Received: 4 May 2021 | Revised: 22 November 2021 | Accepted: 7 January 2022

DOI: 10.1002/eap.2627

ARTICLE

ECOLOGICAL APPLICATIONS
ECOLOGICAL SOCIETY OF AMERICA

Soil Heating in Fire (SheFire): A model and measurement method for estimating soil heating and effects during wildland fires

Mary K. Brady[1] | **Matthew B. Dickinson**[2] | **Jessica R. Miesel**[3] | **Carissa L. Wonkka**[4] | **Kathleen L. Kavanagh**[5] | **Alexandra G. Lodge**[6] | **William E. Rogers**[6] | **Heath D. Starns**[7] | **Doug R. Tolleson**[7] | **Morgan L. Treadwell**[8] | **Dirac Twidwell**[9] | **Erin J. Hanan**[1]

[1]Department of Natural Resources & Environmental Science, University of Nevada - Reno, Reno, Nevada, USA

[2]US Forest Service, Northern Research Station, Delaware, Ohio, USA

[3]Department of Plant, Soil and Microbial Sciences, Michigan State University, East Lansing, Michigan, USA

[4]USDA, ARS, Northern Plains Agricultural Research Laboratory, Sidney, Montana, USA

[5]College of Forestry, Oregon State University, Corvallis, Oregon, USA

[6]Department of Ecosystem Science and Management, Texas A&M University, College Station, Texas, USA

[7]Department of Ecosystem Science and Management, Texas A&M AgriLife Research, Sonora, Texas, USA

[8]Department of Rangeland, Wildlife and Fisheries Management Ecosystem Science and Management, Texas A&M AgriLife Extension Service, San Angelo, Texas, USA

[9]Department of Agronomy and Horticulture, University of Nebraska at Lincoln, Lincoln, Nebraska, USA

Correspondence
Erin J. Hanan
Email: ehanan@unr.edu

Funding information
Joint Fire Science Program, Grant/Award Number: Project ID: 17-1-04-7; National Science Foundation, Grant/Award Number: DEB-1916658

Abstract

Fire has transformative effects on soil biological, chemical, and physical properties in terrestrial ecosystems around the world. While methods for estimating fire characteristics and associated effects aboveground have progressed in recent decades, there remain major challenges in characterizing soil heating and associated effects belowground. Overcoming these challenges is crucial for understanding how fire influences soil carbon storage, biogeochemical cycling, and ecosystem recovery. In this paper, we present a novel framework for characterizing belowground heating and effects. The framework includes (1) an open-source model to estimate fire-driven soil heating, cooling, and the biotic effects of heating across depths and over time (Soil Heating in Fire model; SheFire) and (2) a simple field method for recording soil temperatures at multiple depths using self-contained temperature sensor and data loggers (i.e., iButtons), installed along a wooden stake inserted into the soil (i.e., an iStake). The iStake overcomes many logistical challenges associated with obtaining temperature profiles using thermocouples. Heating measurements provide inputs to the SheFire model, and modeled soil heating can then be used to derive ecosystem response functions, such as heating effects on microorganisms and tissues. To validate SheFire estimates, we conducted a burn table experiment using iStakes to record temperatures that were in turn used to fit the SheFire model. We then compared SheFire predicted temperatures against measured temperatures at other soil depths. To benchmark iStake measurements against those recorded by thermocouples, we co-located both types of sensors in the burn table experiment. We found that SheFire demonstrated skill in interpolating and extrapolating soil temperatures, with the largest errors occurring at the shallowest depths. We also found that iButton sensors are comparable to thermocouples for recording soil temperatures during fires. Finally, we present a case study using iStakes and SheFire to estimate in situ soil heating during a prescribed fire and demonstrate how

Handling Editor: Hinsby Cadillo-Quiroz

observed heating regimes would influence seed and tree root vascular cambium survival at different soil depths. This measurement-modeling framework provides a cutting-edge approach for describing soil temperature regimes (i.e., soil heating) through a soil profile and predicting biological responses.

KEYWORDS
fire dose–response, fire effects belowground, fire energy, fire induced mortality, iButton, iStake, prescribed fire, SheFire, Soil Heating in fire, soil temperature modeling, wildland fire

INTRODUCTION

Wildland fires, which include any kind of vegetation fire, can transform soil biological, chemical, and physical properties that are critical for terrestrial ecosystem functioning (e.g., Badía-Villas et al., 2014; Doerr et al., 2017; Giovannini et al., 1990; Neary et al., 1999; Robichaud, 2000). However, soil temperatures can vary by hundreds of degrees Celsius within a fire event (Busse et al., 2013), which makes it challenging to generalize how soil properties can be transformed. Estimating belowground heat and mass transport, and associated temperature regimes (Massman, 2015; Massman et al., 2010), is essential for understanding how ecosystem services and processes, including carbon storage, primary production, and biogeochemical cycling, are changing across spatially complex fire footprints (Quigley et al., 2020). Many effects of interest, such as effects on soil biota, occur as temperature-dependent rate processes (e.g., Rosenberg et al., 1971) thus characterizing temperature regimes is central to understanding fire effects on soils.

Several tools have been used to estimate fire effects, both above- and belowground. For example, models have been developed to predict specific fire effects belowground given simulated (not measured) fire conditions (e.g., Choczynska & Johnson, 2009). While these models show promise for linking fire characteristics with soil responses, they are difficult to apply broadly given the range of required inputs. Further, the underlying soil heating models and associated software systems (e.g., FOFEM in Lutes, 2017) have not been evaluated for use outside of the laboratory.

Alternatively, remote sensing indices such as the difference normalized burn severity index (dNBR) can provide estimates of aboveground fire severity across ecosystems and landscapes. However, using these indices to assess belowground effects can have extremely high uncertainty because (1) belowground fire effects do not always track predictably with aboveground changes such as vegetation mortality and charring of the soil surface (Hudak et al., 2007; Murphy et al., 2008) and (2) there can be large scaling mismatches between a remote sensing pixel (e.g., 30 m for Landsat) and processes that occur at the scale of microns to centimeters (Morgan et al., 2014; Ramcharan et al., 2018; Regan et al., 2017; Zhang et al., 2020). To address the first issue, some studies have used other remote sensing techniques, such as hyperspectral and multispectral imaging, which can be more sensitive to soil-specific changes (e.g., ash deposition and areas of bare ground; Kokaly et al., 2007). However, this solution still has limitations because even soil-specific metrics are still derived from changes occurring at the surface and do not consider belowground soil properties such as organic matter content, which can influence how heat propagates through a soil profile (Morgan et al., 2014). While ground-based (finer-scale) measurements of burn severity can help address scaling mismatches that occur with satellite data (issue 2 above), local severity estimates still lack mechanistic connections between the fire processes or properties and their effects belowground (Smith, Sparks, et al., 2016).

Using direct measurements of fire behavior and energy to infer belowground responses is likely to be much more powerful than indirectly inferring belowground effects from coarse estimates of aboveground changes (Kreye et al., 2013, 2020; Quigley et al., 2019). However, collecting direct measurements for fire energy and soil heating is challenging. For one, soil heating through time cannot be measured from satellite imagery, (Morgan et al., 2014), and secondly, even though fire energy measurements provide a more direct approach than fire severity, they still do not consider soil properties that can influence belowground responses (Hartford & Frandsen, 1992). Therefore, to quantify soil heating during fires, we need ground-based, subsurface measurements of soil.

There are several logistical challenges associated with field-based soil temperature measurements, resulting in a dearth of data on soil heating during fires. For both prescribed and unplanned wildland fires, access is often a primary limitation. Prescribed fires are typically planned in advance but conducted on short notice when conditions become appropriate, which can complicate sampling and site instrumentation. Unplanned wildland fires are even less predictable and more complicated to sample. Considerably more attention has been paid to developing fire measurements than to developing soil measurements (see reviews in Ichoku et al., 2012;

Kremens et al., 2010; and Moran et al., 2019) and instrumenting plots can be equipment and time intensive regardless of whether or not the fire was anticipated (Ottmar et al., 2016). Finally, fire effects are highly spatially variable so it can be misleading to extrapolate data gathered in one area to try to understand another (Busse et al., 2013; Morgan et al., 2014; Smith, Cowan, et al., 2016).

Thermocouples are the current standard for logging temperature measurements and have been used for decades (e.g., Bova & Dickinson, 2008; Iverson et al., 2004; Kennard et al., 2005; Pereira et al., 2019). They record point-specific temperatures at discrete time intervals and can be placed at any soil depth of interest (Busse et al., 2010; Kreye et al., 2013; Kreye et al., 2020). However, there are some important limitations to the thermocouple approach. For one, thermocouples must be attached to dataloggers, which are not heat resistant. The standard approach for deploying thermocouples belowground involves installing them through the side of an excavated hole, which can protect data loggers but may also disturb soil structure and alter soil heating (Busse et al., 2010). To ease thermocouple installation belowground, Robichaud and Brown (2019) developed a metal canister that deploys thermocouples after once buried. Alternatively, inserting insulated rods vertically into the soil with thermocouples exposed at specified depths may reduce heat transfer that can occur with metal canisters (Kreye et al., 2020). Yet there are still challenges in making these systems heat and flame resistant during intense fires. Finally, deploying thermocouples can be time consuming: a major drawback when attempting to install them in the path of an advancing wildfire. In this paper, we propose and evaluate an alternative method using iButtons deployed along wooden stakes (iStakes) within a soil profile. Because iButtons are integrated sensors and data loggers, there is no need to protect additional equipment from heat (Maxim Integrated, 2002). This approach can minimize soil disturbance, better preserve soil thermal properties, and increase efficiency for measuring soil heating during wildland fires.

Regardless of how the temperature data are collected, we need tools for understanding how they relate to soil changes during and after fire. Attempts to understand how fire-induced heating affects soil properties must take soil depth into account because, in addition to heating, soil properties such as mineral content, moisture, and soil organic matter also vary with depth (e.g., Achat et al., 2012; Balesdent et al., 2018; Kramer et al., 2017). Physical models of soil heating have potential to characterize coupled heat and mass transport at high depth resolutions (e.g., Campbell et al., 1995; Massman et al., 2010) but they require much more development for practical use. Alternatively, instrumenting every possible soil depth of interest to directly record temperatures in the field is also not feasible. To quantify fire effects on soil properties and biota, and to provide validation data for physical models, statistical models can provide a tool for interpolating and extrapolating temperature regimes to a depth of interest based on a limited set of measurements taken at discrete soil depths.

The goals of this paper are twofold: to present an open-source modeling tool to understand soil heating and heating effects across depths over time (the Soil Heating in Fire model; SheFire) and to demonstrate a novel data collection method that provides data at multiple depths and minimizes soil disturbance and installation time (iStakes). To support this measurement-modeling framework, we report a burn table experiment used to validate SheFire temperature estimates at different soil depths and to benchmark our proposed iStake method against thermocouple readings. Finally, we present a case study using iStakes and SheFire to estimate soil heating during a prescribed fire and predict how heating may influence seed and root survival at different soil depths using a thermal tolerance model (Dickinson & Johnson, 2004). The thermal tolerance model is based on temperature-dependent rate processes and associated data. It offers a way to meaningfully summarize highly variable temperature regimes based on their effects on soil biota by accounting for both temperatures and their durations.

METHODS

Below, we describe the SheFire modeling framework (*SheFire model description*), an iStake measurement method (*iStake description*) that provides one way to easily collect the input data needed to fit the SheFire model, validation and benchmarking of the model and method (*Validation and benchmarking*), and a case study (*Case study*) demonstrating the use of iStakes and SheFire. All soil depths discussed in this paper refer to the depth below the mineral soil surface, as the forest floor can combust during fires.

SheFire model description

SheFire is a modeling framework for estimating mineral soil temperatures during fire across a range of soil depths and for predicting biological responses to soil heating. Fitting the SheFire model requires temperature measurements over time from three different soil depths at the same location. The model then interpolates and extrapolates from those data to estimate temperature time series across a range of depths. Using those estimates, functions in the model framework can then be used to explore the nuances of the soil heating and biological responses. The current response functions focus on organismal thermal tolerance, but the SheFire modeling framework can readily be expanded in a modular fashion to incorporate additional response functions that are of interest to model users. The different components of the modeling framework are described in the following sections. The modeling framework is contained in an R package, called *SheFire*, comprised of the model building function (*shefire*), and a series of summary and response functions designed to understand soil heating and its effects.

