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Effects of wind velocity on predictions of wildland fire rate of spread models: A comparative assessment using surface fuel fire tests

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Abstract

In this work, a collection of ten wildland fire rate of spread prediction models that take into account the effects of wind are reviewed and tested against 166 individual laboratory fire tests, available in the open literature. The investigated models include the well-known semi-empirical models of Rothermel, Wilson and Catchpole et al., the empirical models of Rossa and Fernandes, developed using laboratory fire tests and the empirical models of Burrows et al., Anderson et al., Fernandes et al. and the Canadian Forest Fire Behavior Prediction System, developed using field measurements. The performance of the ten models is evaluated, both qualitatively and quantitatively, by employing a range of statistical error metrics. It is shown that the performance of each model is affected by their specific characteristics, in conjunction with the characteristics of the experiments against which the models were evaluated. It is found that the model of Catchpole et al. yields the lowest statistical error metric values in the specific measurement data set employed here. The empirical models that have been developed using field measurements exhibit significant discrepancies against the experimental data, due to the use of specific parameters regarding fuel type, scale and wind speed. Increasing wind velocities up to 3 m/s result, in the majority of the investigated models, in decreasing discrepancies with the experimental data.

1. Introduction

Prediction of the wildland fire Rate of Spread (ROS) is consistently one significant aim of the fire science community, since knowledge of the spatial-temporal evolution of a wildland fire event provides valuable information for a broad range of activities, ranging from fire defence to civilian evacuation. However, a single, catholic model that can accurately predict any potential wildland fire ROS has yet to be presented. This is, partially, due to the complexity of the involved physical phenomena, comprising a synergy of several interacting physical and chemical processes, e.g. combustion, turbulence, kinetics, heat, mass, and momentum transfer. Moreover, a wildland fire is a multi-scale phenomenon, which can manifest in various types of landscapes with potentially different horizontal (continuous-discontinuous) and/or vertical (surface, understory, over-story) fuel configurations. In this frame, a plethora of models has been developed to predict the ROS in various types of wildland fires, each with its own characteristics and limitations.

Wildland fire ROS prediction models are commonly categorized based on their corresponding level of physical foundation. For instance, a ROS model can be developed based on physical-chemical foundational principles and assumptions (physical model), or using statistical correlations stemmed from experimental data (empirical models), or even a combination of both (semi-empirical models) (Pastor et al., 2003). Experimental measurements, necessary for the development of empirical and semi-empirical models, are provided either from laboratory fire tests, which mainly focus on small-scale surface fires, or from large-scale field experimentation (or field observational studies) that, based on the specific characteristics of the landscape, may potentially account for multiple-scale phenomena.

Among the various parameters that influence the behaviour of a wildland fire, atmospheric wind velocity is of particular interest. Early studies recognized the impact of wind as one of the most influential parameters

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affecting the rate of spread and the evolution of a fire front (Rothermel and Anderson, 1966). The majority of the empirical and semi-empirical ROS models is able to incorporate the effects of atmospheric wind, either directly or through a model supplement. More specifically, models developed from field experiments seldom account for the case of a "quiescent" wind environment due to its rarity, as well as the fact that quiescent fires are generally characterised by relatively low ROS values, thus representing a "best case scenario".

In this work, ten different wildland fire ROS prediction models of empirical or semi-empirical nature are being reviewed and validated against 166 individual laboratory fire tests, aiming to quantify their prediction accuracy, by means of various statistical error metrics. Their performance is then discussed in detail, taking into account the specific characteristics and limitations of each model.

2. Investigated ROS models

A collection of ten models has been selected to be evaluated. The investigated models include a first group of the well-known "semi-empirical" models of Rothermel (1972), Wilson (1990) and Catchpole et al. (1998), a second group of the "empirical" models of Rossa and Fernandes (2018a, 2018b) developed using laboratory tests and a third group of the "empirical" models of Burrows et al. (2019), Anderson et al. (2015), Fernandes et al. (2009) and also the Canadian Forest Fire Behavior Prediction System (Forest Canada Fire Danger Group, 1992), which are fuel-specific and have been developed using field measurements.

