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Final Report

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Project Title: Wireless Instrument for Automated Measurement of Clean Cookstove Usage and Black Carbon Emissions

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Executive Summary

Black carbon (BC) emissions from traditional cooking fires and other sources are significant anthropogenic drivers of radiative forcing. Clean cookstoves present a more energy-efficient and cleaner-burning vehicle for cooking than traditional wood-burning stoves, yet many existing cookstoves reduce emissions by only modest amounts. Further research into cookstove use, fuel types, and verification of emissions is needed as adoption rates for such stoves remain low. Accelerated innovation requires techniques for measuring and verifying such cookstove performance.

The overarching goal of the proposed program was to develop a low-cost, wireless instrument to provide a high-resolution profile of the cookstove BC emissions and usage in the field. We proposed transferring the complexity of analysis away from the sampling hardware at the measurement site and to software at a centrally located server to easily analyze data from thousands of sampling instruments.

We were able to build a low-cost field-based instrument that produces repeatable, low-cost estimates of cookstove usage, fuel estimates, and emission values with low variability. Emission values from our instrument were consistent with published ranges of emissions for similar stove and fuel types. The following significant results were demonstrated as part of this work:

- We developed a method to isolate black carbon from organic carbon by using a color transformation on the RGB components of filters exposed to cookstove emissions. Building on previous work by the authors on calculating aerosol concentrations from a single color channel in a photograph of an air filter that has been exposed to pollutants, this method can be integrated into the photographic method already published (Ramanathan et al., 2011). Sensitivity of the measurement was related to the load on the filter. Percent relative difference between predicted and observed for OC is 0.1 ± 21.1% (mean ± SD) and for EC (proxy to BC) is 1.6 ± 19.2%. This is a major step forward for inexpensive particulate analysis. Further, organic carbon is an important component of cookstove emissions and therefore necessary to measure when profiling cookstove emissions in the field.
- We developed mathematical models using temperature data to quantify the cooking duration and the amount of a known type of fuel used during cooking. As part of this work, a method for standard temperature measurements on any cookstove using a low-cost wireless temperature sensor was developed. In field trials using the wireless temperature sensor, estimated cooking time using the decision tree averaged 1.4 ± 0.6 h (n=31) for each event, which was not statistically different ($P > 0.4$; paired t-test) than observed cooking time of 1.5 ± 0.6 h; and fuel use was estimated with an average error relative to the reported fuel consumed of 15.5 ± 25.2% (absolute error of 26.3 ± 20.3%). Cooking duration and fuel weight are a second key component for calculating emissions in the field.
- We also demonstrated the ability to produce repeatable measurements of BC emissions produced by a cookstove using particles sampled with a filter inline with inexpensive gas sensors. Fuel weight and cooking duration is measured with the wireless temperature sensor. The emissions rates estimate for Hickory tests (n=5) averaged 0.65 ± 0.06, for Pine (n=4) averaged 0.52 ± 0.08 and that for charcoal (n=4) was 0.03 ± 0.01, indicating that with a consistent placement of the sampling tube, a repeatable estimate of emissions can be made with low variability. This method can aid researchers and manufacturers in improved cookstove design for testing under real-world conditions in the field, where a greater variation of data is encountered compared to laboratory analyses.

Taken together, these results make it possible to monitor the emissions of a clean cookstove in the field cost-effectively, without the use of a hood or any other labor-intensive or costly infrastructure.

Comparison of Accomplishments with Goals

Increased adoption, performance development, and financing of clean cookstoves can be significantly bolstered and facilitated through in-situ techniques for measuring cookstove usage and emissions. Recent published work by the authors showed that it is possible to calculate aerosol concentrations from a single color channel in a photograph of an air filter that has been exposed to pollutants.

We proposed to show that this basic technique could be extended to enable:

1. The discernment of BC from other light-absorbing particulate matter on collected aerosol samples.
2. The automated detection of stove and fuel types as determined through the collection of temperature and stove use duration data.
3. The application of such data to generate an estimate of BC emissions from overall concentration levels.

Our results are summarized below and encapsulated in Table 1.

Goal 1, the separation of BC from other light-absorbing particulate matter on collected aerosol samples, consisted of three sub-goals: (a) Collect sample sets for testing and validation, (b) calculate spectral dependence of coarse absorption, and (c) isolate black carbon in the samples from other light absorbing or reflecting particles such as organic carbon (OC).

Accomplishments for Goal 1: Laboratory analyses of EC were made as a proxy to BC. (a) 32 analyzed filter samples were provided through collaborators as sample sets for comparing EC to OC content. A further 410 samples were obtained through the Desert Research Institute, collected in three major urban centers in the USA. A further 600 samples were provided by the EPA during laboratory experiments on cookstoves, although metadata is unavailable.