Fitting the model

Input data

Heat transfer through a soil profile is both soil and fire specific (Busse et al., 2013; Pereira et al., 2019; Smith, Cowan, et al., 2016). As a result, the SheFire model must be fit separately for each location from measured temperature data. The model is fit using the *shefire* function in the R package. The inputs to this function are the temperature data and a series of parameters that allow for model fine tuning. An example input data table can be found in Appendix S1: Figure S1 and the parameters are described in detail in Appendix S1: Table S1. The model requires temperature recordings from three soil depths that can be measured with thermocouples, iButtons, or any other temperature sensor that records a time stamp with each temperature reading. The input data can have any data logging rate, but the three sensors must log at the same rate.

Data trimming

The input temperature data do not need to be manually cleaned or trimmed to the beginning and end of the heating period prior to building the model, however, they must all start at the same point in time. The function is designed to extract the fire-induced heating and subsequent cooling period from data sets that may contain measurements collected prior to the arrival of the flaming front and after complete soil cooling. With default settings, the prefire data (i.e., everything up to 30 min preceding the initiation of soil heating) is removed. Initiation is defined as the last time that the temperature rate of change between two sequential measurements was zero before the maximum temperature was reached. The end of the data set is determined by the first of the following events: a temperature rise after soil cooling has begun, a user-determined cut off time, or the last measurement is reached. All three temperature recordings must cover the same time period, so the shallow sensor is used to set the start and end points, as it will be the first to heat, then the data from the deeper two sensors are trimmed to match.

Fitting BFD curves to input data

The base equation of the model is a "Temperature–Time Curve of Complete Process of Fire Development," also known as a BFD curve, which was developed for studying compartment fires such as enclosed rooms in structure fires (Barnett, 2002). However, the equation has been used in other studies of fire and soils (Adie et al., 2011; Grau-Andrés et al., 2017; Massman, 2021). BFD curves calculate temperature at a given time. We use BFD curves to summarize soil temperature regimes and as the basis for interpolating temperature regimes among depths at which we do not have measurements. Note that the nomenclature from here on follows that used in the *SheFire* R package for reasons of clarity.

A BFD equation has four terms that correspond to: initial temperature before the arrival of the flaming front (InitTemp), maximum temperature reached (MaxTemp), time the maximum was reached after heating began (TimeAtMax), and a shape parameter that determines the overall shape of the curve with higher values creating a more acute peak (*Shape*; equation 1 in Barnett, 2002):

$$\text{Temperature} = \text{InitTemp} + \text{MaxTemp} \times e^{-z} \tag{1}$$

where e is Euler's number and the exponent (z) is further defined as

$$z = {(\ln(\text{time}) - \ln(\text{TimeAtMax}))^2}/{\text{Shape}}. \tag{2}$$

BFD equations are fit to each of the three trimmed input temperature data sets. We designed SheFire to use a nonlinear least squares approach to determine the best fit.

Fitting parameter-depth regressions

We then have *SheFire* extract the four BFD parameters (InitTemp, MaxTemp, TimeAtMax, and Shape) from each of the three fitted equations. Using the three values for each parameter, one from each input sensor depth, *SheFire* fits separate regression equations to estimate each parameter value for given soil depths, using the following equations:

$$\text{InitTemp} = A \times \text{depth}^{-B} \tag{3}$$

$$\text{MaxTemp} = e^{C} \times \text{depth}^{D} \tag{4}$$

$$\text{TimeAtMax} = F + G \times \text{depth} \tag{5}$$

$$\text{Shape} = H \times \text{depth}^{-I} \tag{6}$$

where "depth" is the soil depth for which the BFD equation parameter will be calculated (Equations 3–6).

These regression equations allow a BFD parameter to be estimated for any input soil depth.

Equations (4) and (5) are fit using a simple linear model and subsequently evaluated for model performance by calculating R^2, the coefficient of determination. The data for Equation (4) are log-transformed before fitting. Equations (3) and (6) are fit using a nonlinear least squares approach. They are subsequently evaluated with a Pearson correlation coefficient comparing the BFD parameter values from the equations fit to the input data against the parameter values calculated by the regression equations for the same soil depths as the input data.

Once the regression equations have been fit, the model can estimate each of the four BFD parameters for a given soil depth and thus can model temperature over time at any depth.

Setting model constraints

The final portion of model development sets constraints for the model. The time range covered by the model is equal to the time range of the trimmed input data. This may not be the full length of the input data sets if they covered prefire or post-cooling periods. *SheFire* also extracts the timestamp associated with the model start and end points from the input data to allow model-time to real-time conversions. To avoid mathematical problems associated with zero values, model time starts at 0.0001 min. *SheFire* sets the shallowest depth for which the model can predict temperatures as the depth at which the TimeAtMax parameter is 1. That is to say, the soil depth that reaches its peak temperature 1 min after the beginning of model time is the shallowest depth that the model will calculate. This time cut off is used to set the shallowest depth because increasingly shallow depths have increasing uncertainty. See Appendix S1: Section S1 for further comments on this approach. There is no deepest depth limit but the summary and response functions in *SheFire* will print a warning for soil depths more than 5 cm deeper than the deepest sensor used to build the model because deep predictions have not yet been experimentally validated.

Model output

The *shefire* functionb outputs a list of the various equations, values, and constraints that comprise the model (Table 1). The summary and response functions included in the SheFire modeling framework can be applied to this output to explore soil heating, cooling, and biological responses. Users can also build custom functions that interact with the model to address specific research questions. Further details are in Appendix S1: Section S1.

TABLE 1 Names and descriptions of SheFire function outputs; these are needed to run the summary and response functions included in the SheFire modeling framework

Name	Description
BFDEquation	Function to calculate temperature over time given values for the four BFD parameters
MaxTemp.reg	Function to calculate MaxTemp parameter for a given soil depth
TimeAtMax.reg	Function to calculate TimeAtMax parameter for a given soil depth
Shape.reg	Function to calculate Shape parameter for a given soil depth
InitTemp.reg	Function to calculate InitTemp parameter for a given soil depth
MaxTemp.coeffs	Coefficient values for the MaxTemp.reg function
TimeAtMax.coeffs	Coefficient values for the TimeAtMax.reg function
Shape.coeffs	Coefficient values for the Shape.reg function
InitTemp.coeffs	Coefficient values for the InitTemp.reg function
InitTemp.byDepth	An additional parameter needed for InitTemp.reg function, a list of InitTemp values calculated for the input temperature data
SensorDepths	An additional parameter needed for InitTemp.reg function, a list of sensor depths
Shallowest	The shallowest depth (in cm) for which the model will calculate temperature over time
FullTime	Duration (min) that the model covers
StartTime	Timestamp at the beginning of the model time range
EndTime	Timestamp at the end of the model time range

Note: BFD is a "Temperature - Time Curve of Complete Process of Fire Development" (Barnett, 2002).

Heating summary functions

The SheFire modeling framework includes a set of functions to summarize different aspects of soil heating and cooling (Table 2). The most basic function is temp_over_time, which calculates the temperature at a given depth at a specified time resolution. This function is called in all other summary and response functions. More details about the specific summary functions and their implementation can be found in Table 2.

TABLE 2 The summary functions included in the SheFire modeling framework; function name, description, and output are included

Function name	Description	Output
temp_over_time	Calculates temperature over time for a specified soil depth, time range and resolution (i.e., temperature at every 1 min)	A list of the temperature values at each time increment
time_above	Calculates the duration of time at or above a chosen temperature threshold, for a specified soil depth	Duration in minutes
heating	For a specified soil depth, isolates the portion of the model time range that the soil is heating	A list of temperatures at the specified time resolution for the soil depth from the point that it began to warm through the time when it reaches its maximum temperature
cooling	For a specified soil depth, isolates the portion of the model time range that the soil is cooling	A list of temperatures at the specified time resolution for the soil depth from the point it began to cool through the end of model time range
time_temp_ranges	Calculates the time spent in different temperature ranges for a specified soil depth. The breadth of the temperature ranges, but not the boundary temperatures dividing the ranges, is set by the user	A data frame of the temperature boundary values and the time spent in each temperature range
set_temp_ranges	Calculates the time spent in different temperature ranges for specified soil depth(s). User sets the boundaries for the temperature ranges	A data frame of the temperature boundary values and the time spent in each temperature range (for each specified depth)
depth_for_temp	Calculates the deepest soil depth that reaches a specified temperature	The soil depth (cm)
summ_depth_range	Calculates the mean, standard deviation, median, and maximum temperature at each time point for a specified portion of the soil profile	A data frame containing those statistics for the depth range at each time point

Heating response functions

The SheFire modeling framework currently includes two response functions (survival_percent and survival_depth) that use soil heating to estimate survival. Survival_percent calculates the percent survival at the user specified depth. Survival_depth determines the soil depth at which a user specified percent survival will occur. For example, survival_percent could determine the percent survival for a particular species of seed at a specified soil depth, while survival_depth could be used to find the soil depth where a specified percent of those seeds were predicted to survive. We demonstrate these functions in the case study by estimating survival of seeds and vascular cambium cells from soil temperature regimes in an experimental fire.

The two functions rely on a thermal tolerance model for estimating survival (Dickinson & Johnson, 2004). Survival can be thought of as a general dimensionless effects variable where response to heating is quantified relative to pre-fire condition. Thermal tolerance is based on temperature-dependent rate processes, the kinetics of which have been quantified in various ways for different biological systems, including by tissue respiration (Caldwell, 1993; Dickinson et al., 2005), protein denaturation (Rosenberg et al., 1971), cell survival (Dickinson & Johnson, 2004; Lorenz, 1939), tissue survival from visual inspection or vital staining (Lorenz, 1939; Nelson, 1952), and organismal survival (Martin et al., 1969).

The thermal tolerance model is solved numerically in two parts: determining the rate of impact and accumulating that impact over time. We determine the rate of impact from a temperature-dependent first-order rate process equation, termed the "absolute rate theory equation" by Rosenberg et al. (1971). This equation has two parameters that must be estimated for each unique biological system: activation entropy (deltaS) and activation enthalpy (deltaH). These parameters are determined statistically from thermal tolerance data (Dickinson & Johnson, 2004). If needed, a user could incorporate a simpler, single-parameter rate equation (the Arrhenius equation) into *SheFire*, opening up more sources of rate process information. The rate of impact increases exponentially with temperature:

$$k = \frac{\text{kBoltz}\,T}{\text{hPlanck}} \times e^{\left(\frac{\text{deltaS}}{\text{RGas}}\right)} \times e^{\left(\frac{-\text{deltaH}}{\text{RGas}\,T}\right)} \tag{7}$$

where k is the rate parameter (s^{-1}), kBoltz is the Boltzman constant ($J \times K^{-1}$), T refers to soil temperature in Kelvin, hPlanck is Planck's constant ($J \times s^{-1}$), and RGas is the universal gas constant ($J \times K^{-1} \times mol^{-1}$). The accumulation of adverse temperature effects is assumed to be additive with no effect reversal (see Dickinson & Johnson, 2004). Thus, survival is recursively decremented at each timestep at a temperature dependent rate. Survival begins at 100%:

$$S_{\text{current}} = S_{\text{previous}} - k \times t_{\text{length}} \times S_{\text{previous}} \tag{8}$$

where S_{current} is survival up through the current time step, S_{previous} is survival up through the preceding time step, and t_{length} is the length of the time step in seconds. Survival is not decremented at temperatures below the user specified threshold. The temperature threshold is the lowest temperature at which there would be a temperature effect on survival for the biological system of interest.

iStake description

iButton sensors are small, cylindrical devices ~1.5 cm in diameter and 0.5 cm width that measure and record temperatures. They are designed with a circumferential ridge that enables them to be snapped into place within a preprepared hole in any deformable material (like wood). There are a few different models but the two relevant here are the high temperature iButtons (Thermochron 8K High) and the low temperature iButtons (Thermochron, 4K). High temperature iButtons will record temperatures when the sensor is between 0°C and 125°C while the low temperature iButton will record when it is between −40°C and 85°C.

The iStakes are composed of a simple wooden stake with iButton temperature sensors installed in holes drilled along their length such that the iButton surfaces are flush with the outside of the stake to provide thermal contact with the soil (Figure 1). Therefore, with a single stake inserted into the ground, temperatures at multiple soil depths can be measured simultaneously with minimal soil disturbance (Figure 2a). Appendix S2 contains a full description of iStake construction (Appendix S2: Section S1) and field deployment (Appendix S2: Section S2).