All three semi-empirical models are based in the theoretical work of Frandsen (1971), where the steady state rate of spread, R (m/s) of an advancing flaming front is expressed as the ratio of thermal power per unit area (called the propagating heat flux) received by a fuel element from the flame, I_p (W/m^2) over the energy density required from the fuel element to reach ignition conditions, L (J/m^3). Rothermel (1972) modified Frandsen's ratio, employing theoretical reasoning as well as laboratory experiments, resulting in a semi-empirical model that is considered to be a "benchmark". In this model, the effects of wind and slope were decoupled from I_p, resulting in a "basic propagating heat flux", $I_{p,0}$ that in turn is assumed to be a fraction, ξ of the energy generated by the flame front, I_R (W/m^3). Through laboratory experiments, Rothermel statistically related the model's theoretical properties with specific measurable properties of the fuel, as well as the wind velocity and the slope angle. Later, Wilson (1990), based on empirical evidence as well as statistical data from a broader range of additional laboratory experiments on quiescent conditions, re-examined the model of Rothermel. One of the main modifications proposed by Wilson is the hypothesis that the energy generated from the flame front contributing to the propagating heat flux, stems only from the heat content of the pyrolyzed gases. Finally, the Catchpole et al. (1998) model was based on laboratory experiments on a wind tunnel as well as on the two previously cited models. One of the main ideas of this model was the re-coupling of the propagating heat flux with the effect of wind.

The empirical work of Rossa and Fernandes (2018a, 2018b) comprises two models that statistically relate the quiescent rate of spread, R_0 (m/s) with fuel related properties, whereas a complementary model that accounts for the effect of wind is used. Their work is based on laboratory experiments and, despite being of empirical nature, selection of some of the related properties is based on theoretical reasoning.

The remaining four empirical models are based on field experiments or observational studies of actual wildland fires on specific flora environments. Burrows et al. (2019) modeled the flame ROS on spinifex grassland (a horizontally discontinuous surface fuel) yielding a "parsimonious" three-parameter model. Anderson et al. (2015) presented a group of empirical models based on a large database of shrubland fires. Fernandes et al. (2009) developed a model for predicting the flame ROS on maritime pine stands. Lastly, the Forestry Canada Fire Danger Group (1992) developed the Fire Behavior Prediction System (FBP) from various types of field experiments and observational studies. This model has been developed to accept fuel specific parameters from various fuel models of Canadian flora environments.

The general form of the ten models investigated in this work are presented in Table 1, where σ (m^{-1}) is the surface-to-volume ratio, β (-) is the packing ratio, m_d'' and m_n'' (kg/m^2) are the dry and net fuel load, respectively, h and h_v (kJ/kg) are the heat content of the fuel and the fuel pyrolysis gas, respectively, M (%) is the fuel moisture content, Q_p (kJ/kg) is the heat of pyrolysis, Q_w (kJ/kg) is the latent heat of evaporation of water, s (m^2/kg) is the particle specific surface, c (%) is the fuel cover (for a discontinuous, horizontal fuel geometry), U (m/s) is the laboratory wind tunnel velocity and U_z (m/s) is the field wind velocity measured at a height z (m or ft). The rest of the parameters, represented by capital letters, namely A to K, represent specific model constants (different for each model), while the parameters represented by lower case letters, e.g. a, b, and c, represent fuel specific constants for the CFFBPS model.

Table 1 – General form of the main equations corresponding to the investigated ROS models.

