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Climate adjustment of the physical parametrization for the fire-spotting

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Abstract

The aim of the present study is to provide a simple yet complete addition to operational fire spread models for representing the random behavior of fire-spotting in various climate classes through simple inputs related to the wildfires. Results from different test cases highlight the sensitivity of the proposed simple physical parametrization in simulating different scenarios of the generation of secondary fires by fire-spotting under different climatic conditions. Since climate change may cause extreme conditions that contribute to the high fire intensity and larger wildfires, the parametrization here proposed allows us to model the fire-spotting process in various climatic zones and to adjust the existing operational model to the climatic changes.

Fire-spotting involves aspects among scales: from the combustion chemistry in microscale, to fire-atmosphere interaction in macroscale. At the meso-scale level, fire-spotting is affected by the mean wind and fireline intensity, which is found to be in a strong interaction with the surrounding factors, such as fuel and local orography. At the macroscopic level, the atmospheric stability conditions impact the fire-spotting pattern. Both, meso- and macro-scale factors are taken into consideration in the proposed probabilistic model devised to provide a physical meaning to the spread of fire by virtue of firebrands, which allows the integration of the diversity of all these parameters into a few differentiable regions. For this purpose, the classification based on the Köppen-Geiger map is considered, as it is done in the study of complex natural systems in a broad range of topics in hydrology, agriculture, biology, and many others.

Preliminary studies show as well that fire-spotting is a vegetation-dependent phenomena, since not all types of vegetation can generate sufficient combustion energy or produce the firebrands. In order to represent the vegetation component of the fire-spotting generation, the biome world map is incorporated, resulting in the integrated climate-biome classification for the fire-spotting generated fires.

1. Introduction

In present study we are aimed to integrate the diversity of climate-dependent parameters of the fire-spotting into a few differentiable regions basing on an integrated climate-biome classification. For that purpose, ***RandomFront2.3*** routine described in Truccia et al. (2019) is considered to perform the calibration of the fire-spotting parameters to different climate classes by applying the statistical study and simulations. In the considered approach, the effect of the fire-spotting is incorporated into the main fire-front model by adding features related to the statistical description of the firebrands transport, which depends on flame structure and local weather, aerodynamics around firebrands, combustion and heat transfer of firebrands during flight. Since ignition of the fuel at the landing position involves heat exchange over a sufficient period, a delay effect due to "heating-before-burning" is taken into account by the model proposed in Trucchia et al. (2019).

The proposed multi-scale physical parametrization for the fire-spotting phenomena points out the impact of atmospheric stability and fuel moisture on the fire-spotting. This fact motivates us to improve the probabilistic model by including the local climate characteristics. Moreover, since climate change may cause extreme conditions that contribute to the high fire intensity and larger wildfires, the proposed parametrization allows for modelling fire-spotting phenomenon in various geographical zones and adjustment of the existing model to the climate changes. Thus, we focus on the calibration of the fire-spotting parameters to different climate classes by applying the statistical study and simulations.

2. Integrated climate-biome classification

Despite a growing body of literature that recognizes the interaction between climate and wildfires, much less is known about the climate impact on fire-spotting. However, the amount and bark type of fuel determine the energy available for combustion, while wind and hot air are the primary drivers of the fire-spotting. Locality of these factors cause the possible geographical variations of the fire-spotting patterns. Previous studies reported different spotting distributions, number and distances of the secondary fires in various geographical zones, see Storey et al. (2020).

In present research, we integrate the diversity of climate-dependent parameters of the fire propagation into a few differentiable regions basing on climate-biome classification. For the biome, the Walter's vegetation classification by Breckle (2002) is considered, while for the climate the Köppen-Geiger climate classification by Peel et al. (2007) has been applied. This classification distinguishes five climate groups, depending on seasonal precipitation and air temperature and their seasonality. These groups are:

A: Tropical, that is characterized by average temperature ≥ 18◦C with significant precipitation.

B: Arid, where the average temperature is around 20◦C with little precipitation.

C: Temperate, that has the coldest month averaging between 0◦C and 18◦C and at least one month averaging above 10◦C.

D: Cold (continental), where at least one month averaging ≤ 0 ◦C and at least one month averaging ≥ 10◦C.

E: Polar, that includes tundra and ice cap, and characterized by every month average temperature ≤ 10◦C.