It is important to benchmark iButtons against thermocouples because different devices deployed in different ways can result in different temperature measurements because the temperature recorded is the temperature of

FIGURE 1 A complete iButton stake that will measure soil depths 5, 10, and 15 cm when installed with the top of the stake (picture left) 2 cm below the soil surface

the device (Bova & Dickinson, 2008; Kennard et al., 2005). A key advantage of measuring temperatures in soils is that, as long as there is good thermal contact between the device and the soil and the device heats quickly, the device temperature should faithfully reflect soil temperature. Thin thermocouples or thin thermocouple probes (a thermocouple sheathed in, typically, stainless steel) maximize thermal contact with soil and provide a point measurement. A disadvantage of an iButton is that it is in contact with soil over both the front and back surfaces of its metal case, which has high thermal conductivity. Therefore, instead of providing a point measurement, its

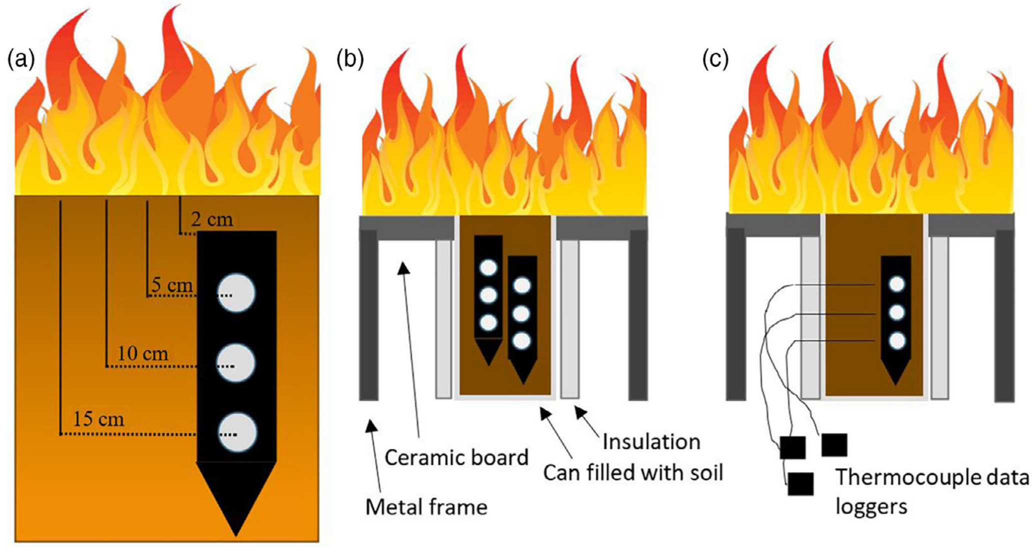

FIGURE 2 (a) Diagram of standard iButton stake deployment in the field and within the soil cans. (b) Diagram of experimental set up for comparing model predictions against measured temperatures. (c) Diagram of experimental set up for comparing iButtons against thermocouples. Diagrams are not to scale

temperature reflects the temperature average over 1.5 cm of the soil column, which could lead to different readings than thermocouples. Further, an iButton has more thermal inertia than a thin thermocouple or thermocouple probe and may heat and cool more slowly.

Validation and benchmarking

To validate the SheFire model and benchmark iButton readings against thermocouple readings, we conducted instrumented test burns. The test burns used a burn table setup that consisted of a metal frame that held ceramic fiber boards flush with the top of 20 cm tall, 10 cm diameter steel cans filled with soil (J. R. Miesel, unpublished; Figure 2b,c). We drilled 10 cm diameter holes in the ceramic board using a circular drill bit such that four cans fit in each ceramic board. The open tops of the cans sat flush with the top surface of the board and the sides of the cans were flush against the inside of the holes in the board so there was no gap between the edge of the board and the sides of the can. The top of the soil, inside the cans, was continuous with the top surface of the ceramic board.

The cans, below the ceramic board, were wrapped in ceramic fiber insulation and a layer of fire-shelter insulating material. The insulation was designed to minimize lateral heat gain or loss from the can so that heat transfer was primarily vertical through the soil. This was designed to mimic soil in situ, which would not be isolated in columns and would heat and cool with the surrounding soil. The cans of soil, while not perfect facsimiles of a continuous soil bed, enabled reliable, precise sensor installation with minimal soil disturbance around the thermocouples.

Once the cans were situated in the burn table, we installed the temperature sensors. For the model validation experiment, we installed one iStake with iButtons at 5, 10, and 15 cm depth below the soil surface and one iStake with iButtons at 4, 7, and 12 cm depth per can. There were nine cans and thus nine replicate paired iStakes. High temperature iButtons were used at 4 and 5 cm depths, while low temperature iButtons were used at all other depths. For the benchmarking experiment, we installed an iStake in each can with iButtons at 5, 10, and 15 cm below the soil surface and we installed thermocouples at the same depths through small holes drilled in the sides of the can. There were 15 cans prepared in this manner. All thermocouples used were type K (Omega Engineering, Norwalk, CT) thermocouple probes (1.6 mm diameter) and thermocouple data loggers were Madge Tech TC101A (Madge Tech, Warner, NH). High temperature iButtons were used at 5 cm deep, low temperature iButtons were used at 10 and 15 cm deep.

After we instrumented the insulated, soil-filled cans, we placed a fuel bed, containing a mixture of dry pine needles, woodchips, and small twigs (<2 cm diameter), loosely stacked on top of the soil and ceramic boards. For each of the experiments described in sections *SheFire validation* and *Sensor benchmarking experiments*, we ignited the fuel bed and supplied additional fuels as needed to maintain active flames for ~10 min, then allowed the fire to extinguish and the soils to cool for several hours so that the entire recorded data set (starting 10 min prior to ignition) was 350 min long. The burns were conducted over the course of 3 days in October 2020.

SheFire validation

For each replicate of paired iStakes, we used the data recorded at 5, 10, and 15 cm deep to fit the SheFire model. We then used the model to predict soil temperatures at 4, 7, and 12 cm deep and compared those predictions against the temperatures recorded at those depths. We compared model predictions against the recorded temperatures using Pearson correlation coefficient, R^2, and root mean square error (RMSE). The 4, 7, and 12 cm comparisons were all analyzed separately in order to determine how the model performed at different depths. Due to two iButtons failing, one lost to a possible software error and one lost to physical damage, we only had enough sensors to test the 4 cm deep predictions in four of the nine replicates. We believe the software error was an isolated incident unlikely to be a consistent problem with iButtons. The instance of iButton mechanical damage was the only occurrence in this study and in subsequent use on wildland fires. Risk of damage could be mitigated by the use of high-tolerance milling equipment to ensure that the holes in which the iButtons are inserted are large enough to allow them to be snapped into place and not too tight to require excessive force to insert and remove. Experimentation with wood from a range of species would also be valuable, the wood should not be too soft or too hard.

While the insulation surrounding the cans mitigated the heat transfer between the soil and air, it did not eliminate it and the soil slowly heated throughout the day (due to heating along the walls of the can from increasing air temperatures and solar radiation) in a manner that is inconsistent with both heating in a continuous soil bed and the soil heating data that have been recorded in situ during fires. The deviation from typical heating and cooling was evident from the soil cooling pattern postfire (Appendix S3: Figure S1). To account for the shifting temperature baseline, we adjusted the data used to build and test the model by fitting a linear regression line between the soil temperature before ignition and the soil temperature at the end of the cool down period and then subtracting the value on the regression line from the temperature recorded at each time step. Then, we added 5°C to the temperatures to ensure final adjusted temperatures were >0. See Appendix S3: Figure S1 for a comparison of adjusted and unadjusted temperatures over time from one replicate.

Sensor benchmarking experiments

To benchmark low and high temperature iButtons against thermocouples, we had 15 replicates of iStakes paired with sets of thermocouples (Figure 2c). In each replicate, we used both iStakes and thermocouples to record temperatures at 5, 10, and 15 cm depths. The readings at 10 cm and 15 cm were combined for the analyses because both depths were measured using low temperature iButtons. The 5 cm readings were analyzed separately because they were recorded using high temperature iButtons. Due to a sensor malfunction, the 5 cm comparisons were not included in one of the replicates. Thus, there were 30 paired low temperature iButton and thermocouple comparisons and 14 paired high temperature iButton and thermocouple comparisons.

The thermocouple and iButton readings were compared at each timestep within each iButton and thermocouple pair using Pearson correlation coefficient, R^2, and RMSE. While each sensor pair is independent, the temperature points within a paired set of sensors are not. To address this, we also fit BFD equations to the data from each sensor. Then we compared the BFD equation parameters between the paired iButtons and thermocouples to measure how the recorded temperatures differed as a set and not just at individual time steps. In order to fit the BFD equations with the *shefire* function, both the iButton data and the thermocouple data were adjusted using the method described in *SheFire validation* to account for the solar heating that occurred over the course of the experiment. We ran the *shefire* function with the *reg* parameter set to False so that it only fit BFD equations to the input data and used the *override.clip* option for both iButton data and thermocouple data, which prevents the model fitting process from shortening the data set. The *override.clip* option ensured that the paired data sets covered identical time periods. Details on the model fitting parameters can be found in Appendix S1: Table S1.

Case study

We used data collected at the Texas A&M Agrilife–Sonora Research Station to demonstrate a simple application of the SheFire framework. This study was originally conducted for other purposes in the summer of 2018. The site is located on the western edge of the Edwards Plateau ecoregion. It is a semiarid savanna with a bimodal precipitation pattern. The dominant vegetation includes a mix of trees (*Quercus*, *Juniperus*, and *Prosopis* species) and grasses. The soils are Tarrant series (Clayey-skeletal, smectitic, thermic Lithic Calciustolls), shallow, and often have limestone bedrock (Hiers et al., 2019; USDA, 2016).

In this project, small experimental fires were conducted with either high or low fuel (LF) loads to create different burn conditions. Each burn was 100 m^2 and had an iButton stake installed with sensors at 5, 10, and 15 cm deep in the soil. Here, we present data and model results from two plots in order to demonstrate the utility of iStakes and SheFire, and to illustrate some of the ways they can be used to examine soil heating and its effects. We present data from one plot with a high fuel (HF) load, and one with an LF load. The LF plot received approximately 61 kg of hay as additional fuel, the HF plot received both 61 kg of hay and 201 kg of air-dried juniper branches as additional fuel. We fit the SheFire model using default parameter values for both plots. For more information on the design and objectives of the original study, please see Hiers et al., (2019).

RESULTS

SheFire validation

SheFire model predictions demonstrated a high level of skill at all soil depths (Table 3; Figure 3). Predictions were most accurate at 12-cm depth (mean $R^2 = 0.97 \pm 0.01$ standard error (SE); mean Pearson's correlation coefficient $= 0.98 \pm 0.01$ SE; mean RMSE $= 0.66 \pm 0.09$°C SE) compared to 7 cm (mean $R^2 = 0.96 \pm 0.01$ SE; mean Pearson's $= 0.98 \pm 0.01$ SE; mean RMSE $= 1.5 \pm 0.15$°C SE) and 4 cm depth (mean $R^2 = 0.92 \pm 0.01$ SE; mean Pearson's $= 0.96 \pm 0.01$ SE; mean RMSE $= 3.6 \pm 0.51$°C SE). Additional information on results by replicate, calculated with both the unadjusted and adjusted temperatures, is provided in Appendix S4: Table S1.

Sensor benchmarking experiments

We found that iButtons produced similar temperature estimates to thermocouples across depths (Table 4 and Figure 4a). However, the high temperature iButtons at the shallowest depth did not match thermocouples quite as tightly as the deeper, low temperature iButtons (mean RMSE of 2.1 ± 0.3 and 0.9 ± 0.1°C, respectively). However, in both cases, the differences were small. A full list of comparisons for individual sensor pairs can be found in Appendix S4: Table S2.