Reference	**Model Equations**
Rothermel (1972)	$R=\dfrac{I_{R,1}(\sigma,\beta,h,M,\eta_S,m_n{}'')*\xi_1(\sigma,\beta)}{L_1(\sigma,\mathrm{M},\rho_b)}(1+\mathrm{A}(\sigma,\beta)*U^{B(\sigma)})$
Wilson (1990)	$R=\dfrac{I_{R,2}(\sigma,\beta,\delta,h_v,M,Q_p,Q_w,m_d{}'')*\xi_2(\sigma,\beta)}{L_2(\sigma,\mathrm{M},\rho_b,Q_p,Q_w)}(1+\mathrm{A}(\sigma,\beta)*U^{B(\sigma)})$
Catchpole et al. (1998)	$R=\dfrac{I_P(U,\sigma,\beta,\mathrm{M})}{L_2(\sigma,\mathrm{M},\rho_b,Q_p,Q_w)}$
Rossa and Fernandes (2018a, 2018b)	$R=R_0*K*[1+E*U^F(R_0*m'')^G(H+M*I)^J]$, $R_0=A*M^B*\delta^C$ (1) or $R_0=A*M^B*\delta^C*\ln(D*s)$ (2)
Burrows et al. (2019)	$R=A*\dfrac{U_z^B*c^C}{M^D}$
Anderson et al. (2015)	$R=A*U_z^B*\delta^C*e^{D*M}$ or $R=A*U_z^B*\left(\dfrac{m''}{\delta}\right)^C*e^{D*M}$
Fernandes et al. (2009)	$R=A*U_z^B*e^{C*M}*\delta^D$
CFFBPS (1992)	$R=a*(1-e^{-b*ISI})^c$, where $ISI=A*e^{B*U_z}*\left\{C*e^{D*M}*\left[1+E*M^F\right]\right\}$

3. Methodology

Aiming to evaluate the prediction accuracy of the ten investigated ROS models, a set of 166 individual laboratory fire tests, performed on surface fuels, was collected from the open literature. All the experiments were conducted in wind tunnels, where fuel beds were linearly ignited. The fire tests set includes experiments with various kinds of fuels, namely pine needles, excelsior and wood sticks, which results in a high variety of the fuel parameters. A summary of the experimental studies used in this work is presented in Table 2.

Table 2 – Summary of the experimental studies used for validation.

Reference	**Number of fire tests**	**Fuel**
Lozano et al. (2008)	6	Bamboo sticks
Anderson et al. (2010)	133	Pine Needles (Pinus Ponderosa) / Excelsior
Mendes-Lopez et al. (2003)	7	Pine Needles (Pinus Pinaster)
Korobeinichev et al. (2014)	6	Pine Needles (Pinus Sibirica)
Korobeinichev et al. (2021)	14	Pine Needles (Pinus Sibirica)

In the Atmospheric Boundary Layer, the axial wind velocity decreases with decreasing height, therefore the wind velocity measured at a given height above the flame can be much higher than the wind velocity close to the flame. In order to use the ROS models developed using large-scale field measurements, i.e., Burrows et al., Anderson et al., Fernandes et al., and CFFBPS , the actual “field” wind velocity, U_z,, measured at a height z, usually in a meteorological station, is required. However, since all fire tests employed in this study were performed in a wind tunnel, there is a need to determine an “equivalent” velocity U_z, using the (usually constant) velocity measured in the wind tunnel, U. This wind velocity “adjustment” is performed using the methodology of Albini and Baughman (1979), where the Wind Adjustment Factor (WAF), which corresponds to the ratio of the “mid-flame windspeed” $\overline{\overline{U}}$ to U_z, was introduced. Under the assumption made by Baughman and Albini (1980) that the flame height (above the fuel bed) is considered to be approximately equal to the height of the fuel bed, the WAF can be estimated using Equation (1), where *z* and *δ* are expressed in "ft" (Andrews, 2012). The adjustment of the wind tunnel velocity, U to U_z is based on the additional assumption that the wind tunnel nominal speed (U), due to the small scale of the laboratory fires, is approximately equal to $\overline{\overline{U}}$, an assumption that is commonly made in studies of similar nature (Weise and Biging, 1997).