Hence, there have been chosen several climate classes with the parameters given in Table 1. The integrated climate-biome parametrization is incorporated to the operational code LSFire+ via ***RandomFront2.3*** post-processing routine, see Trucchia et al. (2019). In the considered probabilistic model, depending on the climate class the ambient temperature, the ABL height and mean biomass are chosen. Rest of parameters are fixed in order to emphasize the impact of the climatic factors. Table 1 connects and systematizes various classifications, such as Köppen-Geiger climate classes, biomes and NFFL fuel models. The flame geometry is found to be proportional to the mean biomass. It is important to notice that the parameters may vary within the same climate class due to season and location.

Table 1. Climate dependent parameters for the wildfire propagation modelling

Climate Class	Biome	Mean biomass, tons/ha	NFFL Model	H_{ABL}	Localization
Af	Tropical rainforest	500	6	1200 / 350	South America, Amazonia
BSh	Savanna	27	3	3500 / 2500	South-East Australia
BWh	Desert	4	1	2700 / 550	South-East Australia
Cfb	Temperate forests	370	7	3500 / 2500	South-East Australia
Csa	Mediterranean vegetation	410	2	3500 / 400	Mediterranean Area
Dfb	Temperate broad leaf forests	400	9	1500 / 400	Eastern Europe, Northern Rockies (USA)
Dfc	Taiga	260	9	1500 / 500	Canada, Finland

In present study, for the simulation of the fire front propagation, we use the NFFL fuel model Scott and Burgan (2005), which allows the consideration of the fuel characteristics in accordance with the chosen climate class. Thus, the climate characteristics are incorporated not only through the parameters of the fire-spotting distribution but also through the parameters of the underlying fire-spread model. Moreover, one of the key vegetation characteristics, net primary productivity, impacts through the fire intensity on the flame length and the maximum loftable height.

3. Multiscale parametrization

The described above climate-biome parameters are incorporated into the fire-spotting probabilistic model of Trucchia et al. (2019). The firebrand landing distribution $q(\ell)$ is here assumed to be lognormal distributed following

$$q(\ell) = \frac{1}{\sqrt{2\pi}\sigma\ell} e^{-\frac{\left(\ln\frac{\ell}{\mu}\right)^2}{2\sigma^2}}, \tag{1}$$

with median μ and mode $\mu e^{-\sigma^2}$.
At the macroscopic scale, fire-spotting is affected by atmospheric conditions. In particular, we plug the depth of the atmospheric boundary layer (ABL), that is related to the atmospheric stability, into the estimation of the smoke-injection height including the uplift against the atmospheric stratification and the plume widening due to entrainment of the surrounding air. Then, it holds

$$\mu = H_{max} \sqrt{\frac{3\,\rho\,C_d}{2\,\rho_f}},$$

where H_{max} is the maximum loftable height, ρ is the air density, ρ_f is the fuel density and C_d is the drag coefficient. In fact, H_{max} depends on the fire intensity and atmospheric stability, the detailed study of this parameter and the impact of the atmospheric stability conditions are provided in Egorova et al. (2020).

The parameter σ is defined in Egorova et al. (2022) as follows

$$\sigma = \frac{1}{z_p} \ln\left(\sqrt{Fr} + \beta \sqrt{\frac{2\,\rho_f U^2}{3\rho C_d g\, L_f}}\right),$$

where Fr is the Froude number, $\beta = 0.945$ is a correcting factor, g is the gravitational acceleration, and L_f is the flame length written in terms of the fireline intensity I_f and some surrounding factors as follows

$$L_f = \beta_0 I_f^{2/3} = \frac{I_f^{2/3}}{\cos\theta\,\left(2g\left(\rho c_p T_a\right)^2\right)^{1/3}},$$

where c_p is the specific heat of air at constant pressure, T_a is the air temperature and θ is the tilting angle in the simplified model of the flame geometry presented in Figure 1.

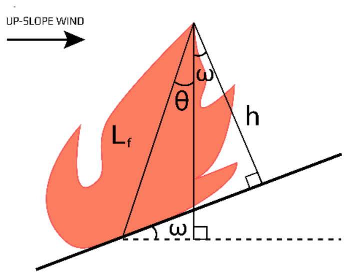

Figure 1: Flame geometry

Considered parametrization of the downwind landing distribution admits the consideration of climatic factors and their impact on fire-spotting, and, consequently, on the fire front propagation, which will be discussed further.