To compare iButton versus thermocouple timeseries estimates, we subtracted the iButton BFD parameter values from those of the thermocouples. The Shape parameter exhibited the smallest difference of the BFD parameters for both low temperature (mean difference <0.1) and high temperature iButtons (mean difference = 0.1; Table 5). The BFD parameters fit to the iButton and thermocouple data matched well for InitTemp where the mean difference was smaller than 0.6°C for both iButton types (Figure 4b). The MaxTemp parameter had slightly larger differences; the high temperature iButtons had a 4.2°C higher mean parameter value for MaxTemp than the thermocouples and the low temperature iButtons had a 1.2°C lower value (Table 5). Thermocouples had TimeAtMax values 3.3 min later than

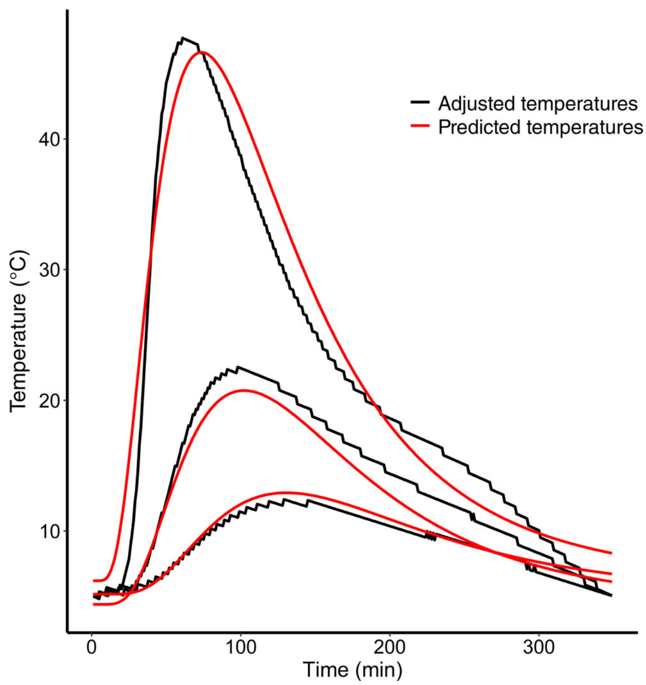

FIGURE 3 Adjusted temperature measurements (black) and model predictions (red) for soil depths 5, 10, and 15 cm deep from an example replicate. The topmost pair of curves are 5 cm, the middle pair are 10 cm, and the bottom pair are 15 cm depth

TABLE 3 A summary of the model predictions compared against actual measurements showing the Pearson correlation coefficient, R^2, and the root mean square error (RMSE)

	12 cm ($N = 9$)			7 cm ($N = 9$)			4 cm ($N = 4$)		
Metric	Pearson	R^2	RMSE	Pearson	R^2	RMSE	Pearson	R^2	RMSE
Mean	0.98	0.97	0.66	0.98	0.96	1.50	0.96	0.92	3.56
SE	<0.01	<0.01	0.09	0.01	0.01	0.15	0.01	0.01	0.51

Note: The mean value and standard error are given for each statistic within each depth.

TABLE 4 Statistical comparisons between thermocouple and iButton readings on a point-by-point basis

Statistic	Low temperature iButtons versus thermocouples: 30 trials	High temperature iButtons versus thermocouples: 14 trials
Pearson	0.98 ± <0.01	0.97 ± 0.01
R^2	0.97 ± 0.01	0.94 ± 0.02
RMSE	0.87 ± 0.08	2.11 ± 0.32

Notes: The mean value and standard error are shown for each statistic (Pearson correlation coefficient, R^2, and root mean square error [RMSE]) in the two sensor's measurements. A table containing the statistics for each replicate can be found in Appendix S4: Table S2.

the low temperature iButtons and 7.6 min later than the high temperature iButtons (Table 5, Figure 4b). Both the thermocouples and iButtons at 5 cm depth experienced faster heating than the sensors at lower depths. The list of all BFD parameters fit to each sensor, organized by depth and by thermocouple–iButton pairs, can be found in Appendix S4: Table S3.

Case study

For the BFD equations fit to the input data, the HF plot had low RMSE between the fitted equation and the input

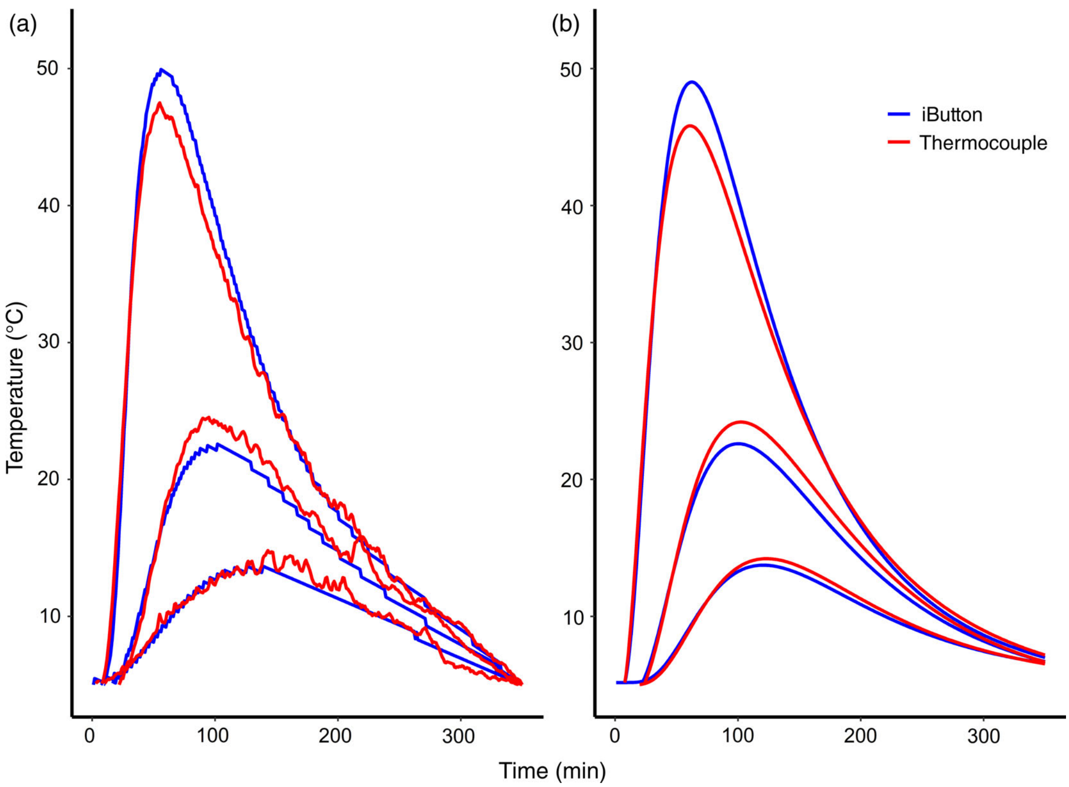

FIGURE 4 (a) Thermocouple (red) and iButton (blue) readings adjusted to shifting temperature baseline for an example replicate. (b) BFD equations fit to thermocouple (red) and iButton (blue) readings from the same replicate. The topmost pair of curves are 5 cm, the middle pair are 10 cm, and the bottom pair are 15 cm depth

TABLE 5 The mean value and standard error for the BFD parameters fit to thermocouple readings minus the BFD parameters fit to iButton readings within a thermocouple–iButton pair

iButton type	InitTemp (°C)	MaxTemp (°C)	TimeAtMax (min)	Shape
High temperature	0.13 ± 0.29	−4.19 ± 3.77	7.63 ± 5.93	−0.09 ± 0.06
Low temperature	−0.50 ± 0.22	1.15 ± 1.56	3.33 ± 3.55	0.04 ± 0.05

Notes: The values are grouped by the sensor depth of the thermocouple–iButton pairs. A table showing the BFD parameters fit to the data from every sensor, organized by thermocouple–iButton pairs, is included as Appendix S4: Table S3.

data; the largest value was 0.6°C at 5 cm, followed by 0.2°C at both 10 and 15 cm (Table 6). The LF plot also had low RMSE values but they were slightly higher than the values in the HF plot (Table 6). In both plots, the best BFD fits for the input data were at 15 cm, then 10 cm, and then 5 cm deep.

The parameter–depth regression equations correlated strongly with the BFD parameters that were calculated to fit to input data (Table 6). We assessed the fit for linear relationships (i.e., MaxTemp and TimeAtMax) using R^2 and nonlinear relationships (i.e., InitTemp and Shape) using Pearson's correlation coefficient. All four BFD terms' regressions had R^2 or Pearson's correlation coefficients at 0.98 or above in both the HF and LF plots (Table 6). The output tables from *shefire* of all fit statistics for each plot can be found in Appendix S5: Tables S1 and S2.

We visually compared measured and predicted soil heating for a selection of soil depths across the LF and HF plots (Figure 5). The temperature over time for unmeasured soil depths was calculated using the temp_over_time function. The differences in soil temperatures experienced by the two plots were largest in shallow soils: at 3 cm depth in the HF plot, soil temperatures reached over 100°C but did not even heat to 40°C at that depth in the LF plot (Figure 5). The duration of heating also differed between the two plots. At 3 cm depth, within 250 min, the HF plot cooled to ~50% of its maximum temperature, while the LF plot had barely begun to cool by 250 min (Figure 5).

Although there are many possible fire-effect applications of the SheFire model, here we focus on survival_percent. Given a sparse literature on thermal tolerance (Dickinson et al., 2005), there are no thermal tolerance data available for the plant species present in these plots. Therefore, we demonstrate the utility of this function by showing how contrasting thermal tolerances and variable soil heating affect the predicted responses for sensitive partridge pea seeds (*Chamaecrista nictitans* [L.] Moench, previously *Cassia nictitans*) and Douglas-fir (*Pseudotsuga menziesii* [Mirb.] Franco) and trembling aspen (*Populus tremuloides* Michx.) stem vascular cambium cells. We estimated the sensitive partridge pea (hereafter partridge pea) seed thermal tolerance parameter values from data on percent germination after heating treatments reported by Martin and colleagues (Martin et al., 1969; Martin & Cushwa, 1966). Vascular cambium cell thermal tolerance model parameter estimates come from studies that used counts of dead and live cells based on vital staining (Dickinson & Johnson, 2004). Because no suitable data on root thermal tolerance exist and to demonstrate the application, we assume that root vascular cambium has a similar heat tolerance to stem vascular cambium. Parameters for the rate process equation (Equation 7) for partridge pea seeds and vascular cambium tissue are in Appendix S5: Table S3.

Predicted survival for aspen cambium was nearly 0 at 5 and 13 cm depths in the HF plot but it took longer for the heating to affect the tissue at the deeper depth (Figure 6). The aspen cambium has 100% predicted survival at both 5 and 13 cm depths in the LF plot, which had cooler soil temperatures (Figure 6). Under the same soil heating regimes, different tissues experience vastly different effects (Figure 7). For example, based on modeled soil temperatures at 13 cm depth in the HF plot, the thermal tolerance model predicted that aspen and Douglas fir vascular cambium cell populations would have experienced nearly complete mortality (0.2% and 2.5% survival, respectively) while partridge pea seeds would have 100% survival at that depth (Figure 7). Using survival_depth run at 0.01-cm increments, the 50% threshold, at which we would predict vascular cambium

TABLE 6 Model fit statistics for the LF and HF plots

	Low fuel (LF)			High fuel (HF)		
Model fit	**RMSE**	**Pearson**	**R squared**	**RMSE**	**Pearson**	**R squared**
BFD fit						
5 cm	2.25	0.99	...	0.55	0.98	...
10 cm	1.19	0.98	...	0.23	0.99	...
15 cm	0.50	0.99	...	0.15	0.98	...
Regressions						
MaxTemp	...		>0.99	...	...	0.99
InitTemp	...	0.98		...	>0.99	
TimeAtMax	...		0.99	...	...	>0.99
Shape	...	>0.99		...	>0.99	

Notes: BFD fit refers to the fit between the input data and the fitted BFD equations. The regression fit measures the fit between the parameters calculated directly by fitting a BFD equation to the input data and the parameters calculated using the parameter–depth regressions. RMSE, root mean square error.

