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Article

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Use of an integrated suite of sensors to simultaneously monitor fuel consumption, air quality, and adoption provides important insights and validates impact metrics for household stoves

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ABSTRACT

The rise in sensor-based monitoring in the cookstove sector has been driven by the need for objective quantitative performance evaluation within context of use, and is especially useful if monitoring activities can be conducted by in-country project staff. This research explores the insights achievable from single and cross-sensor analysis following simultaneous in-home deployment of stove temperature loggers, weight-based fuel use loggers, and indoor PM concentration loggers deployed with remote guidance by researchers. Longitudinal performance metrics of an improved metal biomass stove with a chimney within its context of use were obtained using sensor suites consisting of stove temperature sensors (EXACT), household air pollution sensors (HAPEX), and fuel use sensors (FUEL) deployed in 48 households in the Taplejung and Panchthar districts of eastern Nepal. Households in the Taplejung district, comprised mostly of commercial tea houses, had a median reduction in daily household average PM concentration of 45.7% (n = 17) and a median reduction in logged household fuel use of 24.5%, or 2.17 kg/day (n = 15). Households in the Panchthar district comprised of smaller households had a median reduction in daily household average PM concentration of 64.5% (n = 19) and a median reduction in logged household fuel use of 8.13%, or 0.42 kg/day (n = 23). Cross-sensor analysis included use of household PM concentration to verify cooking event initiation and extraneous rises in PM outside of identified cooking events for potential exclusion. Household fuel use profiles were compared to known cooking events to determine whether a household had consistently interacted with the fuel measurement system as instructed, indicating which data were reliable and those that should be flagged. While both cross-sensor analysis and verification methods were examined as potential ways to obtain more information from the gathered data, further development of automated analytics platforms are needed before they can be used as reporting tools by project staff.

1. Introduction

There is well-documented evidence regarding the detrimental effects on health, environment, and livelihoods caused by reliance on solid fuels for cooking and heating (WHO, 2018; Pratiti et al., 2020; Stanaway et al., 2018; Rehfuess, 2006; Kumar et al., 2013). Recent estimates suggest that 36% of the world's population still predominantly uses these fuels as of 2020 (Stoner et al., 2021). Projections show that even with a significant push toward large-scale infrastructure improvements, such as electrification and compressed gas supply systems, 2.6 billion people will still rely on traditional biomass for cooking by the year 2030 (IEA, 2012). With such a significant population reliant on biomass cooking,

many intermediate alternatives to traditional technologies and fuels will continue to be disseminated. Optimizing technology designs and securing results-based financing such as carbon and health credits requires accurate estimates of intervention impacts regarding fuel use, time savings, and air quality (including personal exposure).

Calls for stove performance measurements obtained within their context of use (i.e., in-home settings under normal operation and behavior) have grown over the years (Wilson et al., 2016; Thomas, 2017; Abdelnour and Pemberton-Pigott, 2018). However, methods for collecting data on these metrics can be time-consuming and expensive as they often require extensive skills and training. Additionally, capturing all metrics needed to fully evaluate stove performance (adoption rate,

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fuel usage, and stove emissions) can be prohibitively difficult, and the results are often susceptible to bias (Barnes, 2010). New methods of sensor-based stove monitoring and evaluation (M&E) have the potential for increased accountability and transparency regarding real-world stove impact while limiting subject reactivity (i.e., changes in participant behavior caused by observation) (Thomas et al., 2016). This research aims to further improve sensor-based stove M&E methods and data analysis by providing an example deployment of a novel suite of sensors to monitor household stove use, air pollution, and fuel use simultaneously. The implementation of the sensor suite included the development of instructional material regarding sensor use by project staff with limited previous experience, and the exploration of cross-sensor data analysis methods that allow for additional insight and validation of results.

1.1. Stove monitoring and evaluation

A comprehensive understanding of stove usage requires a multitude of data points (Harrell et al., 2016). Tracking stove use, air quality (both in the room air and personal exposure to the cook or others), and fuel consumption each independently provide potential insight into different aspects of stove use. Additionally, each of these metrics provides insight into the potential long-term impacts of the stove intervention.