Of the 32 analyzed filter samples obtained, (b) the spectral dependence of coarse absorption was determined for EC and OC. Specifically, (c) the Lightness component of the CIE Lab color space can be used to detect EC and the Normalized Green to detect OC in different samples, but calibration of the source will need to be performed. For example, Indian samples contained colored OC but US urban samples, the 410 EPA filters, had no correlation between EC or OC and color. This was expected from the type of aerosols sampled (U.S. urban cities without significant biomass burning). Spectral analysis of the EPA 410 samples measured to a resolution of 3 nm indicated that the response of both EC and OC loadings were independent of wavelength (Figure 2). This supports the observation that different qualities of pollutants will have to be calibrated separately. The EPA 600 data set did not have a sufficient range of OC values for such color analysis.

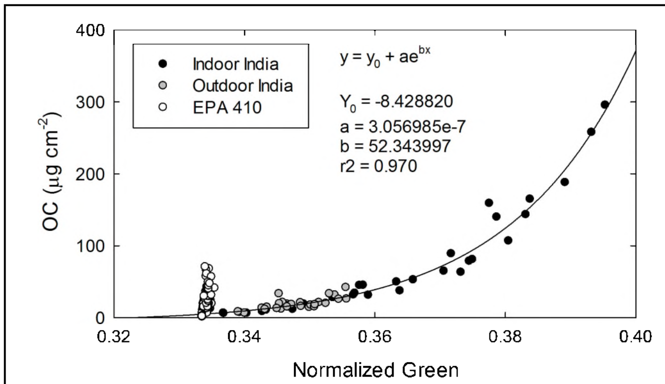


Figure 1. OC laboratory analysis versus color (Normalized Green). Biomass burning (India samples) produce colored OC whereas aged aerosols above US urban centers (EPA 410) with little or no biomass burning do not.

Goal 2, the automated detection of stove and fuel types as determined through the collection of temperature and stove use duration data, consisted of four sub-goals: (a) collect a sample dataset of temperatures during cooking for a set of common stove and fuel types, and (b) create an automated cooking classification from temperature readings to determine the duration of combustion, (c) the maximum temperatures

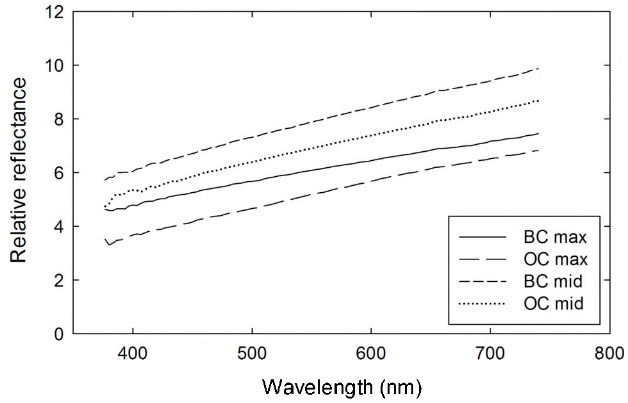


Figure 2. Spectral dependence of max EC loading (32.6 μg cm^{-2}), mid EC (16.05 μg cm^{-2}), max OC (70.4 μg cm^{-2}), and mid OC (35.4 μg cm^{-2}) measured to 3 nm resolution.

produced by a unit of fuel, and (d) the rate at which the fuel was consumed.

<u>Accomplishments for Goal 2</u>: (a) standardization of the location for temperature sampling of the stove body was required for comparison. Thus, a single location was selected on the stove body and on a removable metal J-bar. The temperature at 2.5 cm from the top of the cookstove and on the J-bar were determined to be sensitive enough for reliably identifying when cooking starts and stops, and cool enough (experiencing less than 200°C) to avoid the required use of more expensive, very high temperature sensing components. The J-bar allowed measurement of cooking on more than one type of stove without re-calibration. Cooking events of different durations and intensities conducted in the laboratory had similar temperature signals when measured at 2.5 cm from the top of the cookstove body and at 2.5 cm from the top of the J-bar (Figure 3).

More than 25 individual cooking events were conducted with temperature at various locations and fuel weights and rates of addition recorded. Duration of cooking (b) was determined using a decision tree model, constructed using rpart (Therneau and Atkinson, 2002) to predict cooking time based on sequential 5-second periods within the cooking events of different durations and intensities for the temperature sensor positioned at 2.5 cm from the top of the cookstove and J-bar. The decision tree consisted of 7 "splits" that used the instantaneous temperature, threshold temperature reached during a single cooking event, and the 60 s average rate of change in temperature as parameters to predict cooking. The error of classification and the absolute cross-validated error rate for last decision on the tree was 2.9%. The classification correctly identified cooking 91.8% of the time and correctly identified not cooking 94.8% of the time for the stove body. Cooking events that were misclassified as not cooking totaled 8.1 min and not cooking events misclassified as cooking totaled 20.8 min in the stove body model (74% of this misclassification occurred within the short-duration cooking tests). Classification of the J-bar resulted in a similar tree but with slightly better results.

