Forum: Issues, Management, Policy, and Opinions

Fire Metrology: Current and Future Directions in Physics-Based Measurements

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ABSTRACT

The robust evaluation of fire impacts on the biota, soil, and atmosphere requires measurement and analysis methods that can characterize combustion processes across a range of temporal and spatial scales. Numerous challenges are apparent in the literature. These challenges have led to novel research to quantify the 1) structure and heterogeneity of the pre-fire vegetation; 2) energy released during the combustion process and the ultimate disposition of that energy through conduction, radiation, and convective transport; and 3) landscape-scale impacts of fire on soils, vegetation, and atmosphere. The grand challenge is how to integrate the pre-, active-, and post-fire measurements and physical process models into a single robust and well validated framework. This paper presents a brief review of the current state of fire metrology research and proposes future research to address the measurement grand challenge.

Keywords: energy transport, fire metrology, radiative transport, remote sensing, satellite methods

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INTRODUCTION

Physics-based fire effects models require flame, near-source plume, and landscape spread characteristics from either validated fire models or from quantitative descriptions based on an array of measurement techniques (in the sense of metrology). Selection of the most appropriate measurement has been a difficult proposition for fire ecologists, particularly because they are generally not guided by a physical sciences approach (Johnson and Miyanishi 2002). However, even once chosen, good measurements at the scale necessary for models and monitoring are notoriously difficult to obtain, and scaling measurements to coarser or finer spatial or temporal time scales might be necessary. Scaling must, of course, be guided by good physics. Measurements of interest may be obtained from ground-based sensors (within or above the flames) or remotely from aircraft or satellite sensors. Identification of the basic, underlying physical processes is critical for determination of a measurement scale for a given model; finding the correct scale for any studied fire phenomena also remains a fundamental research issue.

Given measurements of flame and plume characteristics, the energy deposition to the surrounding soil and vegetation matrices can be modeled using conventional thermal transport models, providing the process link between fire behavior and its ecological effects (see Butler and Dickinson 2010, Kavanagh *et al*. 2010, Massman *et al*. 2010, and Stephan *et al.* 2010). Human and faunal exposures to elevated gas concentrations in and near wildland fires may also be important (Reinhardt and Ottmar 2000, Smith 2000, Engstrom 2010), and measurement of gas concentrations in the near-source plume and canopy with sufficient spatial and temporal resolution raises its own challenges. Improved quantification of the flame and plume characteristics that are often used as inputs into regional transport and emission models are needed to improve predictions of smoke impacts on air quality, especially given the 2006 lowering of the US National Ambient Air Quality Standards 24 h fine particulate threshold from 65 $\mu g\ m^{-3}$ to 35 $\mu g\ m^{-3}$. Further, understanding of fire effects may often benefit from quantitative descriptions of the fire effects themselves, as several existing fire effects descriptors are anecdotal (i.e., have no units; Keeley 2009). Linking such quantitative descriptors to hydrological and biogeochemical sources, sinks, and stocks would greatly advance our understanding and prediction of fire effects of varying impact on the short- and long-term carbon, water, and other important environmental cycles, as well as allow direct comparison between experiments at different times, in different regions, and at different spatial scales (Lentile *et al.* 2009).

In this paper, we will describe the current and future work in fire metrology to quantify pre-fire fuels using multiple instruments, active fire energy disposition using a variety of sensors and deployment strategies, and post-fire effects using aircraft and satellite-based (e.g., Landsat) reflectance sensors. Finally, research and application challenges will be discussed, in particular, instrumentation and associated modeling.

PRE-FIRE FUEL AND VEGETATION MEASUREMENT

A current challenge that exists in the parameterization of first-order fire effects models is obtaining the measurement of fine-scale heterogeneity in fuel structure and loading. Assessment of fine-scale spatial heterogeneity of fuels is also important from the standpoint of fire spread, as this knowledge is required by models that simulate fire spread in layered and horizontally variable fuel beds as opposed to the homogenous fuel beds required by the Rothermel (1983) fire spread relations.

A modern tool used to assist with characterizing three-dimensional fuel variability is light detection and ranging (LiDAR), whether airborne or a ground-based terrestrial laser scanner (TLS). A recent review of LiDAR applications in natural resources can be found in Evans *et al.* (2009). LiDAR, analogous to RADAR, measures the distance to a target by measuring the time taken for a light pulse to hit the target and return. In spite of the promise and current excitement concerning the use of LiDAR to measure the shape of the canopy, forest floor, or other reflective surfaces in the instrument field of view, we must remember that the LiDAR data set is at best a pseudo-random statistical sampling of the position (measured from only a few angles) and reflectance (at one wavelength, typically near one micron), and thus a second or third order measure, of a collection of real objects (e.g., fuel particles). The challenge in using LiDAR in wildland fire fuel estimation comes in development of models to relate spatial point data clouds to physically meaningful structural parameters that can, in turn, be related to fuel loads or fuel arrangement. We must also remember that the spatial sampling frequency of most LiDAR data sets is very low compared to the complexity (spatial frequency) of the scene, violating the Nyquist-Shannon sampling theorem (Shannon 1949). Very little attention seems to have been paid to this fact in the literature. Despite these challenges, airborne and TLS LiDAR have been used to some effect in characterizing airborne particulates (Lavrov *et al*. 2006), forest canopy and forest floor structural metrics related to fire fuels (Seielstad and Queen 2003, Anderson *et al*. 2005, Falkowski *et al*. 2008). For example, TLS systems have been used to characterize the fine-scale variability of individual surface fuel elements (Heirs *et al.* 2009). The Missoula Fire Sciences Laboratory has conducted research using a backpack-mounted TLS LiDAR aimed upwards at the canopy to quantify a stand metric of canopy base height (J. Reardon, USDA Forest Service, personal communication). Although TLS LiDAR systems have been used less often than airborne LiDAR systems (Clawges *et al.* 2007; Strahler *et al.* 2008), they hold considerable promise to characterize the 3-D profile of surface and canopy fuels. A central limitation of ground-based LiDAR is that multiple vantage points are needed to produce a 3-D profile of a given fuel matrix as fuels occluded by other fuels will be missed from a single observation point. This occlusion effect is equally pronounced when considering the 3-D arrangement of surface fuels (Evans *et al.* 2009).