$$WAF = \frac{\overline{\overline{U}}}{U_z} = \frac{1.83}{\ln\left(\frac{z + 0.36\delta}{0.13\delta}\right)} \tag{1}$$

4. Results and Discussion

The ten ROS models are used to estimate the ROS values in all 166 individual fire tests considered here. Each "predicted" ROS value, R_p (mm/s), is compared against the respective "observed" ROS value, R_o (mm/s); the results are presented both qualitatively, e.g., Figure 1, and quantitatively, by estimating the values of several statistical error metrics. The error metrics selected to evaluate each model's performance are the Mean Absolute Percentage Error (MAPE), the Mean Biased Error (MBE) and the Root Mean Square Error (RMSE), defined in Equations (2), (3) and (4), respectively, where *n* is the total number of experiments (166 in this case).

$$\mathrm{MAPE} = \frac{\sum_1^n \frac{\left|R_p - R_o\right|}{R_o}}{n} 100\% \tag{2}$$

$$\mathrm{MBE} = \frac{\sum_1^n \left(R_p - R_o\right)}{n} \tag{3}$$

$$\mathrm{RMSE} = \left(\frac{\sum_1^n \left(R_p - R_o\right)^2}{n}\right)^{\frac{1}{2}} \tag{4}$$

The investigated models are evaluated based on their accuracy, i.e., their overall ability to yield predicted values close to the observed ones. The obtained results are graphically presented in Figure 1; the evaluation is assisted by depicting the 10%, 20% and 30% error thresholds, as well.

In Figure 1 (left), results of the semi-empirical and the laboratory-developed empirical models are presented. The models of Catchpole et al. and of Rossa and Fernandes seem to perform well exhibiting, generally, errors lower than ± 30%. The model of Rothermel shows a tendency to under-predict the measured values, thus yielding non-conservative values, a fact that may present an enhanced risk when this model is used in actual operational environments. The model of Wilson, on the other hand, is exhibiting a tendency for over-prediction. Overall, the model of Catchpole et al. seems to yield the most accurate results.

In Figure 1 (right), the performance of the field-developed empirical ROS models is depicted. In general, in this case the results are more sparsely distributed compared to those of the laboratory-developed models. The model of Burrows et al. is found to strongly under-predict the measured values, while the models of Anderson et al. seem to perform slightly better, while still under-predicting the experimental data. The model of Fernandes et al. exhibits the best performance among the five models, while the CFFBPS model predictions are broadly distributed, both over and above the 45 degree slope "line of perfect agreement".