Stove usage and adoption is a key indicator of usability and desirability. Furthermore, it is a predictor of impact when paired with efficiency and emissions data. Temperature sensors provide insights into traditional stove displacement in a household by monitoring stove usage patterns as well as the use of multiple stoves (also known as stove stacking). Various stove use monitors (SUMs) are available, including those that rely on direct thermal-based measurement (e.g., iButtons, Geocene Dots, and Wellzions) as well as those that use infrared technology like the (e.g., EXACT). No matter what type of sensor is used, all SUMS require careful positioning to ensure robust response and prevent damage from heat (Ruiz-Mercado et al., 2012; Wilson et al., 2016).

Estimating a stove intervention's impact on user health outcomes requires the measurement of personal exposure (PE) to specific pollutants. Understanding changes in household air pollution (HAP), specifically fine particulate matter $PM_{2.5}$, carbon monoxide (CO), and black carbon (BC), following a stove intervention allows for analysis of stove performance and potential indoor exposure. While the monitoring of HAP can provide insight into changes in potential PE due to a stove intervention, it may not accurately represent actual changes in PE which is also influenced by a variety of other factors such as cooking time and ambient pollution levels (Clark et al., 2013).

Gravimetric sampler systems, such as the UPAS (Vockens et al., 2016), pull air through filters at regular intervals over a given duration of time. These filters are collected and analyzed in a laboratory setting to identify specific concentrations of pollutant types and species. These systems are often used in conjunction with devices that log estimated concentration levels at intervals over a given period using light scattering technology (e.g., UCB-PATS & UCB-PATS (Chan et al., 2021; Pillarisetti et al., 2017), HAPEX, and the IAP meter). Samples collected using a co-located gravimetric sampler system can then be used to adjust and inform data collected using light scattering technology. However, light scattering technology alone cannot be used to determine concentrations of any specific aerosol or PM and therefore the gravimetric systems are considered the "gold standard" when reporting on pollution levels.

The fuel requirements associated with a household's stove usage have direct implications on household finances, time allocation for fuel collection, health outcomes, and carbon savings. Furthermore, non-renewable biomass harvesting can lead to environmental degradation and deforestation (Bailis et al., 2015). Direct quantification of changes in household fuel consumption following a stove intervention can provide a performance metric important to both end-users and stakeholders interested in stove impact. Fuel consumption data has been historically

recorded using kitchen performance tests (KPT) (Bailis et al., 2007) or other survey-based methods. To our knowledge, the only sensor-based monitoring tool currently available is the Fuel Use Electronic Logger (FUEL) (Ventrella and MacCarty, 2019; Ventrella et al., 2020a,b; Ventrella et al., 2020, 2020) developed at Oregon State University. This sensor requires users to store their fuel supply in a logging tensile or compressive scale, depending on the type of fuel. With fuel stored on the scale, the sensor logs weight changes that represent fuel use over time. The sensor can be left in place for longer durations than is possible through a traditional KPT or similar method. Although reporting accurate metrics using this method does require that households follow all instructions on how to interact with the sensor, it provides the capacity for more extensive data collection with reduced time commitments from study participants, field teams, and researchers. Furthermore, if the FUEL system is used by study participants as directed, the reduction in the number and duration of household visits may lead to a decrease in bias during monitoring.

1.2. Sensor suite

With sensors available for autonomous monitoring of stove temperature, air quality, and fuel consumption over long durations, there is potential for a more holistic and nuanced understanding of performance within context of use. The partnership between Oregon State University and Climate Solutions Consulting has resulted in the development of the suite of wireless sensors that were used in this study consisting of 3 sensor types:

1. EXACT: Stove temperature sensor
2. HAPEX: Household air pollution sensor
3. FUEL: Household fuel use sensor

Fig. 1a illustrates the sensor suite deployed in a household with a single stove monitored. Fig. 1b shows the wireless handheld launcher used for sensor deployment, sensor checks during mid-monitoring check-ins, and sensor data collection. As this launcher allows for project staff to check sensor performance and usage during household visits, more informed household engagement and faster mitigation of many potential errors is possible.

