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The application of a genetic algorithm to estimate fuel bed properties from bench-scale testing

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Abstract

A methodology based on an automated optimisation technique is applied to interrogate the relationship between fuel bed structure and effective heat transfer properties. The methodology uses optimisation of the heat equation to resolve the temperature of the fuel bed upon exposure to an external heat flux and is coupled with thermogravimetric data to generate data on mass loss rate. The experimental mass data are provided by undertaking ignition experiments conducted on Pinus rigida Mill. fuel beds in the Fire Propagation Apparatus. Fuel solid fractions ranging from 0.03 to 0.51 are used. The fuel bed structure is represented by the solid fraction and the effective fuel bed properties (conductivity, convective heat loss coefficient and absorptivity) are posed as a function of the fuel bed structure. Each property is considered individually and the relationship between the property and the fuel structure is optimised using a genetic algorithm. In this way a methodology for interrogating the relationship between the fuel bed structure and the effective properties is presented.

1. Introduction

Wildfires are a natural phenomenon but can occur, and be exacerbated, due to human activity. Regardless of origin an uncontrolled fire poses a potential risk to life, property and environment. Nevertheless, the risk is difficult to define if wildfires are not fully understood. By understanding the processes that control the evolution of a wildfire it is possible to define the risk for different situations and a strategy for tackling the risk can be developed. Furthermore, by intervening with measures that alter the processes underpinning a wildfire the risk can be reduced. There are many parameters that affect the processes that control a wildfire including weather, topology and fuel. In this work we focus on the role of the fuel structure on the processes that underpin ignition.

One of the major challenges in understanding wildfire behaviour is defining the structure of the fuels and how this impacts the burning behaviour. Wildland fuels are defined by their thermophysical and thermochemical properties, and their structure (i.e. arrangement of the fuel elements). The thermochemical properties affect the combustion processes whereas the changes in fuel bed structure lead to changes in the heat and mass transfer mechanisms in the fuel bed. Describing the fuel bed structure in a way that is appropriate to resolve the heat and mass transfer processes remains largely elusive. Therefore, an approach to explore how different fuel bed structures affect the heat transfer mechanisms during ignition of porous fuel beds is presented.

This work develops flammability studies previously undertaken to capture the response of wildland fuels at different fuel bed conditions (Schemel, 2008; Mindykowski, 2011; Simeoni, 2012; Houssami, 2016; Jervis, 2016; Thomas, 2017; Walker-Ravena, 2019). Experiments have been conducted on fuel beds of *Pinus rigida* Mill. needles over a range of solid mass fractions (0.03-0.51) to determine the mass loss (and mass loss rate) before ignition as a function of the fuel solid mass fraction. This approach allows the effects of fuel structure to be studied independently of the species-dependent thermochemical properties.

The porous structure of wildfire fuel beds means that classical ignition theory, in which ignition is defined as a surface temperature (Torero, 2016), is unlikely to apply. Instead, a finite thickness of fuel will be heated and will undergo pyrolysis prior to ignition (an 'active region'). This has been observed previously (Thomas, 2017). Modelling ignition therefore requires that the temperature distribution inside the fuel be modelled, in order that a pyrolyzing region can be identified. This requires knowledge of the effective thermal properties as a function of the fuel solid mass fraction.

To address this issue, Genetic Algorithms (Launtenberger, 2006) are used to identify the relationship between the fuel bed effective properties and the fuel bed solid fraction by simultaneously optimising against experimental data of ignition of a range of fuel bed structures of the same material. The assumed relationship between the effective fuel bed properties and the fuel bed structure is varied until the best agreement between the numerical and experimental results is obtained.

Due to the challenges associated with measuring temperatures in porous media, the numerical and experimental results are compared on the basis of mass loss. Modelled temperatures are used to identify the mass loss using data from thermogravimetric analysis of the fuels. In this way the changes in the heating response are modelled to be due to relationship between the fuel bed effective properties and the fuel bed structure.