Airborne LiDAR systems also hold promise for quantifying the 3-D arrangement of canopy fuels. Specifically, the evaluation of the histograms produced from the number of LiDAR returns occurring within height strata has been shown to enable the remote determination of stand successional stage (Falkowski *et al.* 2009). This method may be useful for fire behavior determination; for example, late stage successional forests have may fuel arrangements (less needle cast, fewer shrubs) that lower the propensity for crown fires. Histograms produced from LiDAR data with high pulse densities can provide information on the abundance of ladder fuels (Skowronski *et al.* 2007, Powell *et al.* 2009) and, thereby, probabilities of crown fire initiation and spread. Research to characterize vegetation structure using LiDAR and optical imagery have been used to derive metrics such as crown sizes, crown base height, tree heights, and others, on a tree-by-tree basis (Falkowski *et al.* 2006, 2008; Strand *et al.* 2006, 2008). Analysis of LiDAR data can also provide important stand level vegetation metrics such as stems per acre, basal area, canopy density, and canopy cover, each of which can be assessed both as pre- and post-fire variables (Wang and Glenn 2009).

Analysis of the 3-D location of LiDAR returns shows great potential in assisting the validation or parameterization of post-Rothermel fire spread models by accounting for canopy fuel heterogeneity. A common approach is to divide the canopy sector into 3-D pixel cubes of equal size, termed voxels (Flores *et al.* 2000), thus allowing the user to flag whether a canopy fuel element was present within that voxel as given by the presence or absence of any LiDAR canopy returns (Evans *et al*. 2009). An alternative approach is to define the voxels as 3-D cuboids extending from the ground surface to the height of the canopy, where the number or density of returns would then equate to a probability of canopy fuels. In either case, such a 3-D representation could enable improved fire spread model predictions in cases of active or passive crown fires.

Two central and compounding limitations exist when using discrete return airborne LiDAR to characterize sub-canopy fuels. First, limitations in the electronics of the LiDAR sensor system result in a short dead time between the recording of consecutive events.

Depending on the speed and altitude of the aircraft, this can correspond to a distance of at least 1 m to 3 m for natural resource acquisitions (Evans *et al*. 2009). Because of this dead time, if a return occurs from a low-lying branch, shrub, or piece of coarse woody debris, then it may not be possible to record a ground return (farther away, later in time) from that same pulse. This dead time error can result in incorrect ground surfaces and associated vegetation heights, and effectively leads to a sub-sampling of the vegetation heterogeneity (Evans *et al*. 2009). The secondary effect is due to absorption of the laser pulse within the canopy and other interrogated material; as more surfaces reflect the energy from a given pulse, there is less energy remaining in the pulse to be reflected by surfaces lower down in the canopy and vegetation. This attenuation creates a bias in the observation towards earlier, stronger returns. Research is needed to evaluate these phenomena under different canopy stand structure and species conditions. One form of validation would be to follow research that has been done to calculate crown bulk density in a per crown basis (Keane *et al.* 2005) and record the number of branches and size of those branches present within each crown, and thus reconstruct the expected height-return histogram based on the density of branches within the canopy for comparison with LiDAR measurements.

An emerging LiDAR technology is the use of analog or waveform LiDAR systems that can provide not only the timing but also the strength of the return. These systems show promise in being able to differentiate woody material from leaves in the canopy, and to determine the type (grass, leaf litter, needles, etc.) of material on the forest floor.

MEASURING DISPOSITION OF ENERGY FROM ACTIVE FIRES

The Energy Field

We introduce the concept of the fire energy field as a way to characterize the radiant, conductive, and convective energy flows produced by a wildland fire. In an ideal world, we would know all the components (magnitude and direction) of the energy field, which would allow coupling (through transport equations) of the energy field to any (well-characterized) object in the field (see Butler and Dickinson 2010). It is impractical to measure the field at all points in space and not yet practical to implement a 3-dimensional time-resolved transport model (Mell *et al.* 2009). Lacking these details, we must resort to simplifications or analogs that are physically relevant and also measurable.

The information needed for completely modeling the energy flux to soils and vegetation include: flame emissivity, flame emissive power, flame geometry (length, height, depth), flame rate of spread, fuel consumption (mass loss rate), radiative fraction (percentage of total energy release that is transported by radiation), thickness of the convective boundary layer, conductivity of the air (working fluid), properties of soils and vegetation targets, and the emissivity and absorptivity of soils and vegetation. We are very far from accurate knowledge of many of these parameters in the current state of the art in wildland fire research.

Energy from a fire is transported by radiation, conduction, and convection. Within subjects of concern to wildland fire (soil, duff and litter, tree bole, fauna), conduction is the predominant energy transport process. Discussion of heat and mass transfer in soils can be found in Massman *et al.* (2010). Conduction of the incident heat flux from the energy field throughout the organism determines the biological or physical effects. Conceivably, if a sufficient number of samples were available and a range of energy fields applied, it would be possible to produce a dose-response curve for fire effects similar to that produced for toxicological or pharmacological effects. These dose-response curves could be generated in a laboratory environment in a controlled way, independent of the vagaries of wildland fire. Efforts are underway by members of our team to perform such experiments for tree boles and crowns (see references in Butler and Dickinson 2010) and roosting bats (M.B. Dickinson, Forest Service, unpublished data).

At long distances (~1 m to 10 m) from the fire front, the dominant component of the energy field is electromagnetic radiation with a wavelength of 1.5 μm to 20 μm. This wavelength region is characteristic of radiators in the 1200 K to 1500 K maximum temperature range of flames from diffusion limited wildland fuel material (J. Cohen, Forest Service, personal communication). In recent laboratory and field experiments, the radiative fraction, that portion of the total energy released as electromagnetic radiation, was found to be in the range of 10 % to 30 % (Roberts *et al.* 2005; Smith and Wooster 2005; Wooster *et al.* 2005; Freeborn *et al.* 2008; R.L. Kremens, Rochester Institute of Technology, unpublished data). Although the radiative component of the fire energy field may not be the dominant mode of energy transport, it is certainly the most easily measurable, especially at long standoff distances, for example, using airborne or satellite remote sensing. Infrared (IR) radiation is also a direct physical measure (first order). Because long-wave IR penetrates smoke and can propagate over long distances, we will use this component of the fire energy field as a measurable analog for the entire energy field. This method is not without its drawbacks, however, because the radiative fraction may be a function of the nature of the fire (intensity, fuel moisture, etc.) and relating the radiated power to a parameter like fuel consumption may be problematic. More experiments are required to determine the radiative fraction as a function of fire type, fuel materials, and other combustion conditions.