1.3. Red Panda Network partnership

For this study, researchers partnered with the Red Panda Network (RPN), a non-profit organization that has been working to save red pandas since 2007 and is currently implementing a "Community-based Red Panda Conservation" project in more than 50% of the red panda habitat in Nepal. RPN is committed to protecting wildlife and preserving their habitat through the empowerment of local communities by adaptive community-based research, education, and sustainable livelihood initiatives. One of these initiatives includes the distribution of an improved metal biomass cookstove with a chimney to rural communities that live alongside red pandas and rely on the biomass from their habitat for energy. RPN's goal in participating in this study was to determine the program's impact on household fuel consumption and air pollution.

1.4. Research objectives

To address the needs of both RPN and Oregon State researchers, this study had two main research objectives; 1) To determine the impact of the RPN stove on rural household fuel consumption and HAP and, 2) To explore the functionality and feasibility of this sensor suite and the resulting data, particularly when deployed in rural areas by field staff with limited previous experience in sensor deployment and data collection. To address these objectives this study sought to answer the following questions.

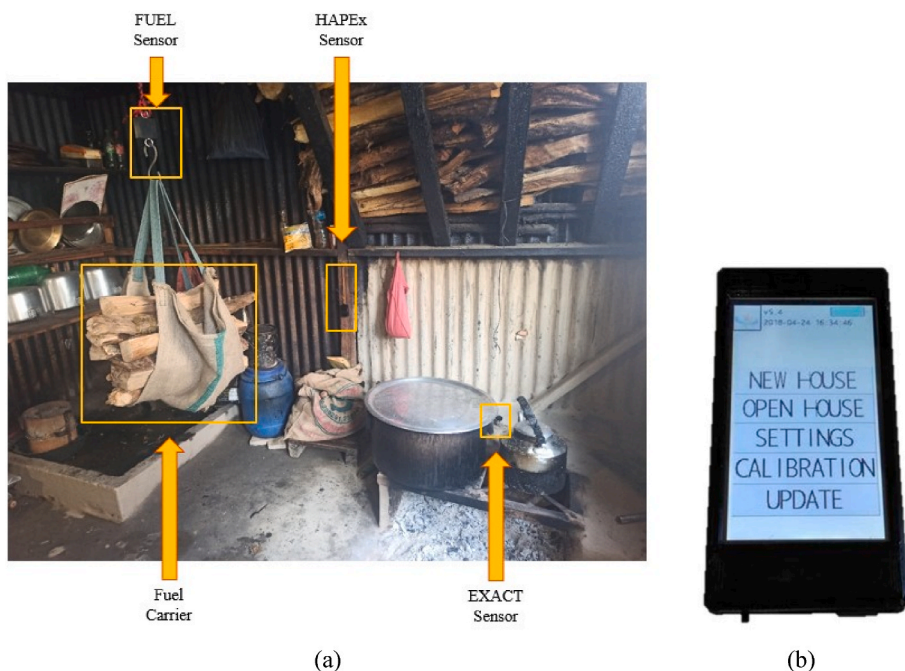


Fig. 1. (a) Sensor suite deployed in a Nepalese household. (b) Climate Solutions Consulting sensor suite Launcher.

1. Does the introduction of the RPN stove reduce overall household fuel consumption and HAP?
2. Given the provided material, can the implementation of sensors and data collection be reliably conducted by field staff with limited prior experience in sensor deployment and data collection?