4. Simulations

The simulations show that by using the considered physical parametrization of the fire-spotting distribution different fire-front patterns can be obtained. We focus mainly on the climate classes with registered fire-spotting events, such as South-Eeastern Australia (BSh and BWh classes) and Mediterranean zone (Csa class).

For BSh and BWh climate classes (see Table 1), which can be considered as a pattern for the South-East Australia, as well as Csa class (Mediterranean class), the stable and unstable atmospheric conditions are considered to compare the fire-spotting patterns not only between the classes but also within the chosen class. The simulated fire fronts are plotted in Figures 2, 3 and 4, respectively.

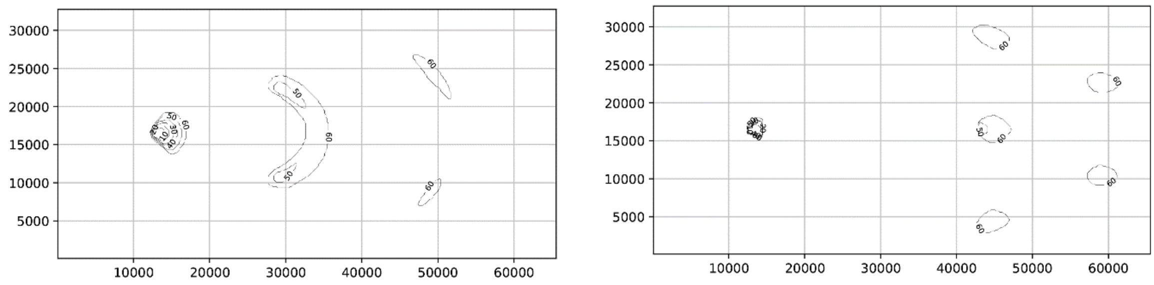

Figure 2: Fire-spotting pattern in the BSh climate class (South-Eastern Australia) during the unstable (left) and stable (right) atmospheric conditions

In the case of BSh, the fire-spotting is observed in both modes: unstable and stable atmospheric conditions. However, with unstable atmosphere, which corresponds to the daylight period, the secondary fires merge, while during the stable conditions the fire-spotting pattern is characterized by longer travel distance of the fire brands and higher number of new independent ignitions.

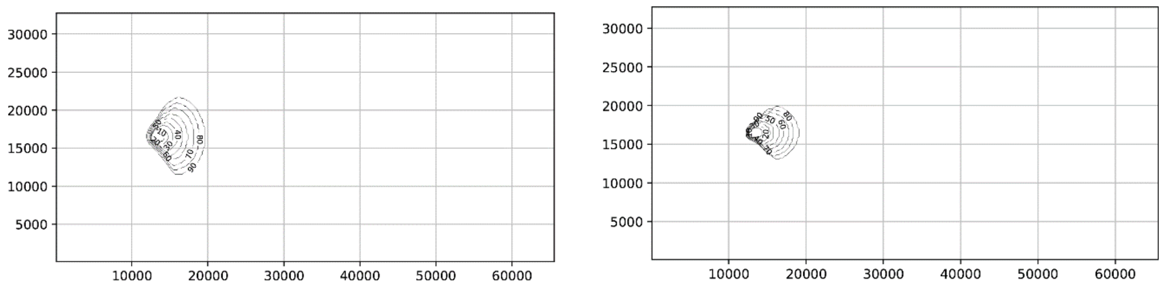

Figure 3: Fire front without fire-spotting in the BWh climate class (deserts in South-Eastern Australia) during the unstable (left) and stable (right) atmospheric conditions.

In contrast, for the BWh class, which represents deserts located in the South-Eastern Australia, fire-spotting is not observed, exposing the effect of the climate factors of the model. Moreover, the main front under the unstable atmospheric conditions is larger due to the turbulence effect, see Egorova et al. (2020) for details.