The radiation field may be measured directly with radiometers that may have narrow or wide wavelength response and narrow or wide fields of view. In general we should use wide spectral response radiometers to approximate the wide spectral response of the subjects. The field of view of the detector should be appropriate for the spatial scale of the model; thus, for large scale smoke transport models, kilometer spatial resolution may be adequate, whereas hyperspatial resolution (centimeter or millimeter) (Greenberg *et al.* 2006) may be required for modeling response of individual plants or animals. The radiometers should have a temporal resolution appropriate to the thermal response time of the subject under study. In most cases for field (ground level) equipment, the response time of the typical thermopile radiometer instrument (~15 ms) is adequate. The temporal resolution of most airborne or satellite measurements (several minutes to many days or longer) is too coarse for study of many short-lived processes, and these measurement techniques should be used with caution.

A persistent challenge is measuring the fine-scale surface variations in the energy field and how these impact the surface boundary conditions for vegetation and soil heating. The application of ground-based thermal imaging cameras gives the required high spatial and temporal resolution. These data can be generalized by aggregating pixels to simulate lower spatial resolutions to determine the proper scale of measurement but, to our knowledge, this work has not been reported in the literature. Technological advances, which produce three dimensional input data sets such as LiDAR mentioned earlier, will require extending the capabilities of physical and fire effects models to allow incorporation of such high spatio-temporal information. For example, the First Order Fire Effects Model (FOFEM; see Reinhardt and Dickinson [2010]) is an excellent model designed for stand-scale predictions. However, the resolution of FOFEM may be incorrect for processes and effects that are occurring at finer or broader scales (e.g., the heating of shrubs and forbs).

The energy released from the fire is transported by conduction, convection, and radiation. If the partitioning of total energy release among these mechanisms is known and constant, one can measure just one component and derive the total energy field of the fire. Experiments are being conducted in the laboratory and in plot-sized outdoor settings to determine the relationship between these energy transport mechanisms.

Inadequacy of the Idea of Fire Temperature Measurement

Numerous studies have recorded fire temperatures in the field using various instruments. Measurements are sometimes made of only the maximum temperature reached by the measuring instrument (Martin and Davis 1960, Batchelder and Hirt 1966, DeBano *et al.* 1979), although other studies have also measured temperature continuously in order to infer, for example, the fire residence time (Stronach and McNaughton 1989, Jacoby *et al.* 1992, Perez and Moreno 1998, Smith *et al.* 2005). Temperatures have been measured with heat-sensitive crayons (Sweet 1982), color-changing paints (Hopkins 1965, Stronach and McNaughton 1989, Hely *et al.* 2003), thermocouples (Stocks *et al.* 1996, Smith *et al.* 2005) and pyrometers (Stronach and McNaughton 1989).

Unfortunately, measurement of fire temperature by these methods does little to predict the fire energy field (Van Wagner and Methven 1978). What has been measured with these techniques is the temperature rise of a particular witness device (paint chip, thermocouple, etc.) in the energy field. Without extensive knowledge of the thermodynamic properties of the witness and a model for heat transport, these temperature measurements cannot be used to uniquely determine the energy field. From thermodynamic considerations and experimental measurements, the maximum temperature of a diffusion limited flame (such as a wildland fire flame) is around 1100 °C, so that a witness object placed in the radiation field of the flame should come to thermal equilibrium with a temperature determined by the object's characteristics (emissivity, reflectivity, mass, and other radiation field coupling coefficients) and the fire's characteristics (geometry of the radiation field, residence time).

Measurements using temperature measuring devices such as thermocouple probes can be used to estimate fireline intensity and related parameters, like fuel consumption, if careful calibration is performed by comparison with field measurements (Bova and Dickinson 2008). Derivation of heat flux through physical modeling of both the thermocouple and the energy field in which the thermocouple is immersed has also shown promise (Bova and Dickinson 2008). The problem here is to infer the energy field from the fire using only the heating of the thermocouple probe. Because of the availability and simplicity of the measuring apparatus, this measurement and modeling scheme may be useful as a way to measure the energy field at many points within the fire.

An example of a useful (and correct) application of the witness concept is the estimation of the heat flux to tree stems during fires using embedded thermocouple probes. A fine thermocouple placed just below the bark allows one to use the tree itself as the witness device. Inverse conduction models are used to extract the net heat flux from thermocouple response (Bova and Dickinson 2009). These methods require knowledge of thermal properties of the tree as well as a model for heat transport within the tree.

Measuring the Radiative Field

Having accepted radiated energy as an analog for the energy field, the fire radiative power (FRP; kW m^{-2}) and its time-integral, fire radiative energy (FRE; kJ m^{-2}) can be measured using remote sensing methods (Lentile *et al.* 2006). Fuel consumption can be inferred if the radiative fraction (that portion of the total energy release that is apportioned to radiative transfer) and FRE is known, since total energy output must be related to the amount of fuel consumed. Measured FRP, FRE, and fuel consumption and other variables can be used to validate and parameterize fire models. For instance, FOFEM, through its sub-model, Burnup (Reinhardt and Dickinson 2010), provides estimates of FRP, FRE, and consumption. The CONSUME program (V.3.0) provides outputs of total biomass consumed (mass per area) and total heat release (energy per area) (Pritchard *et al.* 2006). Other fire models that provide outputs that can be compared with heat release measurements include the Rothermel model (Rothermel 1972), Fire Dynamics Simulator (Mell *et al.* 2009), and FIRETEC (Linn and Harlow 1997, Linn *et al*. 2002).

A recent review of fire-related remote sensing methods by Lentile *et al.* (2006) discussed remote sensing methods in the middle infrared (MIR: 3 µm to 5 µm) and thermal infrared (TIR: 8 µm to 4 µm). Several methods exist that can provide ground-based, airborne and satellite sensor estimates of the energy radiated by the combustion of fuels within each fire-affected pixel (Kaufman *et al.* 1996, Butler *et al.* 2004, Riggan *et al.* 2004, Ichoku and Kaufman 2005, Smith and Wooster 2005).

Using any two infrared bands allows measurement of both the average radiant fire temperature and the emissivity-area product for an individual pixel, which allows calculation of the fire radiated power and, by time integration, the fire radiated energy (Dozier 1981, Matson and Dozier 1981, Riggan *et al.* 2004). Several studies have shown strong linear relationships between the rate of radiant energy release and the rate of fuel consumption (Kaufman *et al.* 1996; Wooster 2002; Wooster *et al.* 2005; R.L. Kremens, unpublished data). These linear relationships have been demonstrated in a range of fuel types including hardwoods (R.L. Kremens, unpublished data), a range of forest types within the western United States (Ichoku *et al.* 2008), and African savannas (Wooster 2002, Roberts *et al.* 2005, Wooster *et al.* 2005, Freeborn *et al.* 2008).