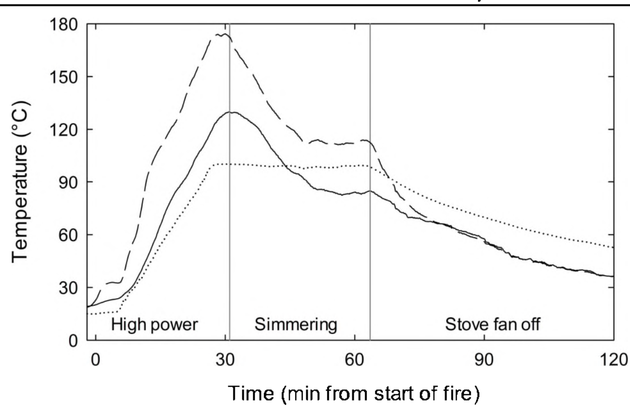


Figure 3. Representative temperatures of the stove body at 2.5 cm from the top (solid line), the J-bar at 2.5 cm (long dash), and in the pot of water on the stove (dotted line) during a 60 minute modified Water Boiling Test. Vertical lines indicate the separation between the "high power" start to bring water to a boil, the "low power" (simmering) phase, and the last fuel addition after which cooking ceased and the internal fan was turned off.

A field test of the cooking time algorithm was performed with collaborators in India. Four households were monitored for stove temperature and cooking times were recorded by an independent observer. Estimates of cooking time using the decision tree agreed well with the observed time in the field (Figure 4). Estimated cooking time using the decision tree averaged 1.4 ± 0.6 h

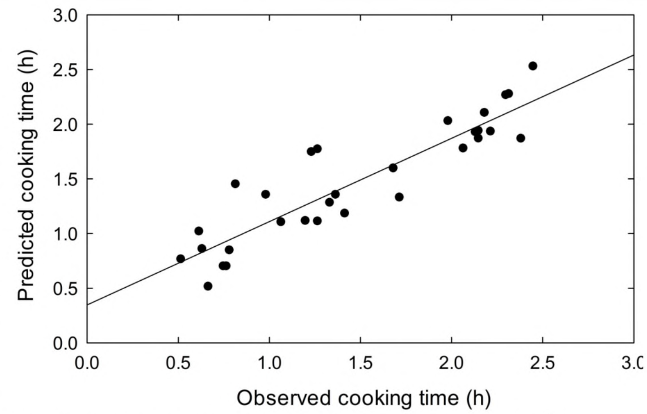


Figure 4. Reported cooking time in during 31 cooking events in 4 households related to predicted cooking time based on stove temperature using the decision tree.

(n=31) for each event, which was not statistically different (P > 0.4; paired t-test) than observed cooking time of 1.5 ± 0.6 h. The total amount of observed cooking time was 45.3 hours and for the decision tree it was predicted at 44.3 h. A regression of observed to predicted had a slope of 0.76 and an r^2 of 0.82 indicating a high degree of accuracy in predicting cooking time.

An energy balance model (Lewis and Nobel, 1977) was constructed to relate the temperature increases of the stove produced by a unit of fuel (c), and the rate at which the fuel was consumed (d). Specifically, parameters of longwave radiation, convection, and heat storage were considered for each cooking trial during conditions of thermal equilibrium before cooking (net energy equal to zero); any excess of energy entering the system was thus due to the combustion of fuel. Excess energy was then smoothed with a bisquare kernel weight function and regressed against the amount of energy contained in dry, non-resinous wood (1.9 MJ g-1; Ashton and Cassidy, 2007, p 189) to determine a transfer coefficient.

The total energy dissipated, as measured by the J-bar at the 2.5 cm position in MJ m^{-2} assuming a uniformly heated 1 m^2 area, was closely related to the total wood fuel, of various types, in kg used during complete laboratory cooking cycles (Figure 5). Oak was used for cooking events for different durations of high or low power cooking. Additional wood types, Hickory and Pine, were also used during one-hour mixed-power cooking tests. Specifically, the relationship had an intercept of 0.008 and a slope of 0.077 with r^2 of 0.97. The relationship between total energy measured by the J-bar and the total energy contained in the fuel used was linear, indicating a constant relationship across all tested fuel addition rates and wood types. The total amount of energy in the fuel lost to heating of the stove body using the J-bar estimation was 3.9%. An additional cooking test using charcoal was conducted, resulting in a different regression of energy to fuel weight consumed. The relationship for charcoal had a slope of 0.04 kg fuel per MJ m^{-2} energy dissipated, about 52% of that of wood, with an r^2 of 0.98 when the intercept is set to zero. Charcoal had about twice the energy content of wood (Figure 5), similar to other studies (e.g., Pereira et al., 2012), which would confound fuel estimations if fuel type were unknown. Thus, predicting fuel accurately in the field may be limited by uncontrolled conditions.