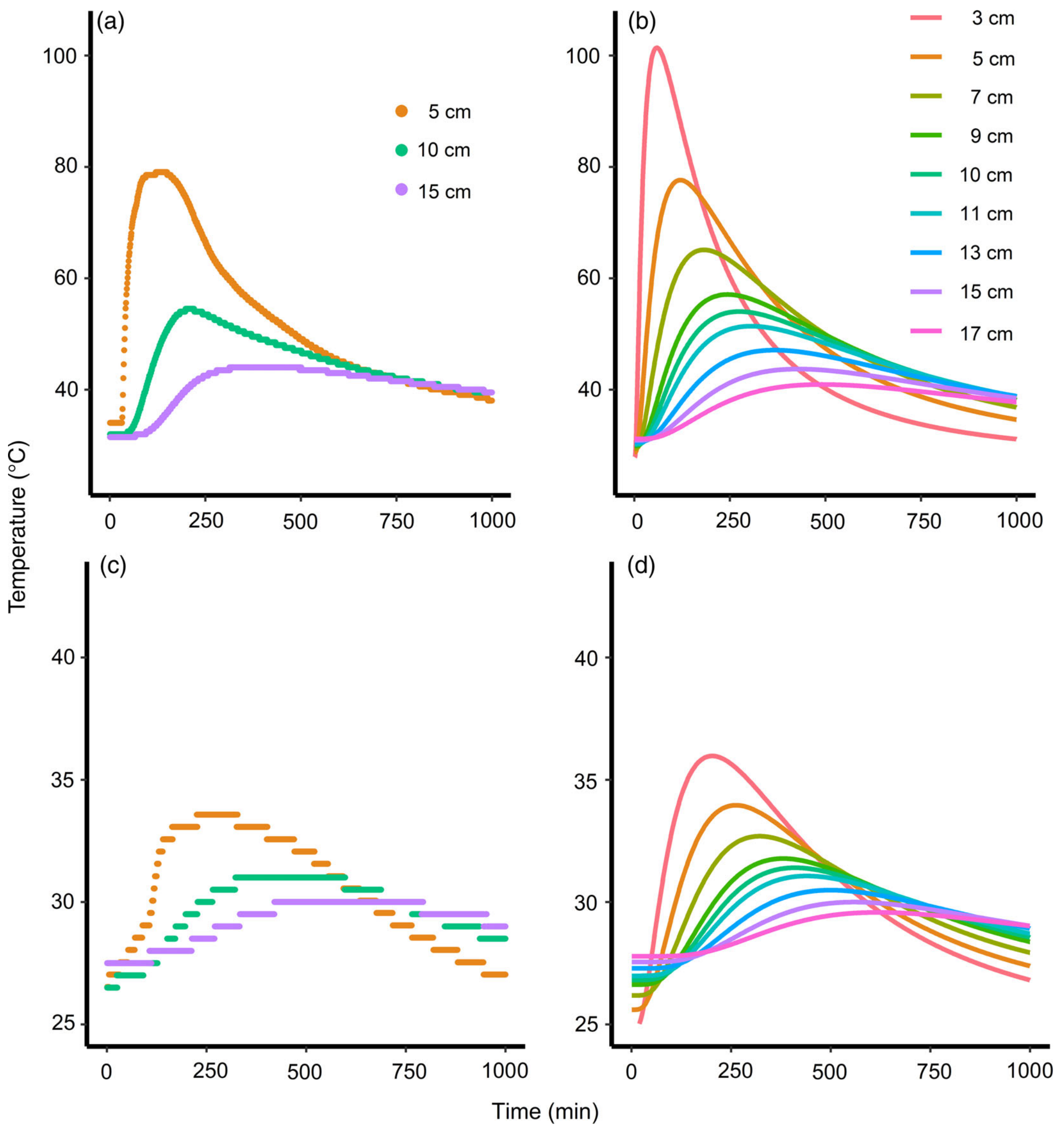

FIGURE 5 (a) Raw temperature data recorded in the high fuel (HF) plot. (b) Model predictions for a range of soil depths for the HF plot. (c) Raw temperature data recorded in the low fuel (LF) plot. (d) Model predictions for a range of soil depths for the LF plot

tissue necrosis (Dickinson & Johnson, 2004), was predicted to occur at 14.2 cm depth for aspen and at 14.1 cm for fir, in the HF plot. In contrast, the 50% threshold for partridge pea seed survival was predicted at 5.9 cm depth, illustrating the higher thermal tolerance of partridge pea seeds relative to tree vascular cambium tissue.

DISCUSSION

Soil heating in fire (SheFire)

Fire is a key reorganizing force in terrestrial soils: soil heating can kill plant roots, seeds, and microbes, which in turn transform biogeochemical processes, including carbon and nitrogen cycling (Gustine et al., 2021; Hanan, D'Antonio, et al., 2016; Hanan, Schimel, et al., 2016; Smith et al., 2008; Swezy & Agee, 2011; Varner et al., 2009). Further, the frequency of severe wildland fires is increasing (Goss et al., 2020; Hanan et al., 2021; Schoennagel et al., 2017). However, soil heating is often perceived as minimal in most surface fires (Hartford & Frandsen, 1992), and as a result, has not been studied as extensively as fire effects aboveground. The SheFire modeling framework is a first step towards collecting, extrapolating, and applying soil temperature data more broadly. The model is a powerful tool for understanding the effects of fires on temperature across soil depths and over time, and how heating directly affects soil biological, chemical, and physical processes. SheFire and iStakes offer a means of describing, understanding, and predicting fire effects on soils in a more mechanistic and accessible way than has been available to date.

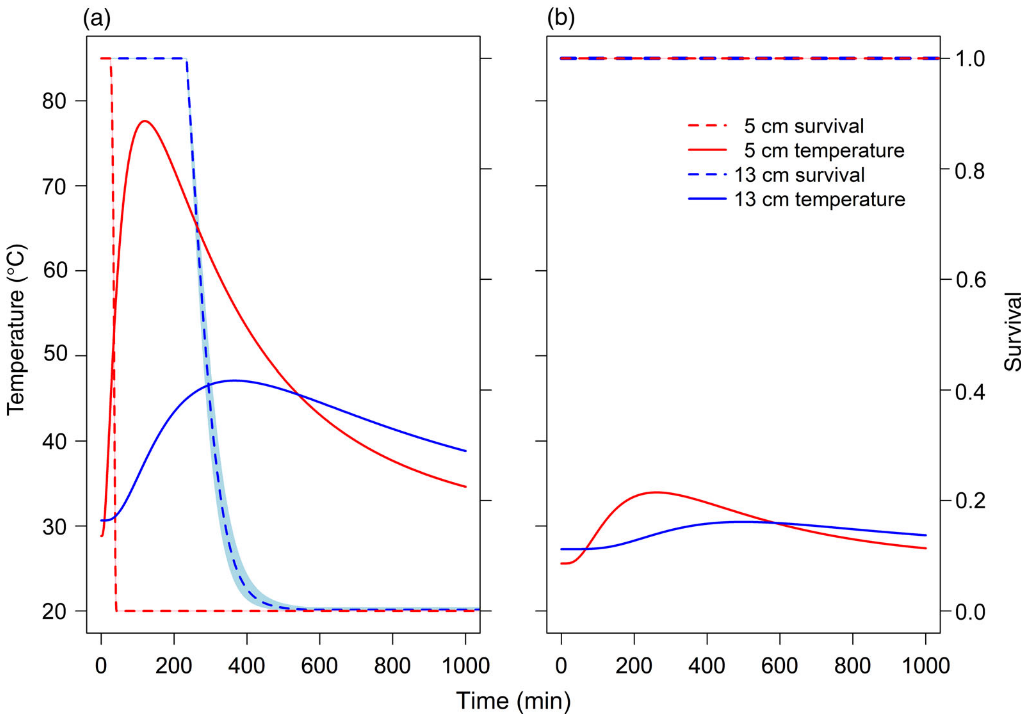

FIGURE 6 Predicted aspen vascular cambium survival (fractional) and soil temperature over time at 5 and 13 cm deep in the soil for (a) high fuel plot and (b) low fuel plot. The survival confidence envelope shows the range of predicted survival based on maximum and minimum thermal tolerances. In some cases, the envelopes are so narrow that they are not visible with the plot scale

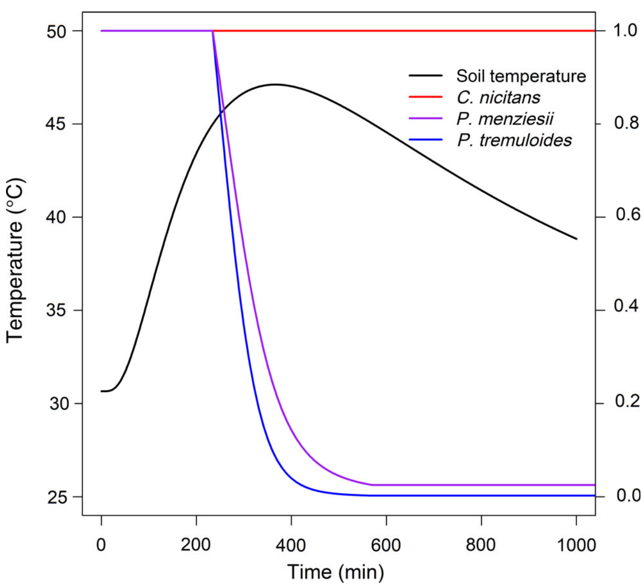

FIGURE 7 Predicted root vascular tissue survival (fractional) for aspen and Douglas fir, predicted partridge pea seed survival (fractional), and soil temperature at 13 cm deep in the high fuel plot. Survival predictions are based on mean thermal tolerance values for each species and tissue type

Keeley (2009) describes a set of measurements termed fire or burn severity that, although easy to obtain, can be indirectly or poorly related to fire characteristics, fire energy, and ecosystem responses of interest. In response to limitations of these severity measurements, Smith, Sparks, et al. (2016) proposed a dose–response paradigm, which relates quantitative measures of fire energy to short-term biological outcomes. However, dose–response relationships have uncertain generality across varying conditions, species, and ecosystems. A more mechanistic option is to elucidate the processes by which the characteristics of fires cause effects of interest, a methodology called the process-response approach (Johnson, 1985). Good measurements of key processes, like soil heating, are key for developing and evaluating process-response models (e.g., Kremens et al., 2010).

SheFire expands our ability to study fire effects on belowground dynamics in a process-response manner. Using the SheFire modeling framework, researchers can explore both soil heating through the temperature summary functions, and belowground effects through the thermal tolerance model that can be used to describe biochemical, organismal, and tissue responses to heating. When used in conjunction with easily deployable iStakes, SheFire is primed to enable laboratory and field measurement of soil heating and biotic effects. We hope SheFire will lead to studies that better describe relationships between fire characteristics and soil heating and encourage more studies that estimate parameters of thermal tolerance models for soil organisms (e.g., Dickinson et al., 2005; Dickinson & Johnson, 2004).

Temperature estimates, "process"

We found that SheFire demonstrated skill in estimating temperature over time at unmeasured soil depths, with R^2 and Pearson correlation coefficient values ≥0.92, and RMSE values <4°C for predictions at 12, 7, and 4 cm depth (Table 3 and Figure 4). The low standard errors indicate that the fit was consistently strong. The predicted temperatures did not differ from measured temperatures in the same manner across depth: the times (i.e., heating, peak temperature, cooling, etc.) and characteristics (i.e., earlier, later, warmer, cooler) in which they differ are a result of subtle variations between each temperature record and not a systemic difference between predictions and measurements (Figure 3). For example, the temperature predictions did not worsen or improve in a predictable fashion with depth. This lack of systemic difference indicates that the model does not have inherent bias relative to depth.

Additionally, we found that SheFire can be used to extrapolate soil temperatures at depths shallower than the shallowest sensor (i.e., 4 cm), but predictions become less reliable near the soil surface (Table 3). SheFire is based on subsurface soil temperatures, it cannot currently be used to characterize temperatures at the mineral soil surface where temperatures may be more strongly influenced by overlying organic layers. Placing iButtons closer to the soil surface would likely improve the shallow predictions; however, an inherent limitation of iStakes is that the maximum recommended temperature exposure for the high temperature model (125°C) limits how close to the soil surface the upper iButton can be placed. While there are situations where fire and soil conditions allow the model to make estimates for soil temperature at depths <0.1 cm from the surface, these estimates should be interpreted with caution because they have not been fully evaluated. To improve extrapolation, we need more soil surface temperature measurements and to improve our understanding and models of the physical processes that determine surface and subsurface heat fluxes during fire (Massman et al., 2010).