2. Methods

2.1. Sample preparation

To manufacture the different fuel beds, individual needles were cut to predefined lengths as shown in Figure and Table 1. The needle size determines the packing efficiency of the fuel bed and hence the solid fraction. Six different types of sample were prepared: two using full length needles with different masses, and four samples with needles cut to different lengths (3-4 cm, 1-1.25 cm, <1.5 cm) and one sample was manufactured by grinding the needles to a powder. The solid fraction was calculated by dividing the mass by product of the volume of the sample basket (diameter = 128 mm, depth = 30 mm) and the density of a single pine needle (density = 607 kg/m^3) (Houssami, 2016).

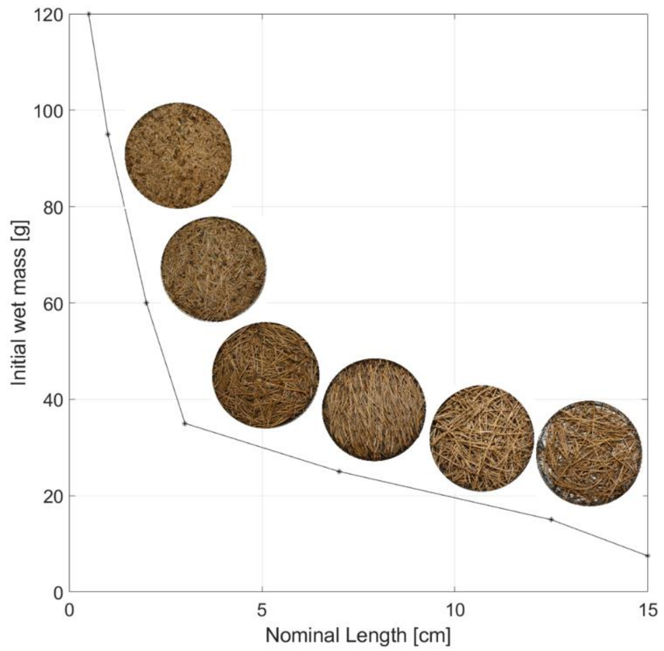

Figure 1 – Initial wet mass of fuel bed as a function of the approximate cut length of the Pinus Rigida needle

Table 1 - Manufactured fuel beds

Sample Preparation	Wet Mass [g]	Solid Fraction [-]
None	7.5	0.03
None	15	0.06
3-4cm	35	0.15
1-2.5cm	60	0.26
<1.5cm	90	0.38
Powder	120	0.51

2.2. Fire Propagation Apparatus

Samples were prepared in closed circular baskets. Closed baskets are used to minimise the contribution of the convective flow. Samples were conditioned by drying in an oven at 60°C for 24 hrs before testing. The preconditioned average fuel moisture content was ~8% whilst the conditioned fuel was <1% (Walker-Ravena, 2019).

Samples were exposed to heating of 25 kW/m^2 using the Fire Propagation Apparatus. The pilot flame was positioned 20 mm above the sample. The sample mass was recorded up to ignition. Repeat tests were averaged at each time-step to compute an average pre-ignition mass loss for each fuel bed.

2.3. Thermogravimetric Analysis

Thermogravimetric analysis (TGA) was carried out in air with a heating rate of 5 K/min for the *Pinus rigida* Mill. needle samples. Needles were ground and put in alumina crucibles. A representative TGA curve was generated by averaging repeat experiments, as shown in Figure 2b. The TGA data are used with the solution of the heat diffusion equation to generate mass data. The temperature at each depth is modelled and the normalised mass, for that temperature, is defined using the TGA data. This is illustrated in Figure 2a and the mapping shown in Figure 2b.