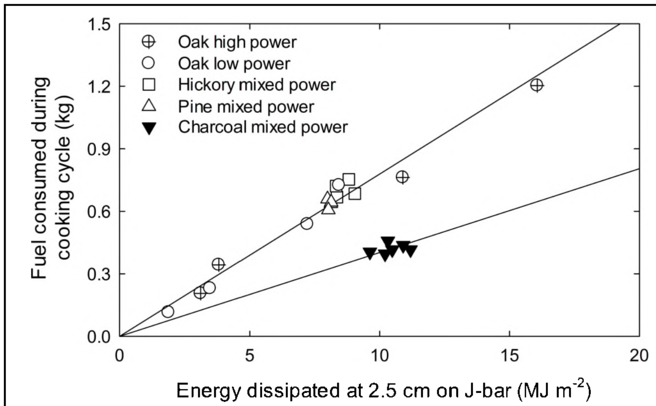


Figure 5. Total energy dissipated by the J-bar at the 2.5 cm position versus the total fuel used during complete cooking cycles. Values are summed 5 s samples of energy balance over the course of laboratory cooking using Oak under high power (open circles) and low power (crossed circles) fuel addition rates along with mixed-power cooking using Hickory (open squares) and Pine (open triangle). Charcoal (closed triangles) was also used in mixed-power cooking trials.

A field trial, similar to that for cooking duration, was also conducted to compare fuel

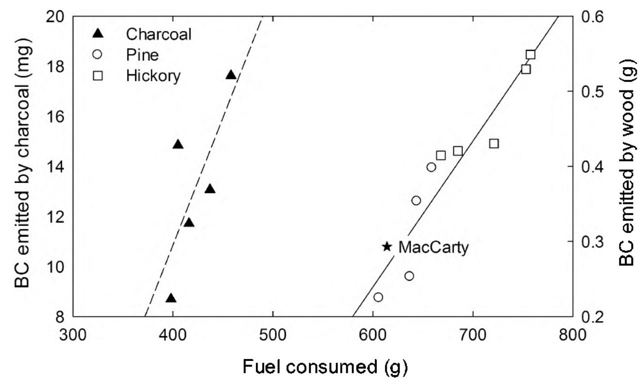


Figure 6. Emissions measured from cooking with two different types of wood and from charcoal.

use with estimates. Fuel use was primarily under-estimated with an average error relative to the reported fuel consumed of 15.5 ± 25.2% (absolute error of 26.3 ± 20.3%). A regression of observed to predicted had a slope of 0.53 and an r^2 of 0.33.

Goal 3, the generation of an estimate of BC emissions, consisted of determining a method to relate BC loading collected on a filter to the fuel type, cooking duration, and total emissions produced during combustion. We employed a carbon balance method for estimating total emissions (Roden et al. 2009). Specifically, this approach relies on the ratio between BC and a fuel "proxy" (CO plus CO_2, the gaseous products of combustion) in the exhaust gas to determine an emission factor. Samples were taken at 1.2 m above the cookstove so that initial dilution occurred through natural plume rise and the carbon contained in wood fuel was assumed to be 50% (Löwe et al., 2000).

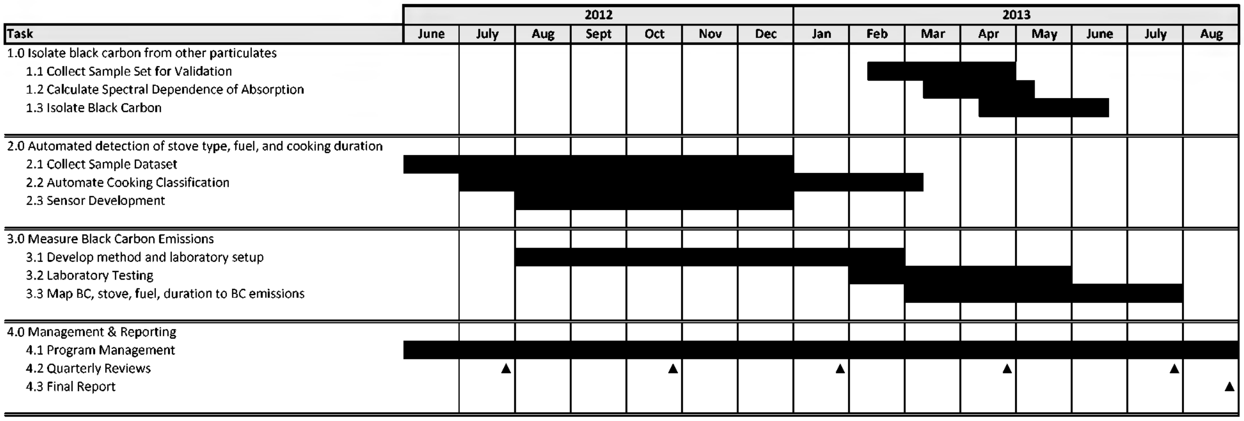
Accomplishments for Goal 3: Five water boiling tests using air-dried Hickory, four with pine, and four with natural wood charcoal were conducted to test the variability of estimating emissions using a high-particulate producing fuel (Hickory and Pine) and a low particulate fuel (charcoal)(Figure 6). An average of about 720 g of Hickory, 650 g of Pine, and 430 g of charcoal were burned per hour-long cooking event. The emissions rates estimate for Hickory averaged 0.652 ± 0.058, for Pine averaged 0.517 ± 0.078 and that for charcoal was 0.031 ± 0.007, indicating that with a consistent placement of the sampling tube, a repeatable estimate of emissions can be made with low variability. A published value for a battery-operated forced-draft stove (the type used in our study) indicated a similar emissions rate for wood (0.477 mg g^{-1}; MacCarty et al., 2011, indicated on Figure 6 by the star). The r^2 value for the linear fit to the data for wood was 0.88 and that for charcoal was 0.56. The dilution factor (averaging 105.4 ± 13.5, similar to 100 as cited by Roden et al., 2009) varied about ± 23% from the mean with ambient conditions (wind) and was not correlated with the emissions factor, indicating that it was possible to collect a representative sample of emissions with only a single inlet tube opening placed above the stove during cooking.