3. Can cross-sensor analysis improve and validate data from individual sensors?

2. Methods

This study was planned and conducted during the COVID-19 global

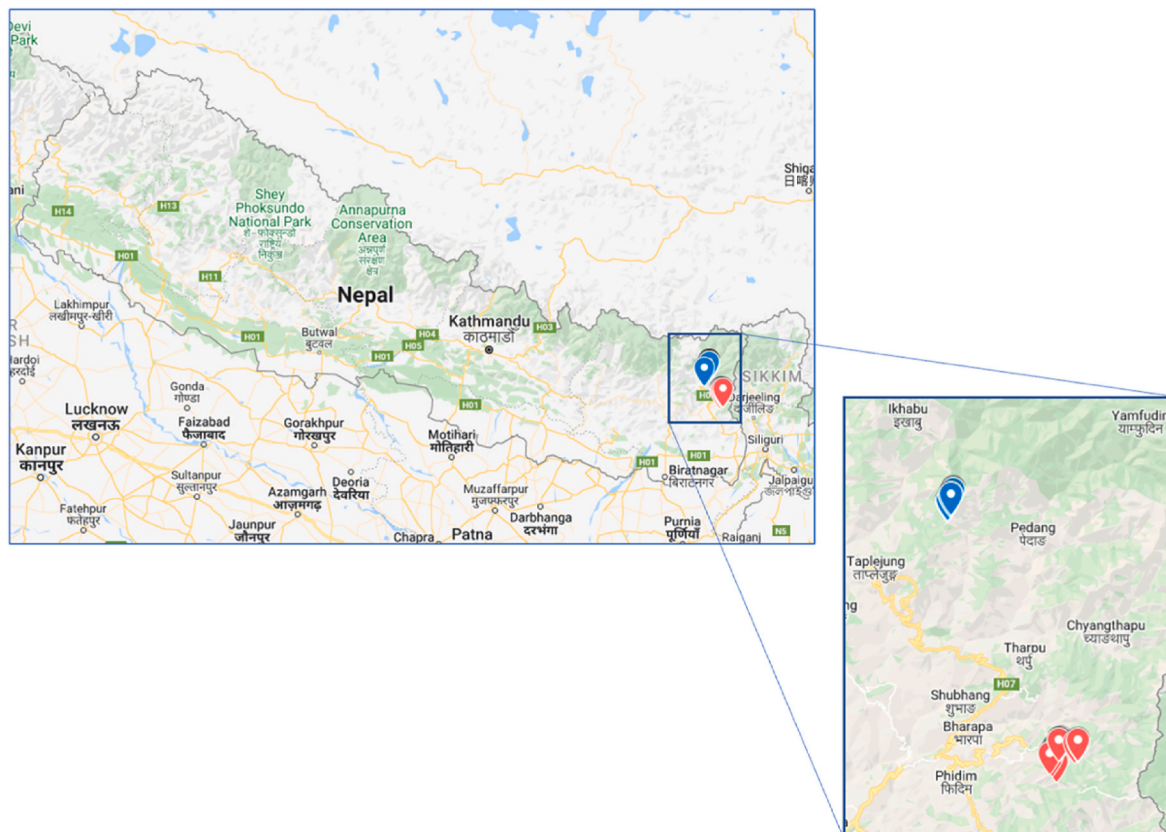


Fig. 2. Map of the study location. Blue pins represent households in the Taplejung District and red pins represent households in the Panchthar district.

pandemic, preventing Oregon State researchers from traveling to Nepal and working directly with RPN partners. With limited direct project oversight by Oregon State researchers, it was possible to test the usability of the sensor suite and its ability to build M&E capacity in local communities using only remote training. Virtual meetings were held between RPN staff and OSU researchers to develop a study timeline and procedures. All sensors, along with training materials, were provided to the RPN staff by Oregon State researchers and Climate Solutions Consulting.

Data collection in two rural mountainous districts of eastern Nepal, the Taplejung and Panchthar district (Fig. 2), were approved by OSU Institutional Review Board 7257. Data were collected on household air quality, stove usage, and fuel usage before and after the introduction of an RPN metal biomass cookstove with a chimney (Fig. 3f). A major objective of the study was to collect more days of data than the traditional 3-day KPTs and cover every day of the week to capture weekly variability. With this in mind, a 10-day sampling for both monitoring periods was selected to balance the longer duration of monitoring capable by the sensors (30+days) with the time available for the study.

The Taplejung and Panchthar districts exist in similar climates but exhibit differences in income-generating activities that contribute to differing household contexts. The households in the Taplejung district (shown as blue pins in Fig. 2) consist mostly of “tea houses” and rely primarily on hosting guests and tourists heading to worship at the Pathibhara temple. Alternatively, households monitored in the Panchthar district (shown as red pins in Fig. 2) reflect more of a traditional Nepalese household and practice livestock herding.