If the heat of combustion of the fuels is known (see, for example, Johnson [1992]) then the biomass consumed per pixel can be calculated (Andrews and Rothermel 1982) by:

$$M_c = \frac{FRE}{F_r\, H_c} \qquad (1)$$

where M_c is the fuel mass consumed per unit area, H_c is the heat of combustion of the fuel, and F_r is the fraction of the total energy release (per unit area) that is transported by radiation. Constancy of F_r with flame size, fuel type, fuel moisture, and slope, etc., is assumed in many cases, but has not been extensively measured. Without knowledge of F_r, estimation of any quantity derived from heat release—smoke production, fuel consumption, or ecological effects —is subject to large errors. Experiments are being undertaken now to determine the validity of the assumption of constant F_r over a range of fire scales and intensities.

Several methods have been developed to measure radiant power using infrared emissions. All of these methods make assumptions about the shape of the emitted radiation spectrum. The most common assumption is that the radiant flux is due to one or more ideal grey- or black-body radiators. In the case of a wildland fire, the radiation from a large flame (~1400 K) dominates any cooler background emission due to the T^4 dependence of blackbody emission. For example, a hot large flame (ε = 0.15) at 1400 K radiates about 10 times more energy per unit area than a warm soil-surface (ε = 0.85) background at 500 K.

For a gray body with emissivity ε that is not a function of wavelength, Planck's radiation law can be written (expressed in wavelength units, e.g., microns or nanometers):

$$W(T) = 2\pi\varepsilon hc^2 \int_0^{\infty} \frac{d\lambda}{\lambda^5 (e^{\frac{hc}{\lambda kT}} - 1)} \quad (2)$$

where the integration is over all wavelengths, c is the speed of light, h is Planck's constant and k is Boltzmann's constant. For a given temperature, integrating over all wavelengths yields the familiar Stefan-Boltzmann law for the total radiant power (per unit area of emitting surface):

$$W(T) = \varepsilon\sigma T^4 \quad (3)$$

where σ is Stefan-Boltzmann's constant and ε is the emissivity of the surface.

For the realistic wildland fire example of a single high temperature gray body (flaming fire front) or two gray bodies with widely different temperatures (flaming fire front and low temperature soil or char background), energy flux from the fire may be estimated using either a radiometer with very wide spectral response (say 0.1 µm to 50 µm, to include all radiation emitted by the fire) or by two or more radiometers with limited spectral response (pass bands of 1 µm to 5 µm FWHM). Using two detectors, an estimate of the radiant temperature T of the source can be obtained, from which the radiant flux may be estimated using Equation 3. A two-detector system with the detectors having wavelength passbands from λ_1 to λ_2 and λ_3 to λ_4, respectively, is assumed. Detector passbands are commonly adjusted to lie within the atmospheric transmission windows at 3µm to 5 µm and 8 µm to 14 µm (that is, the ranges of wavelengths that are least absorbed by atmospheric gases). A further condition is that the entire field of view of the detector is occupied by the target at temperature T. Integrating the Stefan-Boltzmann equation over the passband of each detector:

$$W(T)_{\lambda_1,\lambda_2} = 2\pi\varepsilon hc^2 \int_{\lambda_1}^{\lambda_2} \frac{d\lambda}{\lambda^5 (e^{\frac{hc}{\lambda kT}} - 1)} \quad (4)$$

$$W(T)_{\lambda_3,\lambda_4} = 2\pi\varepsilon hc^2 \int_{\lambda_3}^{\lambda_4} \frac{d\lambda}{\lambda^5 (e^{\frac{hc}{\lambda kT}} - 1)} \quad (5)$$

where $W(T)_{\lambda,x\lambda,y}$ is the flux in the different wavebands (λ_x to λ_y) at temperature T. If the source radiates like a gray body, the ratio of the response of the two detectors is a unique function of temperature and detector passbands, so the equivalent radiative (brightness) temperature T can be determined from the observed ratio, $R(T)$, by iteration or table look-up:

$$R(T) = \left(\frac{W(T)_{\lambda_1,\lambda_2}}{W(T)_{\lambda_3,\lambda_4}} \right) \quad (6)$$

To use two radiometers to measure the fire radiant power where there is also the possibility that the field of view of the detector may not be totally occupied by the fire, the following argument proposed by Dozier (1981) can be used. The power reaching a detector W_d is now a function of both the source temperature and area of the source as compared to the total area subtended by the detector. Defining a parameter A_f, the fractional area occupied by the hot source, $(1\text{-}A_f)$ becomes the fraction of the field of the detector view occupied by the (relatively) non-emitting background. Equation 4 and 5, above, would then be modified to:

$$W_d(T)_{\lambda_1,\lambda_2} = 2\pi A_f \varepsilon hc^2 \int_{\lambda_1}^{\lambda_2} \frac{d\lambda}{\lambda^5 \left(e^{\frac{hc}{\lambda kT}} - 1\right)} \quad (7)$$

$$W_d(T)_{\lambda_3,\lambda_4} = 2\pi A_f \varepsilon hc^2 \int_{\lambda_3}^{\lambda_4} \frac{d\lambda}{\lambda^5 \left(e^{\frac{hc}{\lambda kT}} - 1\right)} \quad (8)$$

and again, rewriting the definitions from equations 4 and 5, above:

$$W_d(T)_{\lambda_1,\lambda_2} = A_f \varepsilon\, W(T)_{\lambda_1,\lambda_2} \quad (9)$$

$$W_d(T)_{\lambda_3,\lambda_4} = A_f \varepsilon\, W(T)_{\lambda_3,\lambda_4} \quad (10)$$

Because the detector output W_d and the temperature T is known, the fractional area-emissivity product can be obtained:

$$A_f \varepsilon = \frac{W_d(T)_{\lambda_1,\lambda_2}}{W(T)_{\lambda_1,\lambda_2}} \quad (11)$$

Knowing T and the εA product, the integrated form of the Stefan-Boltzmann equation is now used to calculate the total radiant flux P (W m^{-2}) emitted per unit area:

$$P = \varepsilon A_f \sigma T^4 \quad (12)$$

A flowchart of the process of extracting the flux and emissivity area product from raw two-band detector infrared data is shown in Figure 1. It should be noted that, in the case just discussed of a detector with a field of view not totally filled with fire (sub-pixel) and the fire at an unknown temperature, it is impossible to determine the radiant flux using a single, limited wavelength response detector.