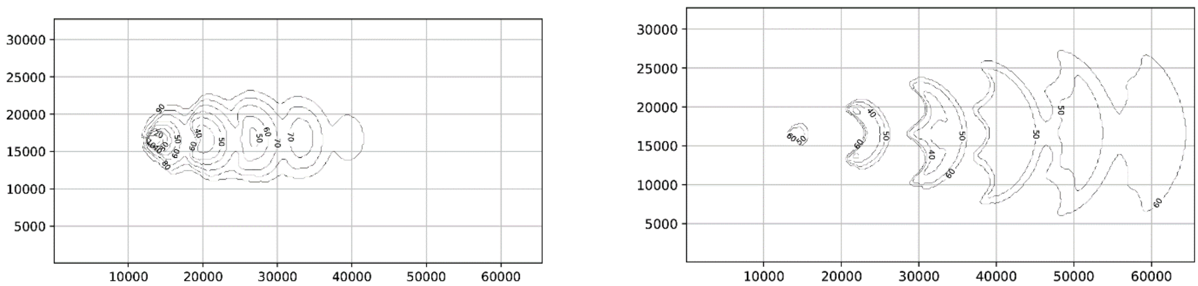

Figure 4: Fire-spotting patterns for the Csa climate class (Mediterranean Area) during the unstable (left) and stable (right) atmospheric conditions

Slightly different patterns can be obtained for the Mediterranean climate class Csa in Figure 4: during unstable conditions fast merging leads to one large fire, while during the stable atmosphere several spotting fires can be observed. Hence, the structure is like for BSh class, but the form of the fire front is completely different.

The performed simulations reflect qualitatively the reality: in different climate classes different fire-spotting patterns are observed. Unfortunately, validation though the comparison with historical data is not feasible. In fact, we cannot get sufficient statistical information about fire-spotting generated fires from wildfires worldwide from satellites' data collected using NASA Fire Information for Resource Management System (FIRMS).

Actually, data are taken from two satellites: MODIS with resolution 1 km and VIIRS with resolution 375 m, which means that VIIRS can capture smaller fires.

The observation horizon is chosen from 2012-01-20 to 2021-08-31. The data were collected for BSh and Csa climatic zones, BWh class is omitted since there is no fire-spotting. Due to this lack of data, we oversimplify the framework by assuming that fires captured by MODIS are primary fires, while the rest "small" ones could be secondary, or spot fires. The results for various climate classes are reported in Table 2. Thus, in order to estimate the proportion of the fire-spotting generated fires, we calculate the percentage of these larger fires and then estimate the number of possible secondary fires for one primary fire.

Table 2. Approximate number of small independent fires for one large fire in various climate classes.

	BSh class	***Csa class***
Total	3.77	4.31
Day fires	2.69	2.19
Night fires	6.50	12.31

The proposed model of fire-spotting with integrated climate-biome classification reflects qualitatively real patterns: during the night the number of small independent fires is higher. In the case of BSh climate class the number of small fires is doubled, see Figure 2, which agrees with the performed simulations where the doubled number of secondary fires is observed during the stable atmosphere conditions comparing to the unstable ones. For Csa class the difference between patterns in unstable and stable atmospheric conditions is rather significant, see Figure 4, which is also reflected by the simulations. Beside these, we remind the case of the BWh class where actually, for the corresponding set of the parameters, no fire-spotting generated fires appear consistently with the property of the class: these also can be considered as a kind of first validation test of the model since simulations reflect the fact that in desert there is no fire-spotting, see Figure 3.

5. Conclusions

In this study, we propose a multi-scale physical parametrization for the fire-spotting phenomena, which includes such climate-dependent factors as atmospheric boundary layer, fuel type, vegetation, in order to adjust the existing model to the changing conditions. Analyzing the different parameters, the integrated climate-biome classification has been proposed for the various climatic zones. The simulations show that by using the proposed parametrization of the fire-spotting distribution different fire-front patterns can be obtained. We focus mainly on the climate classes with registered fire-spotting events, such as South-Eastern Australia, and Mediterranean zone. The South-Eastern Australia is represented by two climate classes with completely different fire-spotting patterns: in the case of desert, the fire-spotting is not observing in the simulations, which agrees with reality. This fact shows the sensibility of the proposed classification for the probabilistic fire-spotting model.

The adjustment of the fire-spread model to the climate class becomes more and more urgent due to the climate change. In other words, the prediction of the wildfire propagation may vary not only in space but also in time. Some parameters, mainly climatic, which are usually considered as constant for a given location may change and the fire will propagate in different manner.

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