Survival estimates, "response"

There has been significant pushback against the once-dogmatic lethal temperature threshold of 60°C as the threshold temperature at which live tissues and cells are killed (Dickinson et al., 2005; Dickinson & Johnson, 2004; Pingree & Kobziar, 2019; Twidwell et al., 2013). The thermal tolerance model we demonstrate here illustrates how variable the response to heating can be (see also Martin et al., 1969). For instance, in the HF loading plot, we observed large differences between highly tolerant seeds, which had 50% predicted survival at ∼6 cm depth, and relatively intolerant vascular cambium, which had 50% predicted survival at just over 14 cm depth (Figures 6 and 7). In both cases, the exponential relationship between temperature and rates of injury (Equation 7) and the corresponding rapid decline in survival as temperatures increased (Figures 6 and 7) explain why lethal effects of heating appear to be threshold phenomena and can often be approximated as such even though the threshold value differs across taxa and tissues. These relationships emphasize both the importance of soil as an insulator and also the variable tipping-point at which different organisms and tissues in the soil survive or perish during a fire.

A second fundamental problem that can be solved by modeling thermal tolerance is that response to heating depends not only on temperatures but also on their durations and different heating regimes can cause the same response. The thermal tolerance model summarizes heating regimes with one number, an estimate of effects such as probability of survival (Dickinson & Johnson, 2004). Using a model thus provides a means of simplifying interpretation of the highly variable heating regimes to which organisms are exposed (Pingree & Kobziar, 2019).

iStakes

There are pros and cons to both iStakes and thermocouples, but our data shows strong agreement between iButton and thermocouple readings, indicating that studies using iButton measurements will contribute to the broader body of knowledge. In most cases, iStakes offer an easier alternative to thermocouple installation in the field and decrease soil disturbance relative to thermocouples.

The iButton and thermocouple benchmarking experiment demonstrates that iButtons provide a comparable alternative to thermocouples. Although our work indicates that iButtons may take slightly longer to heat compared to thermocouples due to sampling a greater range of the soil depth profile, the difference is minimal (7.6 min at 5 cm depth; Table 5) and likely a function of how rapidly the surrounding soil heats. Changing sensor types will not divide the soil temperature literature into two incompatible camps where the data from one sensor type cannot be compared to the data from the other (Tables 4 and 5; Figure 5, Bova & Dickinson, 2008). Whereas thermocouples have been the established standard for measuring soil temperatures during fires (Pereira et al., 2019), iButtons offer many advantages, including lower costs and ease of installation. In terms of ease of use, iStakes are easier to install in the field than thermocouples because they are inserted into the soil by pushing (with or without the use of a pilot-slot, depending on soil characteristics) and the depth of the top of the stake measured as opposed to thermocouples where the sensors must each be buried and precisely measured with additional work put towards protecting the data loggers from the fire (Pereira et al., 2019). In the growing literature of active wildfire studies (Dickinson et al., 2019; Lentile et al., 2007; Miesel et al., 2018), the ability to deploy equipment rapidly allows a team to collect as much data as possible while mitigating risk.

Beyond the ease of deploying equipment, iStakes offer many advantages in the data they collect. Because an iStake is thin and can pushed into the soil, sometimes facilitated by a pilot slot, it causes less disturbance than the hole that must be dug and then back-filled to deploy thermocouples. Disturbed soil heats differently than undisturbed soil, so minimizing disturbance around the sensors is important for recording representative data (Busse et al., 2010). Other researchers have also devised ways to minimize the effects of soil disturbance on the temperature data they record with thermocouples such as Robichaud and Brown (2019) who patented a metal canister that is inserted into an augured hole and then deploys thermocouples that extend horizontally into the soil. However, the metal of the canister may conduct heat down into the soil profile more rapidly than would otherwise occur in the surrounding soils, which transfer heat relatively slowly (Aznar et al., 2016; Badía-Villas et al., 2014; DeBano, 2000; Kreye et al., 2013). The wood of the iButton stake does not conduct heat in the same manner because its thermal diffusivity (determined by the ratio of thermal conductivity to heat capacity) is closer to that of the soil than the metal walls of the canister (Bristow, 1998; Kersten, 1949; MacLean, 1941). A related benefit is that wood gains and loses moisture in concert with the soil, which will have similar effects on thermal properties.

It is, however, worth noting that iStakes are not ideal in all circumstances due to some logistical and data limitations. First, iButtons do not have replaceable batteries and cannot be recharged, thus battery life determines sensor life (Maxim Integrated, 2002). Anecdotal evidence suggests that they can record over 500,000 data points before the sensor must be replaced (Maxim Integrated, 2002). Thermocouples and associated dataloggers (which have replaceable batteries) can be used for as long as they remain undamaged. The second limitation is that iButtons have lower temperature thresholds than thermocouples. For the high temperature iButtons, that limit is 125°C. When soil temperatures exceed that limit, but are not high enough to damage the iButton, the sensor will record a timestamp at the appropriate data logging rate, but it will not record a temperature until it cools back to 125°C and below. Preliminary work indicates that the BFD fitting portion of the SheFire model can be used to accurately interpolate the missing data in the temperature peak when the maximum temperature is above 125°C. In cases where high temperatures are expected, such as under heavy fuel loads in pile burns (Massman et al., 2010) or below deep, smoldering duff (Hartford & Frandsen, 1992), the iButtons can be deployed deeper in the soil profile as peak soil temperatures decline rapidly with depth (Aznar et al., 2016; Badía-Villas et al., 2014; Giovannini & Lucchesi, 1997; Pereira et al., 2019). In our study, we had one thermocouple malfunction for unknown reasons and two iButtons malfunctioned: one lost to a possible software error and one lost to physical damage, not a result of heat damage or limited battery life.

Case study

The few existing studies that investigate thermal tolerance and survival during fires show that survival can be highly variable among species, tissue types, and heating regimes (Dickinson & Johnson, 2004; Michaletz & Johnson, 2007; Michaletz & Johnson, 2008; Pingree & Kobziar, 2019). While the SheFire framework offers a way to predict survival over time during a wildland fire, this use is currently limited by the lack of thermal tolerance data in the literature. As the study of ecological effects of fire grows, we need more research on thermal tolerance across a range of soil microbial taxa (e.g., archaea, bacteria, fungi), life-stages (e.g., vegetative cells, spores), and plant tissues (e.g., seeds and root tissue across a range of species). The survival predictions in our case study are limited to hypothetical predictions because of the dearth of thermal tolerance data for the species present in the burns.

Just as the survival response functions in SheFire will support the increased understanding of soil organism responses to heating, new response functions can be added to the SheFire framework to model both threshold effects and more complex processes. For instance, the effects of fire on soil organic matter are known to vary with the extent and duration of soil heating (González-Pérez et al., 2004). Therefore, soil heating has major implications for soil carbon storage in fire prone landscapes. Current methods for assessing soil carbon storage and fire interactions are often not mechanistic at the level of soil heating and typically focus on fire frequency, severity, and aboveground fuels (Homann et al., 2011; Pellegrini et al., 2018). SheFire may provide a way to expand our understanding by linking soil carbon thermal degradation that occurs during fire to the temperatures experienced and the heating duration at different soil depths. Additionally, knowing how deep into the soil profile heating causes organic soil phosphorus to be converted to its more biologically available form, orthophosphate, could increase our understanding of post-fire plant recovery. Understanding the heat experienced by soil microbial communities is important for predicting microbial community dynamics following fire, which has implications for ecosystem functioning (Whitman et al., 2019). Furthermore, soil temperatures experienced during fires can influence soil ammonium pools after fire, which are a critical component of nitrogen cycling and ecosystem nitrogen budgets (Klopatek et al., 1990). With SheFire, we have established a modeling approach that can be leveraged to fill these knowledge gaps and expand our ability to predict fire effects.

Our case study provided a field test for iStakes, and though the study only examined two plots, it demonstrates the utility of the direct measurement approach for studying fire effects on soil. For example, SheFire provided an opportunity to examine how different fuels resulted in different soil heating and to examine how those heating regimes may influence various soil organisms based on their thermal tolerances. We would not be able to disentangle these relationships using indirect metrics such as burn severity.

CONCLUSIONS

The SheFire framework provides a cutting-edge approach for characterizing temperature regimes (i.e., soil heating) through a soil profile and predicting biological responses. While the current model advances our ability to predict belowground responses to fire, there are many opportunities for future expansion and development. For example, as our understanding of temperature-dependent biological and biogeochemical responses continues to improve, new response functions can be added to the SheFire framework.

In addition to adding new response functions, SheFire could be coupled with other fire effects models. For example, linking SheFire with aboveground dose–response models, such as tree mortality models (Michaletz & Johnson, 2008), could provide a more complete understanding of how fire affects plants, which can experience heating in both their above- and belowground structures. Linking SheFire with soil heating models, such as those that model the coupling of heat and mass transfer, which have been shown to affect soil thermal conductivity, water content, and soil structure (Massman, 2015; Massman et al., 2010; Smits et al., 2016) could strengthen the model's predictive ability and/or provide additional response functions that focus on those physical effects. Further work could also link SheFire with fire behavior and fire regime models, which would enable predictions of soil temperatures and their effects belowground based on the predicted fire characteristics of current and future fire regimes.

SheFire provides a modeling framework that enables researchers to move beyond qualitative and semi-quantitative descriptions of fire severity and explore how soil heating influences specific responses. As we learn to coexist with more extreme wildland fires (Schoennagel et al., 2017), SheFire can help researchers and land managers quantify how unplanned and prescribed wildland fires and pile burns directly influence soil physical, chemical, and biological processes.

AUTHOR CONTRIBUTION

Mary Brady developed and applied SheFire model with guidance from Matthew Dickinson, Jessica Miesel, and Erin Hanan. Matthew Dickinson, Alexandra Lodge, and Jessica Miesel conceived of and designed the iStake approach. Mary Brady and Erin Hanan conducted burn table experiments with guidance from Jessica Miesel and Matthew Dickinson. Carissa Wonkka, Kathleen Kavanagh, Alexandra Lodge, William Rogers, Heath Starns, Doug Tolleson, Morgan Treadwell, and Dirac Twidwell designed, secured funding for, and conducted the research that provided the soil heating data used in our case study. Mary Brady wrote the paper with input from all authors.

ACKNOWLEDGMENTS

Many thanks to Scott Huber for helping construct the burn tables. Funding for this research was provided in part by the National Science Foundation grant DEB-1916658 and the Joint Fire Science Program (Project ID: 17-1-04-7). The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Department of Agriculture of any product or service.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data (Brady & Hanan, 2022) are available in the Open Science Framework (OSF) at https://doi.org/10.17605/OSF.IO/HXYCT. Code (MaryKBrady & Erin, 2021) is available in Zenodo at https://doi.org/10.5281/zenodo.4694828.

ORCID

Matthew B. Dickinson https://orcid.org/0000-0003-3635-1219
Jessica R. Miesel https://orcid.org/0000-0001-7446-464X
William E. Rogers https://orcid.org/0000-0002-3407-1101
Heath D. Starns https://orcid.org/0000-0002-2501-3559
Morgan L. Treadwell https://orcid.org/0000-0003-1211-1712
Erin J. Hanan https://orcid.org/0000-0001-6568-2936

REFERENCES

Achat, D. L., L. Augusto, M. R. Bakker, A. Gallet-Budynek, and C. Morel. 2012. "Microbial Processes Controlling P Availability in Forest Spodosols as Affected by Soil Depth and Soil Properties." *Soil Biology and Biochemistry* 44(1): 39–48. https://doi.org/10.1016/j.soilbio.2011.09.007.

Adie, H., S. Richert, K. P. Kirkman, and M. J. Lawes. 2011. "The Heat Is On: Frequent High Intensity Fire in Bracken (*Pteridium aquilinum*) Drives Mortality of the Sprouting Tree Protea Caffra in Temperate Grasslands." *Plant Ecology* 212(12): 2013–22.

Aznar, J. M., J. A. González-Pérez, D. Badía-Villas, and C. Martí Dalmau. 2016. "At What Depth Are the Properties of Gypseous Forest Soil Affected by Fire?" *Land Degradation and Development* 27(5): 1344–53. https://doi.org/10.1002/ldr.2258.

Badía-Villas, D., J. A. González-Pérez, J. M. Aznar, B. Arjona-Gracia, and C. Martí-Dalmau. 2014. "Changes in Water Repellency, Aggregation and Organic Matter of a Mollic Horizon Burned in Laboratory: Soil Depth Affected by Fire." *Geoderma* 213(January): 400–7. https://doi.org/10.1016/j.geoderma.2013.08.038.