For observations of gross fire location or to roughly estimate total energy release from a fire, satellites can be used. Satellites have spatial resolution from 4 km (GOES I-M) to 30 m (Landsat 5 MSS) and temporal resolution from 30 min (GOES I-M) to weeks (Landsat 5 MSS). For a remote sensing platform, the FRE is calculated by time-integrating the sensor-reaching power from each pixel over the duration of the fire. This can only be done with sufficient time resolution using geosynchronous satellites or by flying repeatedly over the fire with an airborne data collection system. Rough estimates may be made of the FRE using systems that observe the fire infrequently (e.g., data from the Moderate Resolution Imaging Spectroradiometer, MODIS, or from a few overflights by an airborne collection system). These estimates are subject to large errors due to the inability to predict the behavior of the fire adequately between observations (violation of the Nyquist-Shannon sampling theorem in time; Shannon 1949). The MODIS 14 active-fire product estimates the heat flux for all detected fire-affected pixels within a MODIS pass. The product is freely available (http://edcdaac.usgs.gov/dataproducts.asp), and since the MODIS sensor system is aboard both the AQUA and TERRA satellite platforms, the product can be acquired 3 to 4 times per day. Although this temporal resolution remains insufficient for operational or precision

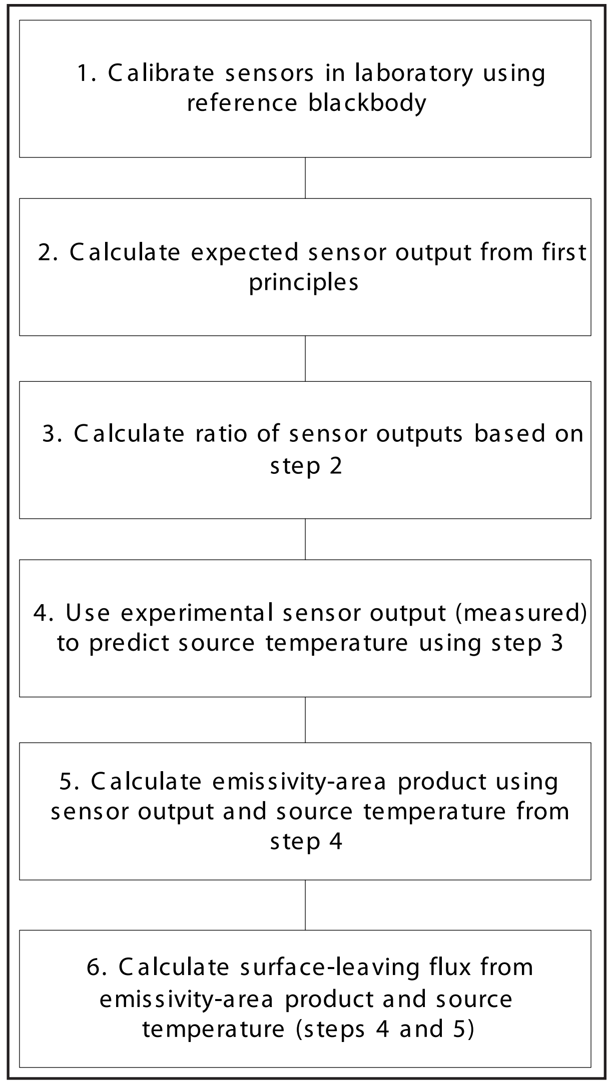

Figure 1. Flowchart of the dual-color thermometry method for deriving the radiative pixel kinetic temperature and emissivity-area fraction product from the ratio of detector outputs in two wavebands. We use this method to estimate the flux from prescribed and experimental (small plot) fires using multi-band infrared sensors.

monitoring of fire behavior, it may provide sufficient detail to accurately evaluate pyrogenic emissions (Wooster *et al.* 2005). The product contains the latitude and longitude, time of day, and heat flux of each pixel in which an active fire is detected. Estimates of FRE can be made from this product, but ground validation of these estimates has been lacking, and the estimates must by nature be suspect because of temporal undersampling.

FRE, FRP, and fire location can be measured more accurately with airborne sensors when operated in a quick return mode. In this mode, the aircraft passes above the fire repeatedly with as short a return time as possible. Depending on the size of the fire and the maneuverability of the aircraft, high spatial resolution (~1 m to 3 m) and fairly high temporal resolution (2 min to 10 min) may be obtained. We consider overhead observation of fires with infrared sensors at short return intervals to be the best technique available for observation of fire phenomena over areas of 20 ha to 2000 ha.

High temporal resolution, geosynchronous satellite sensors such as Meteosat Second Generation (MSG), SEViRI, and GOES Imager have been used for measurement of FRE and FRP, but the usefulness of these instruments is limited because of the low spatial resolution (~5 km) of the sensors (Prins and Menzel 1992, Prins *et al.* 1998, Hufford *et al*. 1999, Wooster *et al.* 2005). Kaufman (1996) remarked that measurements of the radiant heat flux using satellite sensors was likely to accurately represent the fire intensity as the FRP is proportional to the fractional cover of active fire and the fuel consumption within that pixel. The relationship between fire intensity and FRP has been illustrated in different fire types by Smith and Wooster (2005), but Wooster *et al.* (2005) also demonstrated that the energy as measured as radiant sensor-reaching flux by a remote sensing platform only represents about 14% (14% being the fire radiative fraction as defined in Equation 1) of the total energy released from the fire. Although we consider the FRE to be a direct (first-order) measure of fire behavior, accurately relating FRE to total heat release from the fire awaits research to quantify the variation in fire radiative fraction across a range of fire conditions and fuel types.

An example of an overhead field-scale sensor system as implemented by our research group is shown in Figure 2. This system uses

Figure 2. Overhead fire monitoring station for field use consisting of a downward-pointing dual-band infrared sensor, weather and gas (CO, CO_2) sensors, all mounted on a portable 6.2 m tower. The image was captured during a series of experiments (Rx-CADRE) conducted in the longleaf pine-wiregrass ecosystem of the southeastern United States.

a downward-looking dual band infrared sensor to measure FRP and FRE with a time resolution of 1 s. The field of view of the detectors is typically about 10 m^2. The system also contains gas analysis (CO and CO_2), temperature measurement (ground and air temperature), and wind measurement equipment (wind vane and cup anemometer at 3.2 m and 6.1 m). Figure 3 shows a measurement of FRP and FRE (calculated from a time integral of FRP) from a small plot fire experiment using the methods described above.