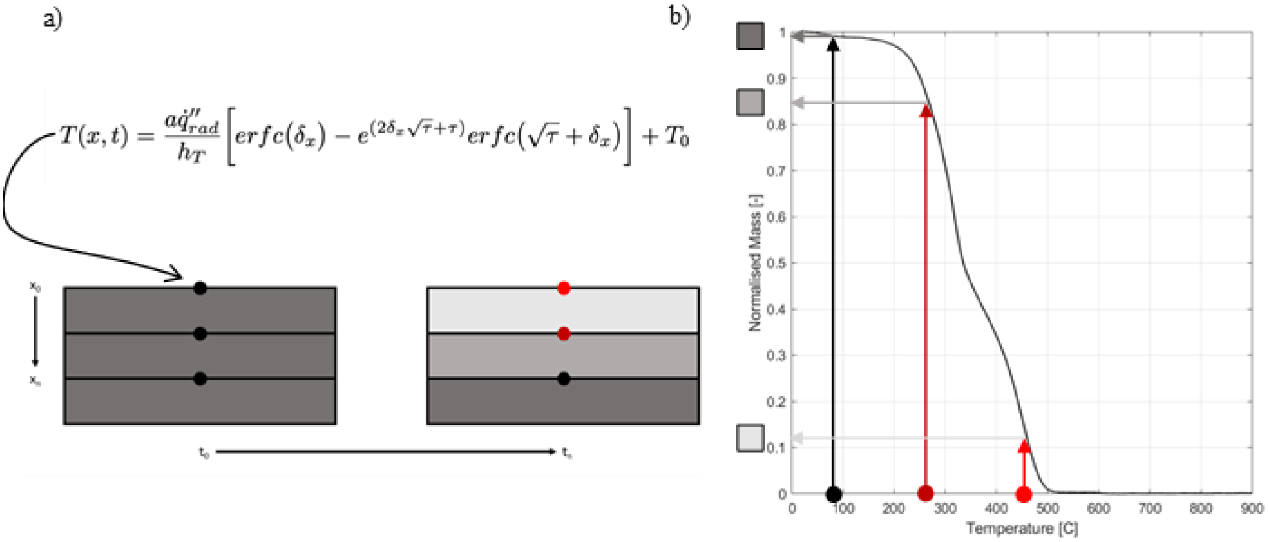

Figure 2 – a) Illustration of heat transfer model at t=0 and t=t$_n$. Red nodes indicate higher temperature and lighter shades of grey indicate increased mass loss b) TGA experimental data used as a look-up table

2.4. Genetic Algorithm

Genetic algorithms have been used to find material properties from bench-scale experiments (Launtenberger, 2006). A similar approach is followed here whereby optimisation of the model to the experimental data is conducted through minimising an objective function.

The solution to the heat diffusion equation (Torero, 2016), as presented in Figure 2a, is used to determine the temperature distribution in the solid phase. The mass loss rate is computed using the TGA data as indicated on Figure 2b. The objective function quantifies the difference between the model and the experimental data. In this work the relationship between the effective fuel bed properties and the fuel bed structure is sought. As such the different conditions are considered simultaneously by summing the value over each experimental condition as well as each time-step. The objective function is split into two parts so that both the mass and mass loss rate are used to compare the model and the experimental data.

$$R_1 = \sum^{\text{exp.}} \frac{\sum^{\text{t}} (m_{exp} - m_{mean})^2 - \sum (m_{exp} - m_{model})^2}{\sum (m_{exp} - m_{mean})^2}$$
$$R_2 = \sum^{\text{exp.}} \frac{\sum^{\text{t}} (\Delta m_{exp} \overset{\text{t}}{-} \Delta m_{mean})^2 - \sum (\Delta m_{exp} - \Delta m_{model})^2}{\sum_{\text{t}} (\Delta m_{exp} - \Delta m_{mean})^2}$$
$$R = R_1 + 0.5R_2$$

Equation 1 - Objective functions minimised in genetic algorithm optimisation.