Balesdent, J., I. Basile-Doelsch, J. Chadoeuf, S. Cornu, D. Derrien, Z. Fekiacova, and C. Hatté. 2018. "Atmosphere–Soil Carbon Transfer as a Function of Soil Depth." *Nature* 559(7715): 599–602. https://doi.org/10.1038/s41586-018-0328-3.

Barnett, C. R. 2002. "BFD Curve: A New Empirical Model for Fire Compartment Temperatures." *Fire Safety Journal* 37(5): 437–63. https://doi.org/10.1016/S0379-7112(02)00006-1.

Bova, A. S., and M. B. Dickinson. 2008. "Beyond 'Fire Temperatures': Calibrating Thermocouple Probes and Modeling their Response to Surface Fires in Hardwood Fuels." *Canadian Journal of Forest Research* 38(5): 1008–20. https://doi.org/10.1139/X07-204.

Brady, M., and E. Hanan. 2022. "SheFire." OSF. https://doi.org/10.17605/OSF.IO/HXYCT.

Bristow, K. L. 1998. "Measurement of Thermal Properties and Water Content of Unsaturated Sandy Soil Using Dual-Probe Heat-Pulse Probes." *Agricultural and Forest Meteorology* 89(2): 75–84. https://doi.org/10.1016/S0168-1923(97)00065-8.

Busse, M. D., C. J. Shestak, and K. R. Hubbert. 2013. "Soil Heating during Burning of Forest Slash Piles and Wood Piles." *International Journal of Wildland Fire* 22(6): 786–96. https://doi.org/10.1071/WF12179.

Busse, M. D., C. J. Shestak, K. R. Hubbert, and E. E. Knapp. 2010. "Soil Physical Properties Regulate Lethal Heating during Burning of Woody Residues." *Soil Science Society of America Journal* 74(3): 947–55. https://doi.org/10.2136/sssaj2009.0322.

Caldwell, C. R. 1993. "Estimation and Analysis of Cucumber (*Cucumis sativus* L.) Leaf Cellular Heat Sensitivity." *Plant Physiology* 101(3): 939–45. https://doi.org/10.1104/pp.101.3.939.

Campbell, G. S., J. D. Jungbauer, Jr., K. L. Bristow, and R. D. Hungerford. 1995. "Soil Temperature and Water Content Beneath a Surface Fire." *Soil Science* 159: 363–74. https://doi.org/10.1097/00010694-199506000-00001.

Choczynska, J., and E. A. Johnson. 2009. "A Soil Heat and Water Transfer Model to Predict Belowground Grass Rhizome Bud Death in a Grass Fire." *Journal of Vegetation Science* 20(2): 277–87. https://doi.org/10.1111/j.1654-1103.2009.05757.x.

DeBano, L. F. 2000. "The Role of Fire and Soil Heating on Water Repellency in Wildland Environments: A Review." *Journal of Hydrology* 231: 195–206. https://doi.org/10.1016/S0022-1694(00)00194-3.

Dickinson, M. B., J. Jolliff, and A. S. Bova. 2005. "Vascular Cambium Necrosis in Forest Fires: Using Hyperbolic Temperature Regimes to Estimate Parameters of a Tissue-Response Model." *Australian Journal of Botany* 52(6): 757–63. https://doi.org/10.1071/BT03111.

Dickinson, M. B., and E. A. Johnson. 2004. "Temperature-Dependent Rate Models of Vascular Cambium Cell Mortality." *Canadian Journal of Forest Research* 34(3): 546–59. https://doi.org/10.1139/x03-223.

Dickinson, M., L. Loncar, A. Reiner, S. Dailey, J. Bednarczyk, C. Drake, J. Gordon, et al. 2019. "2019 Walker Fire, Plumas National Forest, Fire Behavior Assessment Team (FBAT) Report." US Forest Service, 34. https://www.fs.fed.us/adaptivemanagement/reports/fbat/2019_FBATReport_WalkerFire_10112019_Final.pdf.

Doerr, S., C. Santin, J. Reardon, J. Mataix-Solera, C. Stoof, R. Bryant, J. Miesel, and D. Badia. 2017. "Soil Heating during Wildfires and Prescribed Burns: A Global Evaluation Based on Existing and New Data" 19 (April): 17957. https://meetingorganizer.copernicus.org/EGU2017/EGU2017-17957-1.pdf.

Giovannini, C., S. Lucchesi, and M. Giachetti. 1990. "Effects of Heating on Some Chemical Parameters Related to Soil Fertility and Plant Growth." *Soil Science* 149(June): 344–50. https://doi.org/10.1097/00010694-199006000-00005.

Giovannini, G., and S. Lucchesi. 1997. "Modification Induced in Soil Physico-Chemical Parameters by Experimental Fires at Different Intensities." *Soil Science* 162(7): 479–86.

González-Pérez, J. A., F. J. González-Vila, G. Almendros, and H. Knicker. 2004. "The Effect of Fire on Soil Organic Matter—A Review." *Environment International* 30(6): 855–70. https://doi.org/10.1016/j.envint.2004.02.003.

Goss, M., D. L. Swain, J. T. Abatzoglou, A. Sarhadi, C. A. Kolden, A. Park Williams, and N. S. Diffenbaugh. 2020. "Climate Change Is Increasing the Likelihood of Extreme Autumn Wildfire Conditions across California." *Environmental Research Letters* 15(9): 094016. https://doi.org/10.1088/1748-9326/ab83a7.

Grau-Andrés, R., G. Matt Davies, E. Susan Waldron, M. Scott, and A. Gray. 2017. "Leaving Moss and Litter Layers Undisturbed Reduces the Short-Term Environmental Consequences of Heathland Managed Burns." *Journal of Environmental Management* 204(December): 102–10. https://doi.org/10.1016/j.jenvman.2017.08.017.

Gustine, R. N., E. J. Hanan, P. R. Robichaud, and W. J. Elliot. 2021. "From Burned Slopes to Streams: How Wildfire Affects Nitrogen Cycling and Retention in Forests and Fire-Prone Watersheds." *Biogeochemistry* 1–18: 51–68. https://doi.org/10.1007/s10533-021-00861-0.

Hanan, E. J., C. M. D'Antonio, D. A. Roberts, and J. P. Schimel. 2016. "Factors Regulating Nitrogen Retention during the Early Stages of Recovery from Fire in Coastal Chaparral Ecosystems." *Ecosystems* 19(5): 910–26. https://doi.org/10.1007/s10021-016-9975-0.

Hanan, E. J., J. Ren, C. L. Tague, C. A. Kolden, J. T. Abatzoglou, R. R. Bart, M. C. Kennedy, M. Liu, and J. C. Adam. 2021. "How Climate Change and Fire Exclusion Drive Wildfire Regimes at Actionable Scales." *Environmental Research Letters* 16(2): 024051. https://doi.org/10.1088/1748-9326/abd78e.

Hanan, E. J., J. P. Schimel, K. Dowdy, and C. M. D'Antonio. 2016. "Effects of Substrate Supply, PH, and Char on Net Nitrogen Mineralization and Nitrification along a Wildfire-Structured Age Gradient in Chaparral." *Soil Biology and Biochemistry* 95-(April): 87–99. https://doi.org/10.1016/j.soilbio.2015.12.017.

Hartford, R. A., and W. H. Frandsen. 1992. "When It's Hot, It's Hot... Or Maybe It's Not! (Surface Flaming May Not Portend Extensive Soil Heating)." *International Journal of Wildland Fire* 2(3): 139–44. https://doi.org/10.1071/wf9920139.

Hiers, Q. A., M. L. Treadwell, M. B. Dickinson, K. L. Kavanagh, A. G. Lodge, H. D. Starns, D. R. Tolleson, D. Twidwell, C. L. Wonkka, and W. E. Rogers. 2019. "Grass Bud Bank Responses to Fire in a Semi-Arid Savanna System." *Ecology & Evolution* 11: 6620–33. https://doi.org/10.1002/ece3.7516.

Homann, P. S., B. T. Bormann, R. L. Darbyshire, and B. A. Morrissette. 2011. "Forest Soil Carbon and Nitrogen Losses Associated with Wildfire and Prescribed Fire." *Soil Science Society of America Journal* 75(5): 1926–34. https://doi.org/10.2136/sssaj2010-0429.

Hudak, A. T., P. Morgan, M. J. Bobbitt, A. M. S. Smith, S. A. Lewis, L. B. Lentile, P. R. Robichaud, J. T. Clark, and R. A. McKinley. 2007. "The Relationship of Multispectral Satellite Imagery to Immediate Fire Effects." *Fire Ecology* 3(1): 64–90. https://doi.org/10.4996/fireecology.0301064.

Ichoku, C., R. Kahn, and M. Chin. 2012. "Satellite Contributions to the Quantitative Characterization of Biomass Burning for Climate Modeling." *Atmospheric Research* 111(July): 1–28. https://doi.org/10.1016/j.atmosres.2012.03.007.

Iverson, L. R., D. A. Yaussy, J. Rebbeck, T. F. Hutchinson, R. P. Long, and A. M. Prasad. 2004. "A Comparison of Thermocouples and Temperature Paints to Monitor Spatial and Temporal Characteristics of Landscape-Scale Prescribed Fires." *International Journal of Wildland Fire* 13: 311–22. https://doi.org/10.1071/WF03063.

Johnson, E. A. 1985. "Disturbance: The Process and the Response. An Epilogue." *Canadian Journal of Forest Research* 15: 292–3. https://doi.org/10.1139/x85-047.

Keeley, J. E. 2009. "Fire Intensity, Fire Severity and Burn Severity: A Brief Review and Suggested Usage." *International journal of wildland fire* 18(1): 116–26.

Kennard, D. K., K. W. Outcalt, D. Jones, and J. J. O'Brien. 2005. "Comparing Techniques for Estimating Flame Temperature of Prescribed Fires." *Fire Ecology* 1(1): 75–84. https://doi.org/10.4996/fireecology.0101075.

Kersten, M. S. 1949. *Thermal Properties of Soils*, Vol 52. Saint Paul, MN: University of Minnesota, Institute of Technology http://conservancy.umn.edu/handle/11299/124271.

Klopatek, J. M., C. C. Klopatek, and L. F. DeBano. 1990. "Potential Variation of Nitrogen Transformations in Pinyon-Juniper Ecosystems Resulting from Burning." *Biology and Fertility of Soils* 10(1): 35–44. https://doi.org/10.1007/BF00336122.

Kokaly, R. F., B. W. Rockwell, S. L. Haire, and T. V. V. King. 2007. "Characterization of Post-Fire Surface Cover, Soils, and Burn Severity at the Cerro Grande Fire, New Mexico, Using Hyperspectral and Multispectral Remote Sensing." *Remote Sensing of Environment* 106(3): 305–25. https://doi.org/10.1016/j.rse.2006.08.006.

Kramer, M. G., K. Lajtha, and A. K. Aufdenkampe. 2017. "Depth Trends of Soil Organic Matter C:N and 15N Natural Abundance Controlled by Association with Minerals." *Biogeochemistry* 136(3): 237–48. https://doi.org/10.1007/s10533-017-0378-x.

Kremens, R. L., A. M. S. Smith, and M. B. Dickinson. 2010. "Fire Metrology: Current and Future Directions in Physics-Based Measurements." *Fire Ecology* 6(1): 13–35. https://doi.org/10.4996/fireecology.0601013.

Kreye, J. K., J. M. Varner, and L. N. Kobziar. 2020. "Long-Duration Soil Heating Resulting from Forest Floor Duff Smoldering in Longleaf Pine Ecosystems." *Forest Science* 66: 291–303. https://doi.org/10.1093/forsci/fxz089.

Kreye, J. K., L. N. Kobziar, and W. C. Zipperer. 2013. "Effects of Fuel Load and Moisture Content on Fire Behaviour and Heating in Masticated Litter-Dominated Fuels." *International Journal of Wildland Fire* 22(4): 440–5. https://doi.org/10.1071/WF12147.

Lentile, L. B, P. Morgan, C. Hardy, A. T Hudak, R. Means, R. Ottmar, P. Robichaud, E. Sutherland, F. Way, and S. Lewis. 2007. "Lessons Learned From Rapid Response Research on Wildland Fires." U.S. Department of Agriculture: Forest Service, National Agroforestry Center, 10. https://www.fs.fed.us/pnw/fera/publications/fulltext/lentileetal2007.pdf.

Lorenz, R. W. 1939. "High Temperature Tolerance of Forest Trees." University of Minnesota: Agricultural Experiment Station. Technical Bulletin 141. https://conservancy.umn.edu/bitstream/handle/11299/204074/mn1000_agexpstn_tb_141.pdf?sequence=1.