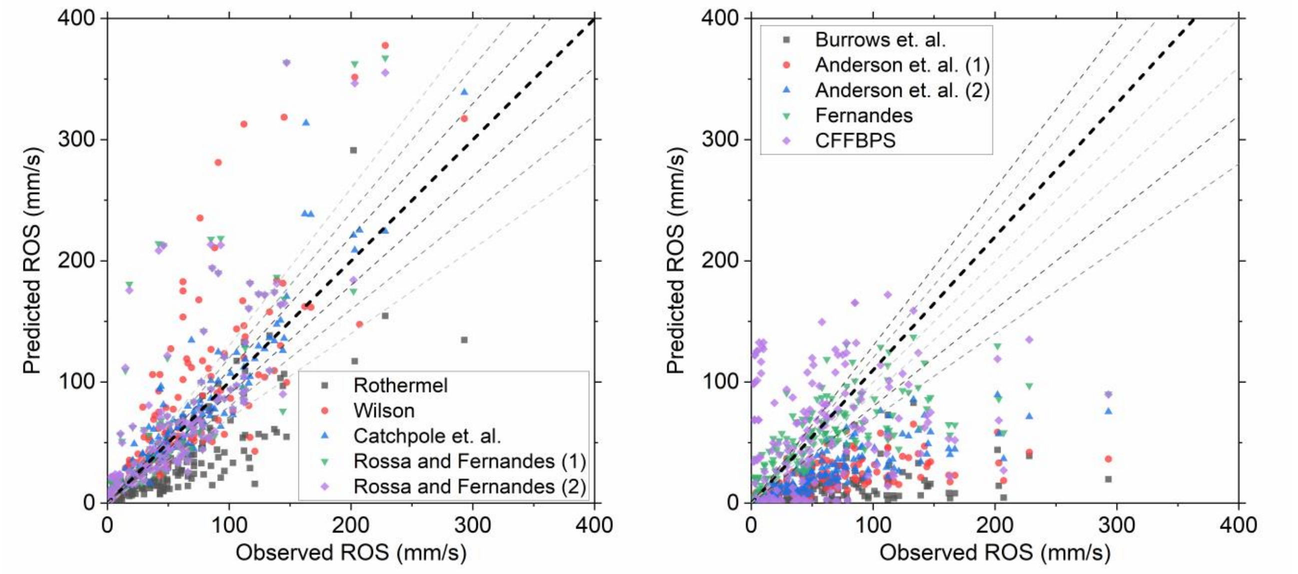

Figure 1 - Comparison of predicted and measured ROS values for the 166 investigated experimental test cases.

The respective values of all calculated statistical error metrics are presented in Table 3. The relative performance of each model may be explained based on their corresponding specific characteristics. For instance, the model of Catchpole et al. exhibits the lowest discrepancies in two out of three error metrics. This may be attributed to the fact that the majority of the experimental data used here (80%, c.f. Table 2) stems from the work of Anderson et al. (2010), who employed the same experimental apparatus used for the development of the Catchpole et al. model. As far as the field-developed models are concerned, their performance mainly depends on four characteristics. Firstly, these models are fuel specific, which means that few fuel-related parameters are required as an input, while the rest of the parameters are integrated in various constants, e.g., statistically fitted coefficient values. For example, the model of Burrows et al. was developed using measurements in fires of spinifex grasslands, a fuel that exhibits horizontal discontinuity. In addition, the only fuel parameter included in the Burrows et al. model is the fuel moisture content. These observations can be related to the fact that the Burrows et al. model exhibited the highest, in absolute terms, MBPE values.

Table 3 - Statistical error metrics for the ten models, validated against the 166 individual fire tests.

Model	**MAPE**	**MBE**	**RMSE**
Rothermel	46 %	-25	40
Wilson	59 %	15	51
Catchpole et al.	**35** %	4	**20**
Rossa and Fernandes (1)	95 %	34	131
Rossa and Fernandes (2)	90 %	33	125
Burrows et al.	79 %	-49	66
Anderson et al. (1)	65 %	-40	58
Anderson et al. (2)	58 %	-35	50
Fernandes et al.	74 %	-6	37
CFFBPS	381 %	**3**	59

Secondly, the fact that field experiments employ live as well as dead fuels may not allow to properly consider the effects of FMC. Thirdly, field experiments usually employ fuel areas exhibiting at least one order of magnitude higher fuel bed width, compared to laboratory tests. Under external wind conditions, the potential ROS depends on the flame front's effective length, which can significantly change during the fire due to the large dimensions of the fuel area as well as the nature of the ever-changing wind (in both magnitude and direction) (Cheney et al., 1993; Cheney and Gould, 1995). Finally, the assumption used to determine the WAF, i.e. that the height of the flame above the fuel bed is considered to be equal to the height of the fuel bed, is usually not valid in small-scale fires, a fact that might induce further deviations from the observed values.

Figure 2 depicts values of each model's prediction MAPE as a function of wind velocity; the experimentally imposed wind velocities are "clustered" in 4 groups. In the case of ROS models developed using laboratory measurements (Figure 2, left), MAPE is generally decreasing with increasing wind velocity, up to 3 m/s; MAPE values of the Burrows et al. and Anderson et al. models, are not significantly affected by the wind (Figure 2, right).