2.5. Effective Fuel Bed properties

The effective fuel bed properties (conductivity, convective heat loss coefficient and absorptivity) were assigned by assuming they are a function of the solid fraction of the fuel bed. This represents how the fuel bed properties are different to the material properties. In Equation 2 the material property is represented by *A* subscript whilst *B* represents the deviation due to the solid fraction. Moreover by assuming a continuous function the number of variables that need to be optimised is reduced.

$$k = k_A + k_B e(m)$$
$$H = H_A + H_B e(m)$$
$$a = a_A + a_B e(m)$$

Equation 2 – Assumed relationships between the heat transfer properties (k is conductivity; H is convective heat loss coefficient and a is absorptivity). Where e(m) is the solid fraction as a function of mass.

3. Results and Discussion

A series of images showing the process of piloted ignition, burning and extinction of a sample is shown in Figure 3. The pyrolysis gases are clearly visible before ignition.

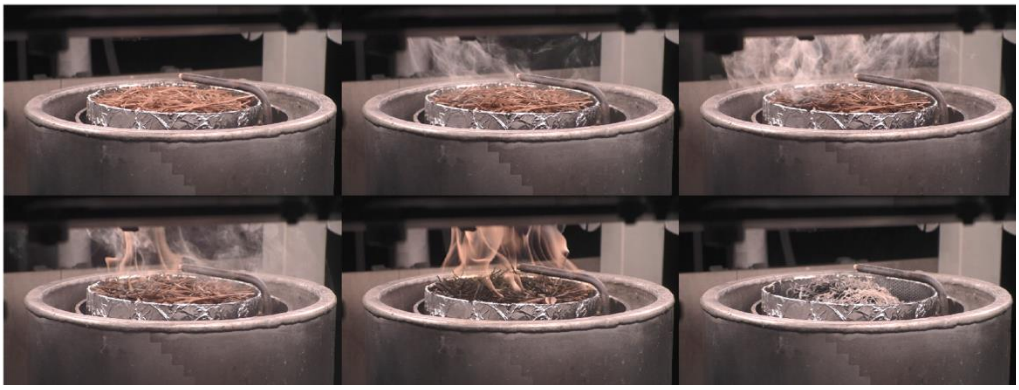

Figure 3 - Collage of 15g subjected to25 kW/m^2. Chronological order from left to right and top to bottom.

3.1. Experimental results

The experimental results shown in Figure 3 show that the mass lost at ignition and time to ignition are non-monotonic functions of the solid fraction. A minimum is observed at a solid fraction 0.15. Changes in the solid mass loss rate will lead to changes in time to form this gas mixture and therefore changes to the time to ignition. A higher mass loss rate indicates that the gas phase environment is such that it is harder to obtain a flammable mixture e.g. it is subject to higher levels of dilution or heat losses.