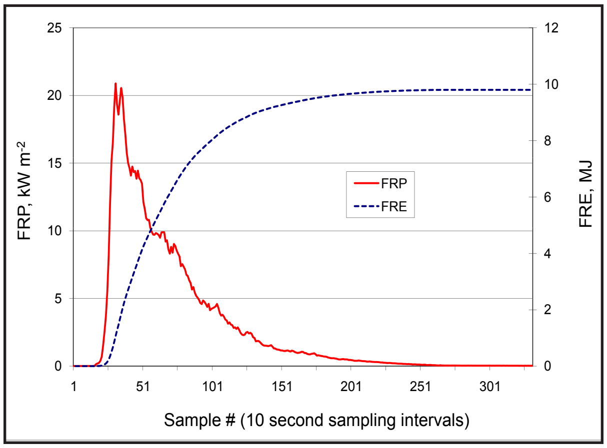

Figure 3. Measurement of FRP and calculation of FRE from a small plot experiment using the overhead sensor system shown in Figure 2. The sampling interval was 10 seconds. Infrared radiation data were collected over a ~20 m^2 area within a 64 m^2 plot in which eastern US hardwood fuels were burned. The fuel loading for this experiment was 3.36 kg m^{-2}. In this experiment, fuel consumption was nearly complete.

Measuring the Fire Convective Field

Key parameters for modeling convective heat flux include: gas velocities in and around flames, gas temperatures, surface temperatures of target materials, and surface characteristics of the target materials (roughness, porosity, shape) that determine the aerodynamic efficiency of convective heat transfer.

Measurement of the relative intensity of the convective field (as a fraction of the total energy field) has been performed previously using thermopile bolometers. In this method, two ground-based bolometers observe the same field of view. One bolometer is covered with a window that blocks convective and conductive flows, while the other is open to all energy transport mechanisms. The open sensor gives the total flux, whereas the covered sensor measures the radiative flux transmitted through the limited bandpass window. The ratio of the radiative and total flux gives the radiative flux fraction, which is an important parameter in fire predictive models as this ratio determines the long range transport of energy from the flames due to radiation vs. the short range energy transport due to direct flame contact with the hot working fluid from the fire. While this method determines the convective and radiative energy flows to a surface at a point (e.g., the bolometer imbedded within a tree bole; Jones *et al.* 2006), there is little hope of measuring the convective field in the same way that the radiative field can be measured (over a landscape), as convective measurements are by nature short-range measurements.

While the radiative field around a wildland flame is fairly isotropic, that is, equal in all directions (B. Butler, Forest Service, personal communication), the convective field is highly non-isotropic and must be measured by a number of sensors simultaneously. Efforts are underway at Rochester Institute of Technology to produce low-cost (2009 150 US$) flow-temperature sensors and recording packages to enable the convective energy field to be monitored practically at high spatial resolution in three dimensions. The sensors are based on the relationship between flow and pressure (McCaffrey and Heskestad 1976, Newman 1987) and consist of silicon differential pressure sensors and simple flow probes. Recently, sonic anemometers suitable for use within fire plumes have become available commercially (Clements 2007). These devices show promise as an alternate means to measure convective flux averaged over longer path lengths (several meters).

Measuring the Fire Conductive Field

Conduction is the dominant energy transport mechanism in soil and within biological subjects, although soil convective fluxes have also been quantified (see Massman *et al.* [2010]). High spatial resolution (~ cm) assessment of soil heating profiles can be obtained using thermocouples placed *in situ* within the soil profile. The main challenge is the placement of these thermocouples in undisturbed soil or underneath existing fuel strata. Disturbing the soil can change its packing fraction and density, which can cause significant changes in soil thermal conductivity, modifying energy transport. In spite of these difficulties, pre- and post-fire vertical profiles of soil temperature, soil moisture, and soil thermal properties have been directly measured (Kay and Goit 1975, Campbell *et al.* 1994, Massman *et al*. 2010). Fiber-optic temperature profilers that have the capability to produce three-dimensional profiles of soil heating have been deployed over sampling distances of a kilometer with meter resolution. These systems are already being used to measure temperature profiles within lakes and along riparian channels, and we await experiments to apply these techniques to the fire soil matrix at large scales.

POST-FIRE REMOTE SENSING OF FIRE EFFECTS

The challenge with the majority of applied remote sensing studies is that a dichotomy often exists between the need for 1) direct quantifiable physical linkages between the satellite sensor metric and the surface property being assessed, and 2) methods that can be easy to understand and can be applied efficiently across a series of different environments and scenarios. This dichotomy is readily apparent in the remote assessment of fire effects (Lentile *et al.* 2006, Keeley 2009).

In fire ecology, and indeed most of fire-related land management, there is a widespread acceptance of maps derived from remote sensing data that describe the severity of a fire event. Burned Area Reflectance Classification (BARC) maps that can be produced with data from numerous satellite sensors are widely used by Burned Area Response (sometimes Rehabilitation) (BAER) teams to characterize burned areas by fire impacts on numerous kinds of values including social, ecological, and economic (Lentile *et al.* 2006).

The prevailing challenge from a physics standpoint is that in most cases the severity is a dimensionless measure, often characterized by the qualitative descriptors of low, moderate, and high (Lentile *et al.* 2006, Keeley 2009). Given that land managers are familiar with the concept of severity for post-fire rehabilitation and mitigation efforts, it has been suggested that usage of such familiar terms should continue, but should be limited to total fuel consumption in fires (Keeley 2009), and that other post-fire effects should be clearly described (Lentile *et al.* 2006). Although severity has many meanings, and thus generates confusion, it is a term widely used by US organizations from the US Geological Survey and the Forest Service to the North American Carbon Program. For example, the 2005 North American Carbon Program science plan observed that, “ultimately, the severity of a burn event has important consequences for the long-term (decadal) trajectory of carbon accumulation” (Denning 2005).