Table 1. Description of Original, Accomplished, and Unfinished Goals for Phase I.

Original Exit Criteria for Goal 1	Accomplished Exit Criteria	Unfinished Exit Criteria
1.1 Collect sample set. 100 filter samples for analysis, data for OC, EC, BC, spectral absorption, and coarse absorption for each sample.	410 filter samples from EPA urban areas analyzed for EC and OC and color analysis. 32 Indian filter samples analyzed for OC, EC, and coarse absorption. 600 EPA filters sampled for EC only.	
1.2 Calculate Spectral Dependence of Absorption. Our instrument produces spectral dependence values that are within ± 30% of those produced by the gold standard measures.	Spectral dependence was independent of EC and OC on the 410 filters spectrally analyzed to a resolution of 3 nm but dependent on coarse absorption for 32 Indian filters; percent relative average error of 0.1% ± 21.1% (mean ± SD).	
1.3 Isolate Black Carbon. Completed when our instrument produces BC values that are within ± 30% of those produced by gold-standard measures.	Percent relative difference between predicted and observed for OC is 18.4 ± 14.4% (mean ± SD) and for EC (proxy to BC) is 3.2 ± 2.5%.	
Original Exit Criteria for Goal 2	**Accomplished Exit Criteria**	**Unfinished Exit Criteria**
2.1 Collect sample data set. Ground-truth emissions established for 2 different stoves, 3 different fuel types, over 20 cooking events, fuel weight consumption, and cooking duration.	Standardization of the location for temperature sampling eliminated need for multiple stoves. Emissions established within published values for 3 fuel types. Fuel weight and cooking duration established over 25 cooking events.	
2.2 Automate Cooking Classification. Automatically determine the stove type, fuel type, and cooking duration to within ± 25%.	Stove type not important with use of J-bar. The field classification had an error of 18.6 ± 19.5%, correctly identified cooking 91.8% of the time.	Fuel type was determined to be impossible to ascertain from temperature alone.
Original Exit Criteria for Goal 3	**Accomplished Exit Criteria**	**Unfinished Exit Criteria**
3.1 Measure Black Carbon Emissions. A cost-effective solution to measure BC emissions with accuracy to within ± 30% as compared with gold standard.	A repeatable, low-cost estimate of emissions can be made with low variability that determines emission values consistent with published ranges of emissions.	

Summary of Project Activities

Table 2. An updated calendar version of the activities for the entire period of funding.



Approaches and problems encountered are listed by section hypothesis:

1. It is possible to isolate true black carbon from background materials (dust, organic carbon) by using all the color channels in the visible spectrum.

   Approach: Following the same methodology already established for determining BC using images of exposed filters, laboratory-analyzed filters with OC data were examined.

   Results: OC was detectable on exposed filters using the coarse absorption average pixel values in images transformed to remove lightness-darkness effect on color (CIE Lab and Chromatic color spaces).

   Problems: Dust and other contaminants remain to be analyzed on filters due to the speed at which such external laboratory analyses are made. Additionally, the threshold for separating BC from OC occurred at low filter loading such that no separation could be established.

   Impact and solutions: The impact is moderate, because an estimate of OC can be established for filters with a threshold of loading. This is a limitation of the method employed and we are currently exploring other methods, including inexpensive spectrometry that may be more sensitive. The impact of waiting for laboratory results is significant for estimating dust or other contaminants, although this was a minor aspect of the project and is thus deemed of low importance.

2. There is a temperature signature that identifies the cooking duration, type of stove and the type of fuel used during cooking.

   Approach: Laboratory testing of one stove with temperature modeling during repeated cooking events of different duration and fuel types.

   Problems: Because different stoves have different temperature characteristics, a universal model for stove temperature could not be established. Additionally, different fuel types could be confounded with different rates of fuel addition (e.g., high quality fuel added at a low rate produced a nearly identical temperature signature as a low quality fuel added at a higher rate).