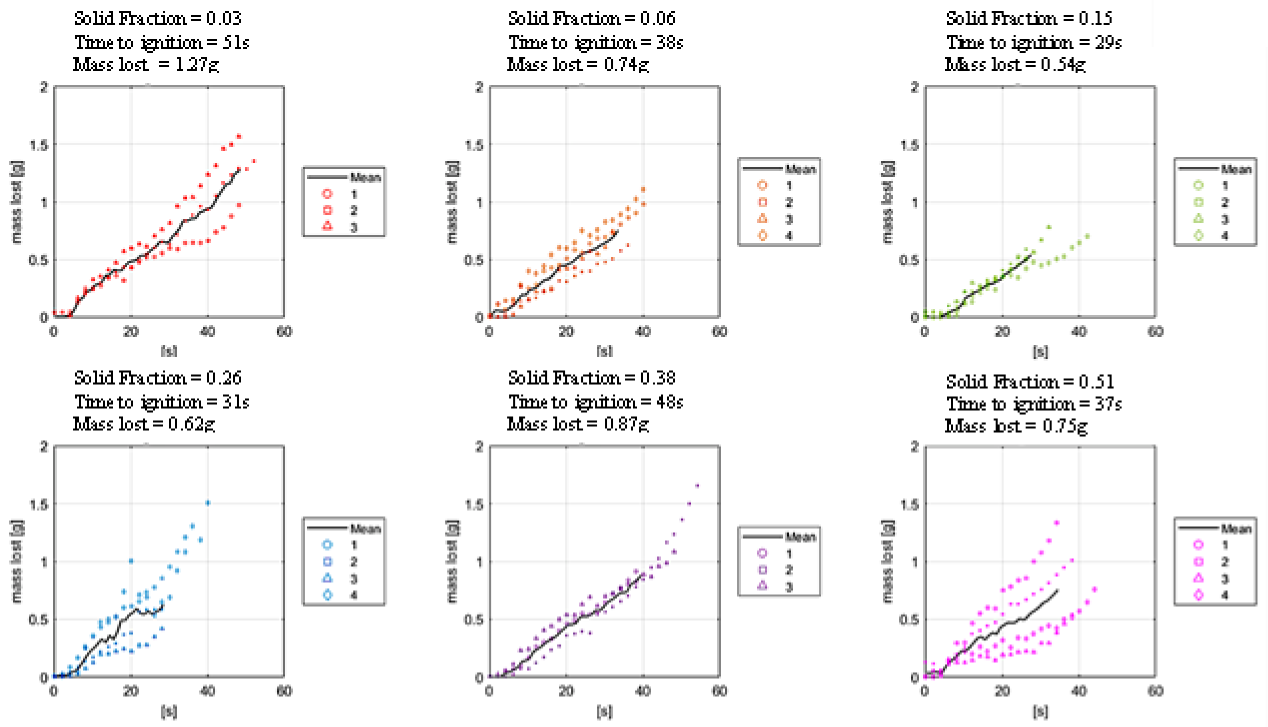

Figure 3 - Pre-ignition data for bench-scale testing conducted in the FPA. Markers represent individual tests whereas the black line is the experimental average. The values above are the experimental averages.

3.2. Genetic Algorithm

The changes in the fuel structure will be affect the conductivity, absorptivity and convection. To determine which is the most sensitive to the changes in fuel structure they are considered on a case-by-case basis. These cases are positive linear conduction, positive linear absorptivity and negative linear convection. These respectively represent the assumed trends of an increase in heat transfer through the bed due to an increase in needles connectivity; an increase in heat absorbed at the upper surfaces due to an increase in needle density per depth and decrease in convective heat loss due to a decrease in the fuel bed permeability causing lower fluid flows. The effective fuel bed properties are compared to literature values (Houssami, 2016).

3.2.1. Positive Linear Conductivity

The first case is positive linear conductivity as a function of the fuel solid fraction. The intention here was to represent the increase in conductivity that is assumed to occur with a decrease in the porosity of the fuel bed. That is to say smaller spacing between needles is assumed to lead to an increased effective thermal conductivity due to increased particle to particle contact. An increase in conductivity may also represent the heat transferred through the fuel bed due to needle-to-needle radiation (Simeoni, 2012). Optimisation gave the values for k_A and k_B as 2.41x10^{-6} W/mmK and 8.96 x10^{-5} W/mmK, respectively.

Nevertheless, the output values did not capture the experimental behaviours appropriately. The lowest solid fractions showed similar behaviours but the mass loss at the high fuel loads were over estimated. In the low solid fractions it is expected that radiation penetration into the depth of the fuel bed is significant resulting in higher in depth temperatures.