Lutes, D. C. 2017. "FOFEM 6.4: First Order Fire Effects Model User Guide." Missoula, MT: U.S. Department of Agriculture: Forest Service, Rocky Mountain Research Station, Fire Modeling Institute.

MacLean, J. D. 1941. *Thermal Conductivity of Wood.* Madison, WI: Forest Products Laboratory: Heating, Piping & Air Conditioning. https://www.fpl.fs.fed.us/documnts/pdf1941/macle41a.pdf.

Martin, R. E., C. T. Cushwa, and R. L. Miller. 1969. "Fire as a Physical Factor in Wildland Management." In Proceedings Annual [9th] Tall Timbers Fire Ecology Conference 9: 271–88. https://www.fs.usda.gov/treesearch/pubs/42405.

Martin, R. E., and C. T. Cushwa. 1966. "Effects of Heat and Moisture on Leguminous Seed." In Proceedings Annual [5th] Tall Timbers Fire Ecology Conference 5:159–175. https://talltimbers.org/wp-content/uploads/2014/03/MartinandCushwa1966_op.pdf.

HananMaryKBrady and Erin. 2021. "Fire-and-Dryland-Ecosystems-Lab/SheFireModel: SheFire version v1.0.0 (v1.0.0)." Zenodo. https://doi.org/10.5281/zenodo.4694828.

Massman, W. J. 2015. "A Non-Equilibrium Model for Soil Heating and Moisture Transport during Extreme Surface Heating: The Soil (Heat–Moisture–Vapor) HMV-Model Version 1." *Geoscientific Model Development* 8(11): 3659–80. https://doi.org/10.5194/gmd-8-3659-2015.

Massman, W. J. 2021. "The Challenges of an In Situ Validation of a Nonequilibrium Model of Soil Heat and Moisture Dynamics during Fires." *Hydrology and Earth System Sciences* 25(2): 685–709. https://doi.org/10.5194/hess-25-685-2021.

Massman, W. J., J. M. Frank, and S. J. Mooney. 2010. "Advancing Investigation and Physical Modeling of First-Order Fire Effects on Soils." *Fire Ecology* 6(1): 36–54. https://doi.org/10.4996/fireecology.0601036.

Maxim Integrated. 2002. *Book of IButton Standards*. San Jose, CA: Maxim Integrated Products, Inc. https://www.maximintegrated.com/en/design/technical-documents/app-notes/9/937.html.

Michaletz, S. T., and E. A. Johnson. 2008. "A Biophysical Process Model of Tree Mortality in Surface Fires." *Canadian Journal of Forest Research* 38(7): 2013–29. https://doi.org/10.1139/X08-024.

Michaletz, S. T., and E. A. Johnson. 2007. "How Forest Fires Kill Trees: A Review of the Fundamental Biophysical Processes." *Scandinavian Journal of Forest Research* 22(6): 500–15. https://doi.org/10.1080/02827580701803544.

Miesel, J., A. Reiner, C. Ewell, B. Maestrini, and M. Dickinson. 2018. "Quantifying Changes in Total and Pyrogenic Carbon Stocks across Fire Severity Gradients Using Active Wildfire Incidents." *Frontiers in Earth Science* 6. https://doi.org/10.3389/feart.2018.00041.

Moran, C. J., C. A. Seielstad, M. R. Cunningham, V. Hoff, R. A. Parsons, L. L. Queen, K. Sauerbrey, and T. Wallace. 2019. "Deriving Fire Behavior Metrics from UAS Imagery." *Fire* 2(2): 36. https://doi.org/10.3390/fire2020036.

Morgan, P., R. E. Keane, G. K. Dillon, T. B. Jain, A. T. Hudak, E. C. Karau, P. G. Sikkink, Z. A. Holden, and E. K. Strand. 2014. "Challenges of Assessing Fire and Burn Severity Using Field Measures, Remote Sensing and Modelling." *International Journal of Wildland Fire* 23(8): 1045–60. https://doi.org/10.1071/WF13058.

Murphy, K. A., J. H. Reynolds, and J. M. Koltun. 2008. "Evaluating the Ability of the Differenced Normalized Burn Ratio (DNBR) to Predict Ecologically Significant Burn Severity in Alaskan Boreal Forests." *International Journal of Wildland Fire* 17(4): 490–9. https://doi.org/10.1071/WF08050.

Neary, D. G., C. C. Klopatek, L. F. DeBano, and P. F. Ffolliott. 1999. "Fire Effects on Belowground Sustainability: A Review and Synthesis." *Forest Ecology and Management* 122(September): 51–71. https://doi.org/10.1016/S0378-1127(99)00032-8.

Nelson, R. M. 1952. *Observations on Heat Tolerance of Southern Pine Needles. U.S.* Asheville, NC: U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station. https://www.fs.usda.gov/treesearch/pubs/54149.

Ottmar, R. D., J. Kevin Hiers, B. W. Butler, C. B. Clements, M. B. Dickinson, A. T. Hudak, J. J. O'Brien, et al. 2016. "Measurements, Datasets and Preliminary Results from the RxCADRE Project – 2008, 2011 and 2012." *International Journal of Wildland Fire* 25(1): 1–9. https://doi.org/10.1071/WF14161.

Pellegrini, A. F. A., A. Ahlström, S. E. Hobbie, P. B. Reich, L. P. Nieradzik, A. Carla Staver, B. C. Scharenbroch, et al. 2018. "Fire Frequency Drives Decadal Changes in Soil Carbon and Nitrogen and Ecosystem Productivity." *Nature* 553(7687): 194–8. https://doi.org/10.1038/nature24668.

Pereira, P., A. Cerdà, X. Úbeda, J. Mataix-Solera, and G. Rein. 2019. *Fire Effects on Soil Properties*. Clayton South Victoria, Australia; CSIRO Publishing.

Pingree, M. R. A., and L. N. Kobziar. 2019. "The Myth of the Biological Threshold: A Review of Biological Responses to Soil Heating Associated with Wildland Fire." *Forest Ecology and Management* 432(January): 1022–9. https://doi.org/10.1016/j.foreco.2018.10.032.

Quigley, K. M., R. E. Wildt, B. R. Sturtevant, R. K. Kolka, M. B. Dickinson, C. C. Kern, D. M. Donner, and J. R. Miesel. 2019. "Fuels, Vegetation, and Prescribed Fire Dynamics Influence Ash Production and Characteristics in a Diverse Landscape under Active Pine Barrens Restoration." *Fire Ecology* 15: 1–15. https://doi.org/10.1186/s42408-018-0015-7.

Quigley, K. M., R. Kolka, B. R. Sturtevant, M. B. Dickinson, C. C. Kern, D. M. Donner, and J. R. Miesel. 2020. "Prescribed Burn Frequency, Vegetation Cover, and Management Legacies Influence Soil Fertility: Implications for Restoration of Imperiled Pine Barrens Habitat." *Forest Ecology and Management* 470: 118163. https://doi.org/10.1016/j.foreco.2020.118163.

Ramcharan, A., T. Hengl, T. Nauman, C. Brungard, S. Waltman, S. Wills, and J. Thompson. 2018. "Soil Property and Class Maps of the Conterminous United States at 100-Meter Spatial Resolution." *Soil Science Society of America Journal* 82(1): 186–201. https://doi.org/10.2136/sssaj2017.04.0122.

Regan, K., B. Stempfhuber, M. Schloter, F. Rasche, D. Prati, L. Philippot, R. S. Boeddinghaus, E. Kandeler, and S. Marhan. 2017. "Spatial and Temporal Dynamics of Nitrogen Fixing, Nitrifying and Denitrifying Microbes in an Unfertilized Grassland Soil." *Soil Biology and Biochemistry* 109(June): 214–26. https://doi.org/10.1016/j.soilbio.2016.11.011.

Robichaud, P. R. 2000. "Fire Effects on Infiltration Rates after Prescribed Fire in Northern Rocky Mountain Forests, USA." *Journal of Hydrology* 231–232(May): 220–9. https://doi.org/10.1016/S0022-1694(00)00196-7.

Robichaud, P., and R. E. Brown. 2019. "High Temperature Soil Probe." United States of America Patent: US20190072434A1. https://www.freepatentsonline.com/y2019/0072434.html.

Rosenberg, B., G. Kemeny, R. C. Switzer, and T. C. Hamilton. 1971. "Quantitative Evidence for Protein Denaturation as the Cause of Thermal Death." *Nature* 232(5311): 471–3. https://doi.org/10.1038/232471a0.

Schoennagel, T., J. K. Balch, H. Brenkert-Smith, P. E. Dennison, B. J. Harvey, M. A. Krawchuk, N. Mietkiewicz, et al. 2017. "Adapt to More Wildfire in Western North American Forests as Climate Changes." *Proceedings of the National Academy of Sciences USA* 114(18): 4582–90. https://doi.org/10.1073/pnas.1617464114.

Smith, A. M. S., A. M. Sparks, C. A. Kolden, J. T. Abatzoglou, A. F. Talhelm, D. M. Johnson, L. Boschetti, et al. 2016. "Towards a New Paradigm in Fire Severity Research Using Dose–Response Experiments." *International Journal of Wildland Fire* 25(2): 158–66. https://doi.org/10.1071/WF15130.

Smith, J. E., A. D. Cowan, and S. A. Fitzgerald. 2016. "Soil Heating during the Complete Combustion of Mega-Logs and Broadcast Burning in Central Oregon USA Pumice Soils." *International Journal of Wildland Fire* 25(11): 1202–7. https://doi.org/10.1071/WF16016.

Smith, N. R., B. E. Kishchuk, and W. W. Mohn. 2008. "Effects of Wildfire and Harvest Disturbances on Forest Soil Bacterial Communities." *Applied and Environmental Microbiology* 74(1): 216–24. https://doi.org/10.1128/AEM.01355-07.

Smits, K. M., E. Kirby, W. J. Massman, and L. Scott Baggett. 2016. "Experimental and Modeling Study of Forest Fire Effect on Soil Thermal Conductivity." *Pedosphere* 26: 462–73. https://doi.org/10.1016/S1002-0160(15)60057-1.

Swezy, D. M., and J. K. Agee. 2011. "Prescribed-Fire Effects on Fine-Root and Tree Mortality in Old-Growth Ponderosa Pine." *Canadian Journal of Forest Research* 21: 626–34. https://doi.org/10.1139/x91-086.

Twidwell, D., S. D. Fuhlendorf, C. A. Taylor Jr, and W. E. Rogers. 2013. "Refining Thresholds in Coupled Fire-Vegetation Models to Improve Management of Encroaching Woody Plants in Grasslands." *Journal of Applied Ecology* 50: 603–13. https://doi.org/10.1111/1365-2664.12063.

USDA. 2016. *Official Series Description - TARRANT Series*. U.S. Department of Agriculture. https://soilseries.sc.egov.usda.gov/OSD_Docs/T/TARRANT.html.

Varner, M. J., F. E. Putz, J. J. O'Brien, J. Kevin Hiers, R. J. Mitchell, and D. R. Gordon. 2009. "Post-Fire Tree Stress and Growth Following Smoldering Duff Fires." *Forest Ecology and Management* 258(11): 2467–74. https://doi.org/10.1016/j.foreco.2009.08.028.

Whitman, T., E. Whitman, J. Woolet, M. D. Flannigan, D. K. Thompson, and M.-A. Parisien. 2019. "Soil Bacterial and Fungal Response to Wildfires in the Canadian Boreal Forest across a Burn Severity Gradient." *Soil Biology and Biochemistry* 138-(November): 107571. https://doi.org/10.1016/j.soilbio.2019.107571.

Zhang, Y., H. Shen, Q. Gao, and L. Zhao. 2020. "Estimating Soil Organic Carbon and PH in Jilin Province Using Landsat and Ancillary Data." *Soil Science Society of America Journal* 84(2): 556–67. https://doi.org/10.1002/saj2.20056.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Brady, Mary K., Matthew B. Dickinson, Jessica R. Miesel, Carissa L. Wonkka, Kathleen L. Kavanagh, Alexandra G. Lodge, William E. Rogers, et al. 2022. "Soil Heating in Fire (SheFire): A Model and Measurement Method for Estimating Soil Heating and Effects during Wildland Fires." *Ecological Applications* 32(6): e2627. https://doi.org/10.1002/eap.2627