   Impact and solutions: The impact of the necessity to standardize a measurement method was high, but in a positive scope. This re-directed our efforts to avoid variations due to stove design, and develop a standard "J-bar" that could be used in conjunction with any stove type, thus creating a repeatable measurement device. With the J-bar, a universal cooking time algorithm and estimates of fuel mass used (provided the information of fuel type) was achieved. We feel that this is an optimal solution. If resources are available, the characterization of individual stove models can be accomplished as needed following our model of the J-bar.

The ability to detect fuel type by temperature signature alone was deemed an intractable problem at this time with this level of technology. In impact to our goals can be low if methods, such as self-reporting of fuel type use, or regional estimates of fuel type are employed.

3. It is possible to relate BC concentration measured using a filter to total cookstove emissions in the field.

   Approach: Given the temperature signature of the J-bar and the fuel type, the cooking duration can be calculated as above. With this information, data from two small and inexpensive gas sensors (CO and CO_2) in-line with the gas sampler used for filter-based particulate capture was combined with the carbon balance method for accurately and reliably estimating emissions.

   Problems: Inexpensive gas sensors were calibrated and found to be acceptable for this use, although the reliability of the sensors was moderate – sensor failure occurred several times for the CO_2 sensor specifically.

   Impact and solutions: Sensor failure was low-impact because of the concurrent and parallel use of a high-end gas analysis system. Nevertheless, we are exploring alternative sensors to find more reliable hardware.

Products Developed and Technology Transfer

A publication is being submitted to the journal Energy for Sustainable Development, titled WiTSS: A Wireless Temperature Sensing System to Measure Cookstove Usage and Consumption of Hard wood Fuel.

Models for (1) cooking time estimates, (2) fuel consumption, and (3) carbon emissions have been established:

1. Cooking time model
   a. The cooking time model consists of a decision tree (Therneau and Atkinson, 2002) to predict cooking time based on sequential 5-second periods within a cooking event using the instantaneous temperature, threshold temperature reached during a single cooking event, and the 60 s average rate of change in temperature as parameters to predict cooking. Assumptions include a standard placement of the temperature sensor and stove design, although we have shown that different placements and different stove models can be used with adjustment to the parameters of the model. Intended use is on the backend server where temperature data is sent and also to be implemented on small microcontrollers in the field.
   b. Performance criteria are related to error of misclassification of time as cooking or not cooking.
   c. Test results from the laboratory indicate that the error of classification and the absolute cross-validated error rate for last decision on the tree was 2.9%. The classification correctly identified cooking 91.8% of the time and correctly identified not cooking 94.8% of the time for the stove body in the laboratory. Cooking events that were misclassified as not cooking totaled 8.1 min and not cooking events misclassified as cooking totaled 20.8 min in the stove body model (74% of this misclassification occurred within the short-duration cooking tests in the laboratory).

Test results from the field indicated good performance of the model with the observed cooking time. Estimated cooking time in the field averaged 1.4 ± 0.6 h (n=31) for each event, which was not statistically different ($P > 0.4$; paired t-test) than observed cooking time of 1.5 ± 0.6 h. Specifically, the average difference between observed and estimated cooking time (average error) was 0.03 ± 0.31 h (the absolute value difference averaged 0.23 ± 0.20h) with a maximum error of 0.83 h. The total amount of observed cooking time was 45.3 hours and for the decision tree it was predicted at 44.3 h. A regression of observed to predicted had a slope of 0.76 and an r^2 of 0.82.

d. The hypothesis of the model is that cooking on a wood burning stove heats the stove body sufficiently and predictably for estimating cooking duration. The heat generated by a short cooking event is sufficient to pass model temperature thresholds and rates of temperature change. Longer cooking duration is proportional to longer periods of time between model temperature thresholds and is different from short cooking events only in duration for the specific model parameters.

e. The model is generated from instantaneous temperature, threshold temperature reached during a single cooking event, and the 60 s average rate of change in stove temperature. Each value of the three parameters above is assigned a category of "cooking" or "not cooking" and the model is generated with the freely available statistical analysis program R (version 2.13.1; R Development Core Team, 2011) and the recursive partitioning and regression tree (rpart version 3.1-50; Therneau and Atkinson, 2002) algorithm. The result is a decision tree (Figure 7) that can be implemented with current or historical data sets.

f. The decision tree model is currently included in the submitted article to the journal Energy for Sustainable Development (see above).

g. Hardware requirements include a temperature sensor and data logging capabilities with a temperature resolution greater than 10 degrees C and a frequency of data collection greater than once every 5 minutes.

h. No additional documentation (e.g., users guide) is provided beyond the available documentation for rpart version 3.1-50 (Therneau and Atkinson, 2002).