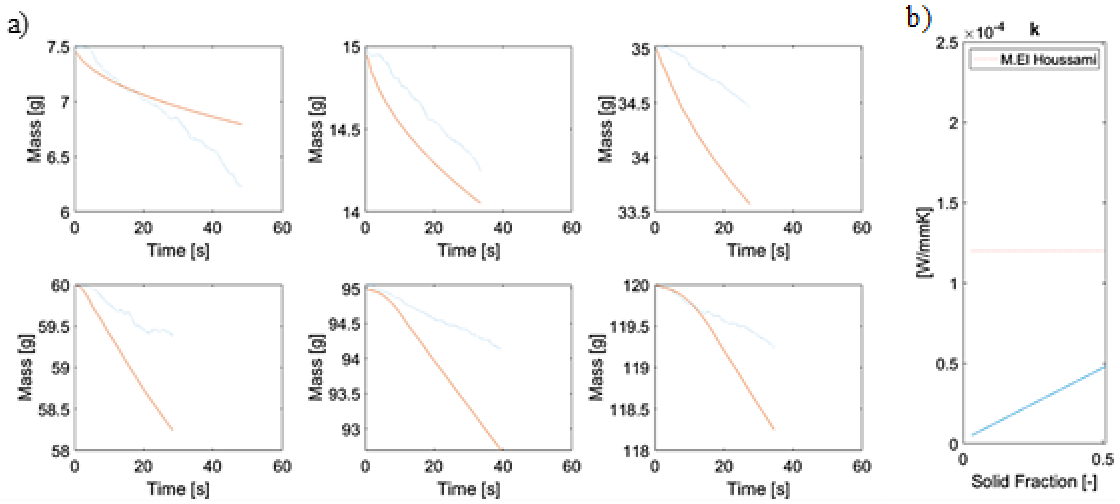

Figure 5 - Positive Linear Conductivity model outputs. Blue line shows experimental mean whilst red line shows the model output. Clockwise from top left, the fuel loads shown are 7.5g, 15g, 35g, 60g, 95g, 120g. b) Conductive coefficient as a function of solid fraction.

3.2.2.Positive Linear Absorptivity

The next case is positive linear absorptivity. Here the intention is to represent the increase in heat absorbed at the upper surfaces of the fuel bed due to there being a greater amount of exposed surface area due to increase in needle density. Optimisation gave the values for a_A and a_B as 0.46 and 0.56 respectively.

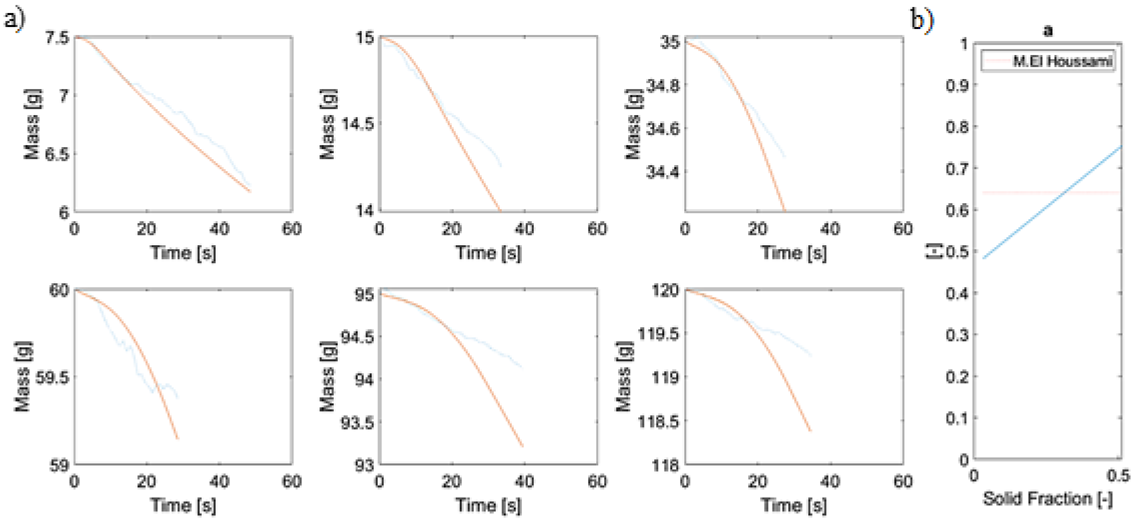

Figure 6 - Positive Linear Absorptivity model outputs. Blue line shows experimental mean whilst red line shows the model output. Clockwise from top left, the fuel loads shown are 7.5g, 15g, 35g, 60g, 95g, 120g. b) Absorptivity coefficient as a function of solid fraction.