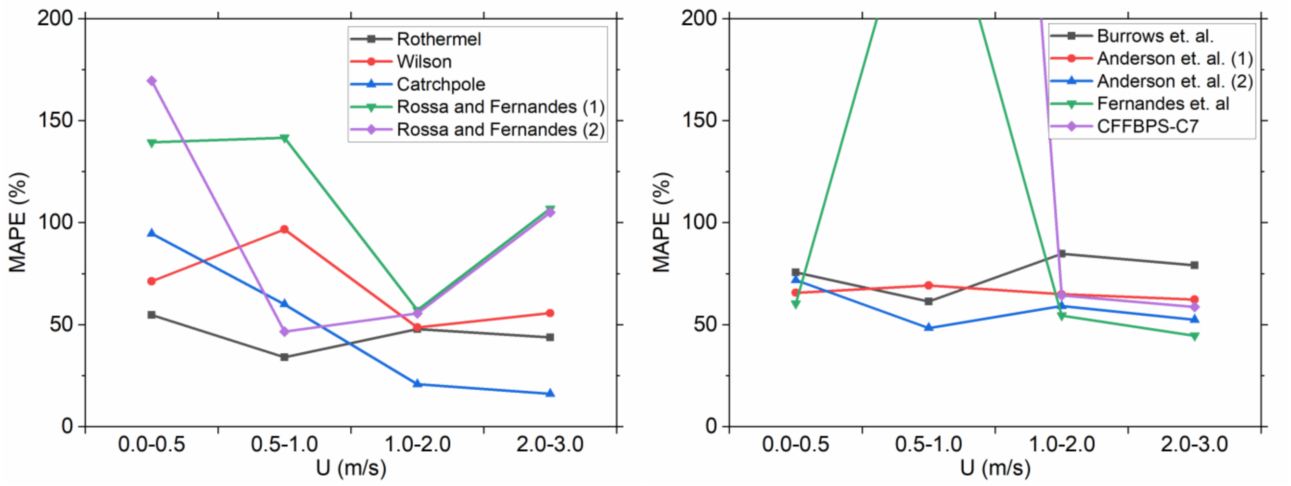

Figure 2 – Effect of wind velocity on the Mean Absolute Percentage Error (MAPE) of each model's predictions.

5. Concluding Remarks

Ten wildland fire rate of spread prediction models were evaluated against laboratory experiments of surface fires. As expected, models that were developed using laboratory data exhibit higher levels of agreement compared to models developed using field data. The field developed models may not be able to accurately predict fires from laboratory experiment due to their fuel specific development (that might differ from the laboratory fuel beds), the fact that field cases are of different scale and are comprised of both live and dead vegetation and, finally, due to the use of severe assumptions in adjusting the laboratory wind speed to the wind velocity. In addition, increasing wind velocities up to 3 m/s result, in the majority of the investigated ROS models, in decreasing discrepancies with the experimental data.

6. References

Albini F.A., Baughman R.G., Estimating Windspeeds for Predicting Wildland Fire Behavior (1979), USDA Forest Service, Research Paper INT-221, Intermountain Forest and Range Experiment Station, Ogden, Utah.

Anderson W.R., Catchpole E.A., Butler B.W., Convective heat transfer in fire spread through fine fuel beds, Int. J. Wildland Fire 19 (2010) 284-298.

Anderson W.R., Cruz M.G., Fernandes P.M., McCaw L., Vega J.A., Bradstock R.A., Fogarty L., Gould J., McCarthy G., Marsden-Smedley J.B., Matthews S., Mattingley G., Pearce H.G., van Wilgen B.W., A generic, empirical-based model for predicting rate of fire spread in shrublands, Int. J. Wildland Fire 24 (2015) 443-460.

Andrews P.L., Modeling wind adjustment factor and midflame wind speed for surface fire spread model. Gen. Tech. Rep. RMRS-GTR-266, U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station (2012).

Baughman R.G. and Albini F.A. (1980), Estimating Midflame Windspeeds, Northern Forest Fire Laboratory, Missoula, Montana, p. 88-92.