From the physics perspective, the measurables that remote sensing systems can directly acquire are all derived from sensor-reaching radiance and include the spectrally modified sunlight reflected from surface features, the emitted radiation from warm surfaces and the vertical locations of objects derived from laser or radio ranging systems. Second-order metrics are often inferred or modeled from these fundamental physics measurables. These secondary measures can include an estimate of fractional cover from multi-spectral data or object heights from structural (LiDAR) data. Tertiary metrics can include derived parameters used in applied problems such as assessments of carbon stocks and net primary productivity.

The farther the derived quantity is from the fundamental physical measurable, the more the measurement becomes speculative or dependent on the exact physics in a model or chain of models. In our opinion, many of these derived quantities should be used with caution. For example, deriving primary productivity from measurement of normalized-difference-vegetation index (NDVI) (Rouse *et al.* 1974) requires several modeling steps in succession, all of which are subject to details that cannot be directly measured.

Historically, remote sensing research can be considered to have evolved due to advances in acquisition and digital analysis capabilities. The goal at each stage of evolution has been to increase the quantity of first- and second-order metrics that can be obtained from imagery. Prior to the wide availability of spectral datasets, digital image analysis focused on the analysis of moments. The first moment represents the digital number values, whereas the second moment represents the variation of values; analysis of first and second moments and their distributions have been widely used for the assessment of burned areas and fire effects (e.g., Hudak and Brockett 2002, Smith *et al.* 2002). The availability of multi-spectral remotely sensed data has allowed development of methods to derive fire effects or fire severity using spectral indices, signatures, and more sophisticated spectral analysis techniques. Work has begun to derive assessments of vegetation and surface morphology using LiDAR point cloud data, but these efforts are still preliminary and subject to large errors. Object-oriented remote sensing, where neighboring pixels that share similar characteristics are classified into objects (Smith *et al.* 2008), has enabled production of additional second-order metrics, including the crown sizes of shrubs and trees (Strand *et al.* 2006, Falkowski *et al.* 2008).

Early research that used remote sensing data to evaluate post-fire effects mostly focused on comparisons between metrics derived from reflectance data and those derived from field data (Lentile *et al.* 2006). Examples included directly measurable field features such as vegetation mortality as a proportion of live plants per unit area, vegetation consumption in mass per unit area (Hall *et al.* 1980, Miller and Yool 2002), and vegetation recovery described by post-fire spectral index trajectories (Henry and Hope 1998). Other studies have focused on comparing spectral datasets to characteristics of post-fire soil surfaces, such as the presence of soil charring that occurs due to the oxidation of iron present in the soil matrix. Soil charring has been observed with hyperspectral remotely sensed images as well as with field studies. As with the deposition of mineral ash due to complete vegetation consumption, the presence of orange deep soil char is spatially heterogeneous and is not likely to be quantifiable with satellite based sensors (Smith and Hudak 2005).

Since 2000, the majority of remote sensing studies that are developing maps of the post-fire environment have focused on the application of spectral-index-based approaches to infer a suite of field-based post-fire measurables (Lentile *et al.* 2006). These studies are attempting tertiary assessments because they use reflectance to produce indices, and then use empirical rather than physics-derived relationships to estimate surface metrics from those indices. By their nature, these empirical models do not address causality between surface and remotely sensed metrics (Lentile *et al.* 2009). For example, the field metrics of the amount of duff consumption and change in shrub foliage (Key and Benson 2006, De Santis and Chuvieco 2009) are often used in the composite burn index (CBI) that is often regressed against the spectral index, termed the differenced normalized burn ratio (dNBR).

Several studies have compared secondary measures such as remotely sensed modeled fractional cover to fractional cover of the same measurable on the ground. Hudak *et al.* (2007), Smith *et al.* (2007), and Lentile *et al.* (2009) compared remotely sensed measures of percentage green and cover of charred material with ground based measurements. Although shrub cover may have an impact on reflectance, and thus the spectral indices in low-canopy-cover forested areas or in rangelands, no causal link was apparent between vertical duff consumption and a reflective satellite sensor metric. These same studies have indicated only indirect relationships between the duff and litter consumption, fire intensity, and, in turn, fractional charred cover (Lentile *et al.* 2009).

Although the normalized burn ratio (NBR) family of indices has been widely adopted for operational use, numerous studies have observed fundamental problems with their application (Roy *et al.* 2005, Hudak *et al.* 2007, Smith *et al.* 2007, Lentile *et al.* 2009). The relationships between NBR and commonly observed post-fire effects are non-linear and exhibit dependencies on scale, ecosystem, and soil type (van Wagtendonk *et al.* 2004, Epting *et al.* 2005, Wimberly and Reilly 2007, Lentile *et al.* 2009). Therefore, to employ such methods in describing the post-fire environment in an operational setting, field calibration that captures the variability in the vegetation and soil properties is essential.

For research on remote sensing of fire effects to continue to develop and evolve, the fire ecology and management community must be willing to consider alternatives to NBR and similar indirect assessments of fire effects, because these indices are too far removed from the physical measures of the energy field. Ultimately, what are needed are methods that directly measure or infer the consumption (absolute or proportion) of fuels in a manner that is compatible with both the physics-based active fire measurements (such as FRP) and fire behavior models (Linn *et al.* 2002, Mell *et al.* 2009) that are under development.

In each of these cases, different potentials and gradients will govern the subsequent productivity of the vegetation or status of the soil. For example, the soil water potential determines the ability of water to be drawn through the soil stratum, and the stomatal conductance determines the ability of the plants to transpire. As such, perhaps as an analogy to the radiation fields, we can consider the pre- and post-fire environments to occupy potential fields, described by the water potentials in the soils, vegetation, and atmosphere. Alternatively, through techniques including the fuel cell concept (Hiers *et al.* 2009), this environment could be considered as a biomass field, where the biomass field would be characterized by its volumetric arrangement, abundance, and status (live-to-dead or carbon-to-nitrogen ratio). It is essential that whatever metrics are used, post-fire effects are described in terms of common units (Keeley 2009), whether this is flux of carbon, nutrients leaving a system, or changes in soil water potential between the post- and pre-fire environment (Lentile *et al.* 2009).

RESEARCH AND APPLICATION NEEDS FOR MEETING THE GRAND MEASUREMENT CHALLENGE

Even using the most modern sensor systems, not all of the radiative energy from the combustion of fuels within an active fire pixel will be recorded at the sensor. Specifically, some of the radiative energy may be absorbed by the ground or obscured by cooler smoke, cloud, and ash existing between the fire and the sensor (Kaufman *et al.* 1996, Wooster *et al.* 2005). Wooster *et al.* (2005) formulated a model to correct measured FRE for the effects of clouds obscuration for satellite sensor observations. These impacts on the measured radiative energy are governed by the fuel moisture, fuel chemistry (e.g., oils), and fuel arrangement. Research using modeling and closely coupled experimentation is needed to evaluate the effects of the emitted smoke and aerosols on the atmospheric opacity, and thus the measured radiant energy. The goal of this research should be to characterize the variability in FRE not only under a range of fuel and fire conditions, but also under atmospheric conditions. Until these relationships are known, we must use even these direct, first-order methods of fire energy estimation with caution.