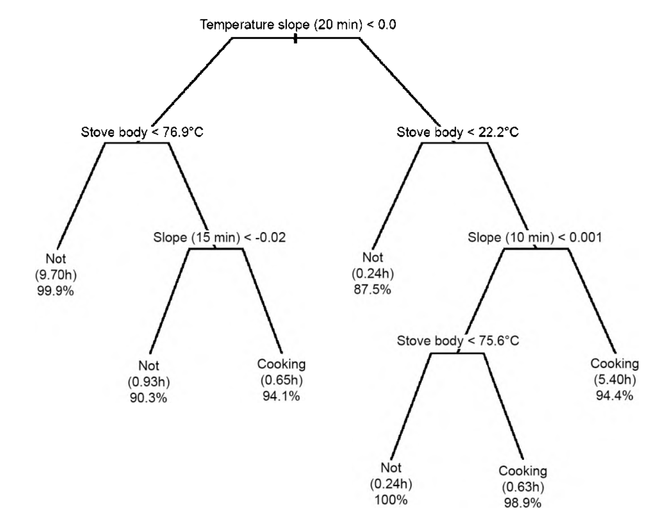


Figure 7: Decision tree model for identifying cooking periods. Left-handed branches satisfy the True case for the Boolean decision described at the top of each branch. Resulting end points are labeled as "Not" (period before or after cooking) or "Cooking" (period during active cooking). Below the category results in parentheses are the number of 5 second intervals correctly categorized with the percentage of intervals correctly categorization below that during model construction.

2. Fuel consumption model

a. An energy balance model was constructed to estimate the rate of energy released during burning of wood fuel during a WBT, and ultimately to calculate the weight of wood burned by the FD stove. Calculations were based on heat transfer and storage processes (Lewis and Nobel, 1977) with the assumption that absorption of shortwave radiation was zero for shaded cooking conditions, heat conduction into the ground was negligible through the stove supports contacting the ground, and latent heat loss was zero (no evaporation from the stove surface). Additionally, the combustion chamber was assumed to change temperature proportional to the temperature measured on the stove body or J-bar and the hardwood fuel used (oak) contained 1.9 MJ g^{-1} (FAO 2002).

b. Performance criteria are related to error of estimates of fuel used compared to that observed.
c. Test results from the laboratory indicated that the total energy dissipated was closely related to the total fuel in kg used during complete laboratory cooking cycles (Figure 5). A field trial, similar to that for cooking duration, was also conducted (Figure 8). Fuel use was slightly under-estimated with an average percent error relative to the reported fuel consumed of 15.5 ± 25.2%. A regression of observed to predicted had a slope of 0.53 and an r^2 of 0.33. Different fuel types and the effect of moisture content on fuel calorific value can alter the energy balance results considerably, indicating that a calibration for fuel type and conditions may be necessary to increase accuracy of predictions. Thus, predicting fuel accurately in the field may be limited by uncontrolled conditions.

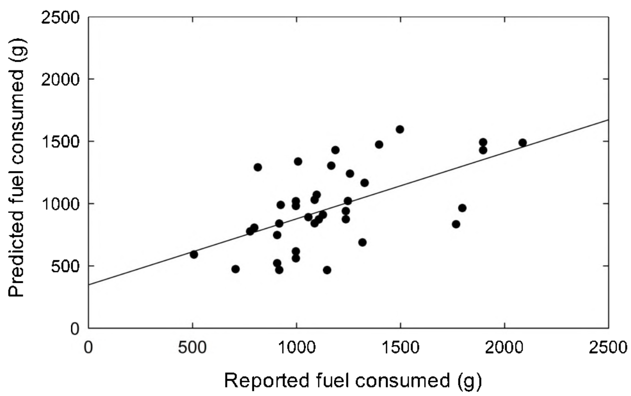


Figure 8. Reported fuel consumption in Ashrafpur, India, during 37 cooking events among 4 households related to predicted fuel consumed based on the energy balance of the stoves.

d. The theory behind the model is that all energy released by the burning of fuel can be accounted for with a constant proportion of that energy being dissipated by the stove ("waste heat") that can be measured. The energy that is released from the fuel and that heats the stove results in repeatable increases in temperature, if the stove does not change in material composition. The change in temperature can be modeled by a simple summation (Equation 1) of the radiative cooling of the stove when it is above ambient temperature, the loss of heat of the stove body to the air (convection), and the heat stored in the body of the stove. The proportion for the stove tested was 3.9% for the temperature measured by the J-bar (96.1% of the energy in the fuel is spent heating the pan or is lost to the exhaust plume). Thus, the amount of fuel used can be back-calculated using this proportion.
e. A net energy balance was calculated with stove- and laboratory-specific parameters fit for each cooking trial during conditions of thermal equilibrium before cooking (net energy equal to zero); any excess of energy entering the system was thus due to the combustion of fuel. Excess energy was then smoothed with a bisquare kernel weight function and regressed against the amount of energy contained in dry, non-resinous wood (1.9 MJ g^{-1}; Ashton and Cassidy, 2007, p 189) to determine a transfer coefficient. Thus,

$$\text{Energy flux} = \text{net longwave radiation} + \text{net convection} + \text{heat storage} \qquad \text{Eq. 1}$$

