – 6500	5249 – 6562
SA/V Live Woody (m^2 m^{-3})	–	4200 – 5500	8810 – 10560
Fuel Bed Depth (cm)	9 – 53	100 – 200	19 – 70
Extinction Moisture (%)	12 – 25	20 – 40	27 – 55
Heat content Dead (kJ kg^{-1})	18000 – 19000	18000 – 22000	18719 – 19919
Heat Content Live (kJ kg^{-1})	18000 – 19000	18000 – 22000	20000 – 22504

2.2. Heathland fuel model calibration

We implemented the GA-optimization to calibrate a custom fuel model for *Calluna* dry heathlands against ROS and fire weather data recorded under experimental conditions (Ascoli *et al*. 2013; Vacchiano *et al*. 2014). We measured ROS in nine wind-driven field fire experiments using a microplot approach (Simard *et al*. 1984; Fernandes *et al*. 2001). We discarded data recorded during the acceleration, backfire and flank fire phases, retaining a total of 40 ROS observations ranging between 0.9 and 26.3 m/min. Environmental variables (min-max) were as follows: ignition line length = 25-50 m; fire plot size = 1250-4000 m^2; 1h fuels moisture = 10-27%; live woody fuel moisture = 50-70%; wind speed = 0.4-7.9 km/h; slope = 0%.

We obtained ranges of fuel model parameters (Table 1, column C) related to fuel load (1-h, 10-h, 100-h, Live Herb, Live Woody) and structure (Fuel Bed Depth) by a field survey in both fire experiment plots and additional *Calluna* stands in North-West Italy (twelve stands x 6 obs.). Ranges of fuel flammability parameters (SA/V, Moisture of extinction, Heat content) were derived from published datasets and laboratory studies. The fuel model was conceived as Dynamic.

We divided fire experiments into a calibration (four experiments, 20 ROS obs.) and a validation dataset (five experiments, 20 ROS obs.). We ran GA-optimization using the same setting as for the test analysis. Then, we predicted ROS in the validation dataset by using the *ros ( )* function of the Rothermel package for R, and compared goodness-of-fit (RMSE; R^2adj) of predictions obtained by the following fuel models: i) GA-optimized fuel model; ii) the Standard Fuel Model which minimized RMSE against observations, as determined by the *bestFM ( )* function of the Rothermel package (Vacchiano and Ascoli 2014); iii) a custom fuel model for *Calluna* heaths, parameterized with modal values from the overall fuel inventory (72 obs.); iv) a custom fuel model parameterized with modal values from fuels inventoried in each fire experiment plot (6 obs. per plot). Predictions of the Rothermel's model reformulation implemented in the Fuel Characteristics Classification System (FCCS) (Sandberg *et al*. 2007), using modal values at the vegetation complex or at plot scale, were also evaluated.

3. Results and discussion

GA-optimized fuel models improved the fit of Rothermel's model for both grass and shrub tests, relative to the published fuel models. RMSE decreased from 5.35 to 4.32 m/min and from 7.18 to 5.45 m/min, respectively. R^2-adj increased from 0.83 to 0.84, and from 0.73 to 0.83, respectively.
In heath fire experiments, ROS predictions obtained by GA-optimized fuel model against the calibration dataset had a RMSE of 1.66 m/min and R^2-adj of 0.96. When tested against the validation dataset, GA-optimized fuel model produced the lowest prediction error in comparison to all the alternative fuel models (Figure 1).

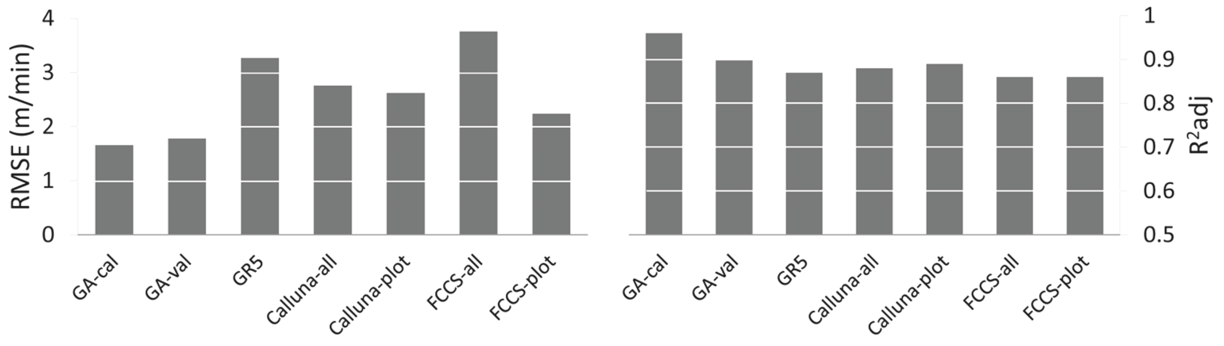

Figure 1. RMSE (left) and R^2adj (right) values for alternative fuel models predictions against the validation dataset

In accordance with previous studies, our results confirms the usefulness of calibrating a custom fuel model to improve Rothermel's model prediction, rather than limit its use to the set of Standard Fuel Models (Cruz and Fernandes 2008). Given the relative homogeneity of fuel conditions in heath vegetation at the study site, our results show that site-specific fuel parameters assessed at the plot scale did not improve predictions of Rothermel's model. However, when using variables measured at the plot scale, FCCS performance was second only to GA. This supports the potential of Rothermel's model reformulation embedded in FCCS, which aims to improve ROS predictions by using modal values of measured plots, bypassing the need to calibrate a stylized custom fuel model (Sandberg *et al*. 2007).
GA-optimization provided an objective and accurate calibration of custom fuel models. It can be implemented in several fire behaviour prediction systems based on Rothermel's model, including the Rothermel package for R. Increasing the range of fuel model parameters beyond the measured values (e.g., +25%, +50%) can further improve GA model performance (analysis not showed). However, this raises the question on how far apart from the field truth a fire behaviour fuel model should be stylized.

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