Burrows N., Gill M., Sharples J., Development and validation of a model for predicting fire behaviour in spinifex grasslands of Arid Australia, Int. J. Wildland Fire 27 (2019) 271-279.

Catchpole W.R., Catchpole E.A., Butler B.W., Rothermel R.C., Morris G.A., Latham D.J., Rate of Spread of Free-Burning Fires in Woody Fuels in a Wind Tunnel, Combust. Sci. Technol. 131 (1-6) (1998) 1-37.

Cheney N.P., Gould J.S., Catchpole W.R., The influence of Fuel, Weather and Fire Shape Variables on Fire-Spread in Grasslands, Int. J. Wildland Fire 3(1) (1993) 31-44.

Cheney N.P., Gould J.S., Fire Growth in Grassland Fuels, Int. J. Wildland Fire 5(4) (1995) 237-247.

Fernandes P.M., Botelho H.S., Rego F.C., Loureiro C., Empirical modelling of surface fire behavior in maritime pine stands, Int. J. Wildland Fire 18 (2009) 698-710.

Forestry Canada Fire Danger Group, Development and Structure of the Canadian Forest Fire Behavior Prediction System, Information Report ST-X-3, Forest Canada Science and Sustainable Development Directorate, 1992.

Frandsen W.H., Fire Spread through Porous Fuels from the Conservation of Energy, Combust. Flame 16 (1971) 9-16.

Korobeinichev O., Tereshchenko A., Paletsky A., Shmakov A., Gonchikzhapov M., Chernov A., Kataeva L., Maslennikov D., Liu N., The Velocity and Structure of the Flame Front at Spread of Fire Across the Pine Needle bed Depending on the Wind Velocity, Proceedings of the 10th Asia-Oceania Symposium on Fire Science and Technology (2014), 771-779.

Korobeinichev O., Kumaran S.M., Shanmugasundaram D., Raghavan V., Trubachev S.A., Paletsky A.A., Shmakov A.G., Glaznev R.K., Chernov A.A., Tereshchenko A.G., Experimental and Numerical Study of Flame Spread Over Bed of Pine Needles, Fire Technol. 58 (2022) 1227-1264.

Lozano J., Tachajapong W., Pan H., Swanson A., Kelley C., Princevac M., Mahalingam S., Experimental Investigation of the Velocity Field in a Controlled Wind-aided Propagating Fire Using Particle Image Velocimetry, Fire Safety Science - Proceedings of the 9th International Symposium, 255-266 (2008).

Mendes-Lopez J.M., Ventura J.M., Amaral J.M.P., Flame characteristics, temperature-time curves, and rate of spread in fires propagating in a bed of Pinus Pinaster needles, Int. J. Wildland Fire 12 (2003) 67-84

Pastor E., Zarate L., Planas E., Arnaldos J., Mathematical models and calculation systems for the study of wildland fire behaviour, Prog. Energ. Combust. Sci. 29 (2003) 139-153.

Rossa C.G., Fernandes P.M., Empirical Modeling of Fire Spread Rate in No-Wind and No-Slope Conditions, Forest Sci. 64 (4) (2018a) 358-370.

Rossa C.G., Fernandes P.M, An Empirical Model for the Effect of Wind on Fire Spread Rate, Fire 1 (2) (2018b) 31.

Rothermel R.C., Anderson H.E., Fire Spread Characteristics determined in the Laboratory, (1966), U.S. Forest Service, Research Paper INT-30, Intermountain Forest & Range Experiment Station, U. S. Department of Agriculture, Ogden, Utah.

Rothermel R.C., A Mathematical Model for predicting Fire Spread in Wildland Fuels, USDA Forest Service Research Paper INT-115, 1972.

Weise D.R., Biging G.S., A Qualitative Comparison of Fire Spread Models Incorporating Wind and Slope Effects, Forest Sci. 43 (2) (1997), 170-180.

Wilson R.A., Rothermel's Fire Spread Equations in No-wind and No-slope Conditions, USDA Forest Service Research Paper INT-434, 1990.