The net longwave radiation exchange of the stove with the surrounding environment was calculated in Watts m^{-2} as:

$$\text{Net longwave exchange} = e\,\sigma\,(T^4_{(stove)} - T^4_{(environment)}) \qquad \text{Eq. 2}$$

where e is the emissivity of the stainless steel body of the stove (set to 0.7; Cverna, 2002), σ is the Stefan-Boltzman constant, $T_{(stove)}$ is the temperature of the stove body in Kelvin and

$T_{(environment)}$ is the temperature of the surroundings, set to the linear change in temperature between the initial stove temperature from before cooking began to the temperature projected after cooking stopped. Projected temperature after cooking was modeled on stove body temperature after cooking ceased following an exponential decay to ambient temperature to account for localized heating of the laboratory. Convection was calculated as:

$$\text{Convection} = h_c \left(T_{(stove)} - T_{(air)}\right) \quad \text{Eq. 3}$$

where h_c is the heat convection coefficient, set to 10 W m^{-2} °C^{-1} for low wind conditions across a similarly sized cylindrical object (Lewis and Nobel, 1977) and $T_{(air)}$ is the air temperature, set to the environmental temperature as above. Heat storage was calculated as:

$$\text{Heat storage} = C_p\, m\, (\Delta T_{(stove)}/\Delta t) \quad \text{Eq. 4}$$

where C_p is the heat capacity (0.9 J g^{-1} K^{-1} for Fire Brick; Lienhard and Lienhard, 2003) of mass m (5 kg; the combustion chamber), $\Delta T_{(stove)}$ is the change in temperature in time Δt of the stove.

f. The fuel consumption model is currently included in the submitted article to the journal Energy for Sustainable Development (see above).
g. Hardware requirements include a temperature sensor and data logging capabilities with a temperature resolution greater than 10 °C and a frequency of data collection greater than once every 5 minutes.
h. No additional documentation (e.g., users guide) is provided.

3. Carbon emissions model
   a. We employed a carbon balance method for estimating total emissions (Roden et al. 2009). Specifically, this approach relies on the ratio between BC and a fuel "proxy" (CO plus CO_2, the gaseous products of combustion) in the exhaust gas to determine an emission factor. Samples were taken at 1.2 m above the cookstove so that initial dilution occurred through natural plume rise and the carbon contained in wood fuel was assumed to be 50% and in charcoal fuel to be 90% (Löwe et al., 2000).
   b. Performance criteria are such that emissions estimates are within 20% of those in the literature.
   c. Five water boiling tests using air-dried Hickory and four with natural wood charcoal were conducted in the laboratory to test the variability of estimating emissions using a high-particulate producing fuel (Hickory and Pine) and a low particulate fuel (charcoal). The emissions estimate for Hickory was 0.652 ± 0.058, for Pine was 0.517 ± 0.078, and that for charcoal was 0.033 ± 0.005, indicating that with a consistent placement of the sampling tube, a repeatable estimate of emissions can be made with low variability. Values are consistent with published values. The dilution factor varied about 34% with ambient conditions (wind) and averaged19.2 g carbon captured per kg of carbon burned and was not correlated with the emissions factor, indicating that the assumption of a representative sample was met with only a single inlet tube opening placed above the stove during cooking.
   d. The theory behind the carbon balance model is that all the carbon in the fuel that is burned can be accounted for. The products of combustion of fuel are only (1) ash that stays in the combustion chamber, (2) carbon particulates that escape in the cooking plume, (3) the gaseous products of carbon dioxide (CO_2) and carbon monoxide (CO). Assuming that a representative sample is taken from the plume zone of carbon particulates, CO and CO_2, then a proportion of the carbon sampled from the fuel can be constructed (a dilution factor) and that is used to calculate the total carbon particulates, total CO_2, and total CO emissions.
   e. The amount of carbon particles captured on a filter during sampling of the cooking exhaust plume was estimated from photographs of the filter placed on a reference chart (Ramanathan

et al., 2011). The amount of CO_2 captured during sampling was measured in parts-per-million (ppm) by a laboratory-grade infrared gas analyzer (Model 6262, LI-COR Biosciences, Lincoln, Nebraska USA) simultaneously with an inexpensive sensor (Telaire T6613, General Electric Company, Measurement and Control, Fremont, CA USA). The amount of CO captured during sampling was measured in ppm by an inexpensive sensor (MQ-7, Hanwei Electronics Co., Ltd., China). All gas sensors were calibrated with 1000 ppm laboratory-grade standard gas mixtures obtained through Mesa Specialty Gasses and Equipment (Santa Ana, CA, USA). Gas concentration was converted to mass of carbon using molecular mass values (12.01 g mol^{-1}) and the ideal gas law ($PV = nRT$) with air temperature measured away from the cook stove. Mass of carbon particles was summed with mass of gases sampled to calculate the dilution factor.

f. The carbon emissions model is currently included in the submitted article to the journal Energy for Sustainable Development (see above).
g. Hardware requirements include an air temperature sensor, a pump and filter assembly for collecting carbon particulates, and CO_2 and CO gas sensors.
h. No additional documentation (e.g., users guide) is provided.

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