A detailed sensitivity analysis of the FRP estimation method is included in Wooster *et al.* (2005). Although it is clear that remote sensing can provide a measure of FRP, FRE, and landscape spread (patterns), an important next step in the calibration of these measures is to provide fire characteristics that can actually be used to predict fire behavior and ecological effects (for instance, fuel consumption, flame geometry, flame emissivity, gas emissions, etc.). Further research is therefore warranted to assess these relationships under a variety of fuel types and fire intensities. For example, research is needed to evaluate the relationship between radiative energy and biomass consumed at very high fuel loads; experiments such as those done on the Canadian Crown Fire (Stocks *et al.* 2004) may be appropriate for answering such research questions. The fire radiative fraction has only been directly measured in a limited number of cases under a restricted set of fire size, fuel, weather, and topographic conditions.

Massman *et al*. (2010), Butler and Dickinson (2010), Kavanagh *et al*. (2010), and Stephan *et al.* (2010) demonstrate that fires affect vegetation, soils, and airflow, each of which have substantial effects on the terrestrial, subterranean, and atmospheric biogeochemical and hydrological cycles. However, there are substantial unknowns related to the magnitude, duration, and wider impact (temporally and spatially) of fires of varying characteristics on local- to regional-scale fluxes. For example, after wildfires, evapo-transpiration (ET) is diminish due to the lack of canopy and, consequently, water storage within the soil profile increases; yet increases in exposed bare soil can cause high soil temperatures and high soil evaporation rates. Linking remote measures with these effects, from a process standpoint, requires that any remote measure ultimately reflects material cycles (e.g., fluxes and storage of carbon, nitrogen, water, etc.) and ecosystem states, and this cannot be done through the use of non-transferable or non-scalable qualitative indices.

If studies persist in using remote sensing-based methods to characterize the post-fire environment, several steps should be considered. First, the use of definable, repeatable, and transferable (across ecosystems) units in the post-fire metrics are essential (Keeley 2009). Units enable connection with physics models of the energy field and will simplify scaling. Second, consistency should be sought in the comparison between the remote sensing and validation data. Specifically, as noted by Miller *et al.* (2009) and others, if differenced spectral indices are used (i.e., indices that subtract the value at one date from another), then similarly differenced field measurables should also be used.

Third, it is essential that both the fire ecology and remote sensing communities encourage the publication of repeated and retested experimental approaches, whether these involve new metrics or physical process models. This fundamental technique from the physical sciences has been lost in most applied disciplines, with most journals and reviewers seeming to adopt a "first come, first published" attitude. However, the retesting of the same research methodology in an identical environment is essential for the community to understand the robustness and sensitivity of any particular metric or model. In a similar manner, research should be encouraged that retests methodologies in alternate environments and ecosystems, or with different initial conditions or instrumentation. As an example, the majority of NBR based research and validation focused on forested environments (Lentile *et al.* 2006); however, some assessments in non-forested environments have found limitations with this approach (Epting *et al.* 2005, Roy *et al.* 2005, Smith *et al.* 2005, De Santis and Chuvieco, 2009). Similarly, the relative differenced Normalized Burn Ratio (RdNBR) was initially developed in Californian vegetation types (Miller and Thode 2007, Miller *et al.* 2009), but has been shown to exhibit limitations in some forested environments (Hudak *et al.* 2007). Finally, field measurables should exhibit a clear and transparent linkage to a first- or second-order remote sensing metric.

It is clear that the next advances in fire research will take place when new instruments and methods, and new modeling codes capable of assimilating the data produced by these new instruments, become widely available. A large number of fundamental measurements of wildland fire phenomena have not been made with sufficient accuracy or over a sufficient range of fire and fuel conditions. For flames, measurements of emissivity, fine scale (local) temperatures, spectral characteristics, radiant energy fraction, and detailed analysis convective flows are needed. Some of these measurements require development of new instrumentation and experimental techniques, with appropriate funding. For targets (biological or soil), measurements are needed of emissivity, thermal conductivity, surface roughness, and the evolution of water vapor and other gasses with heating.

Some instruments, such as spectrometers, high resolution thermal imaging cameras, and similar devices, will in the short term remain expensive and cumbersome to operate outside the laboratory, while instruments designed specifically for the field will become smaller, lighter and less expensive and so will allow fine-scale point measurements to be made within the fire. The instruments will be used not only for improving modeling codes, but also to provide critical tests of the validity of overhead observations from airborne and satellite platforms.

Wireless integrated sensor networks may be needed to measure fine-scale soil, weather, and vegetation parameters. Wireless networks will allow sensors to be set up quickly and over a wide spatial area without cumbersome and interfering wires. A nested design consisting of microsite, stand, and landscape sensor networks may allow measurement of physical observables at all spatial scales.

Studies using high spatial resolution ground LiDAR to capture fine-scale surface and fuel heterogeneity are exciting because these techniques may prove to be the only methods capable of observing fuel arrangement (and possibly fuel size) rapidly over large areas. Ground-based LiDAR may be used before and after the fire to determine consumption. LiDAR maps of fuel arrangement and mass are required to allow accurate benchmarking of physics-based fire behavior models. Airborne LiDAR collection is just as exciting as it may provide a method to assess fuel loadings over landscape scales at reasonable costs (Evans *et al.* 2009). As we have mentioned, though, the excitement of the LiDAR technique must be tempered by the fact that the technique is only relevant when practical models have been developed relating the point cloud to actual physical observables. So far, this data-model connection is lacking.

To meet the grand measurement challenge, it is essential that research be conducted that seeks to bring together scientists who work across the temporal gradient from pre-, active-, and post-fire, and across a range of spatial scales (from the plant to the landscape). An example of this is the current Rx-CADRE (Prescribed Fire Combustion-Atmospheric Dynamics Research Experiments) project being conducted by the Core Fire Science Caucus, a self-organized group of North American wildland fire science researchers that seeks to advance fire behavior and fire effects model development and validation.

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