These conditions seem to capture the behaviours at low fuel loads well however the high fuel loads are seen to overestimate the mass loss rate at longer times. This indicates that the temperature in the system is too high. This suggests that, the effects of fuel structure are not represented by the change in the absorptivity alone.

3.2.3. Negative Linear Convection

The next case is negative linear convection. This intention here is to represent the increase in convective heat loss that is assumed to occur as the bed becomes more porous. The increase in the porosity of fuel bed leads to an increase in its permeability and so the fuel bed is more susceptible to fluid flows and therefore convective losses (Simeoni, 2012). Optimisation gave the values for H_A and H_B as 3.35e-5 W/mm^{2}K and -8.54e-6 W/mm^{2}K respectively.

The output leads to improved representation of the experimental results in both the low and high fuel load cases. Although the lines do not overlap in the high fuel cases, a similar gradient is found at long time. This indicates that the rates of degradation are similar and as such some of the experiment physics are being captured.

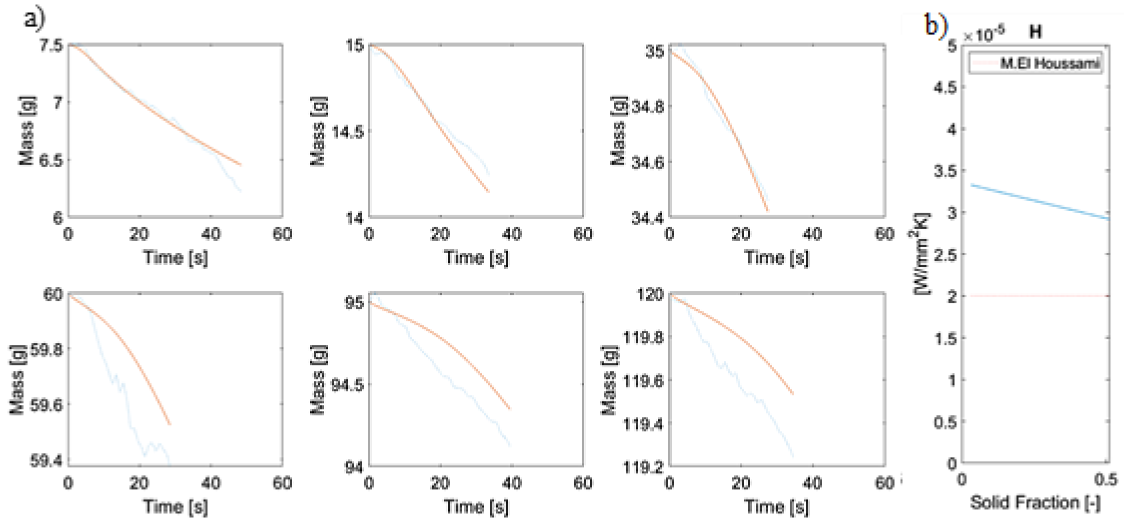

Figure 7 – a) Negative Linear Convection model outputs. Blue line shows experimental mean whilst red line shows the model output. Clockwise from top left, the fuel loads shown are 7.5g, 15g, 35g, 60g, 95g, 120g. b) Convective coefficient as a function of solid fraction.

4. Conclusion

This study has explored the effect of fuel solid fraction on the ignition of fuel beds. Experimentally the mass lost from the fuel bed before ignition and the time to ignition is shown to vary as a function of the fuel solid fraction. This indicates that the structure of the fuel bed and the heat transfer within the fuel bed play a key role in determining the ignition characteristics. Using a simple genetic algorithm approach, we show that the absorption of radiation and the heat losses of the system play a governing role in these experiments. The study also showed that the convective flow through a porous fuel has a large impact on determining the flammability due to convective cooling of fine elements air. This finding is important for the design of future studies of the burning of wildland fuels as the fuel bed structure is generally not considered beyond the level of fuel loading or bulk density. This approach also results in the need to move away from a surface temperature condition for ignition of porous fuel beds to one that considers the temperature distribution through the porous media.

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