2.1. Stoves

Each household used a range (and at times a combination) of traditional stoves. Table 1 provides the names, descriptions, and number of stoves monitored in each district. Fig. 3 shows an example of each stove type along with the RPN stove that was disseminated to the households.

Table 1
Biomass stoves monitored in study households.

Stove Type	Stove Description	Taplejung	Panchthar
Traditional Open Fire	A metal frame open fire indoor cookstove (Fig. 3a).	7	7
Three Stone	An open fire cookstove constructed of three large stones. Both indoor and outdoor (Fig. 3b).	0	8
Mud Stove	Stove made of stone and mud, often attached to a specific place within household. Can be in or outside (Fig. 3c).	4	10
Metal Frame Mud Stove	Framework made of iron surrounded by mud on three sides. Cement occasionally used as an alternative (Fig. 3d).	10	0
Mud Stove with Chimney	Like a mud stove but with an inbuilt chimney (Fig. 3e).	1	1

2.2. Monitoring timeline

Before the collection of data, a community workshop was arranged in both districts. These workshops were held to inform study participants of the purpose of the study, gain their consent to participate in the study, and provide instructions on how to properly install and use the stoves. Participants were also provided with a pictorial user manual (“Installation and User Manual of Metallic Improved cookstove”) that included instructions on RPN stove installation and usage. A fully installed RPN stove was set up for participants’ observation and to allow for consulting with trained staff to encourage proper usage.

Sensors were deployed in households between February 2021 and April 2021. Table 2 provides detailed date ranges regarding the monitoring periods for the 22 Taplejung district households and the 26 Panchthar district households. Households were monitored using the sensor suite for 10 days before the introduction of the RPN stove to develop a baseline metric for household fuel consumption, stove use patterns, and HAP. After the introduction of the stove, the households



Fig. 3. Study stoves. (a) Traditional Open Fire (b) Three Stone (c) Mud Stove (d) Metal Frame Mud Stove (e) Mud Stove with chimney (f) RPN stove.

Table 2
RPN household monitoring dates in 2021.

	Taplejung	Panchthar
Households	22	26
Sensor Deployment Before RPN Stove	Feb. 20th	March 8th
Mid Monitoring Check-in	Feb. 28th	March 15th
Data Collection and Sensor Removal	March 5th	March 22nd
Sensor Deployment After RPN Stove	March 25th	April 9th
Mid Monitoring Check-in	April 2nd	April 15th
Data Collection and Sensor Removal	April 6th	April 21st

were given a minimum of 14 days to grow accustomed to their new RPN stove before the sensor suite was re-installed in the households for another 10 days.

During each monitoring phase, households were visited 3 times. The initial visit involved sensor installation, deployment, and training on sensor use. Explicit instructions shared with household members regarding FUEL sensor usage included:

- All firewood for household stove use must be stored in the holder before using it on a stove.
- Only use fuel from the holder for stove use in your household, do not give or sell firewood to other households once it has been placed in the holder.
- The holder must be filled with as much firewood as possible and only refilled when near empty.
- Remove the fuel needed just before use.
- Do not put firewood back in the holder after its removal including the partially burnt firewood (leave it out for next stove use).
- If additional wood is added, it must be in the holder for at least 1 min before removal for use.

A mid-monitoring check-in was conducted to ensure proper sensor performance and as a means of guiding households as needed. The final check-in was focused on data collection and sensor removal.

Fuel moisture readings were collected using an EXTECH M0210 Moisture Meter. It is understood that these devices only give an estimate of moisture level due to inconsistent drying patterns of wood (Price-Allison et al., 2019). To account for the potential that wood may be drier in some locations than in others, measurements were collected in three different locations on three separate pieces of wood during each household visit. These values were all recorded and later averaged together to obtain the moisture level associated with that visit.

During the initial visits, households were provided with a feeding chart and asked to track the number of people fed each day in each category. During the mid-monitoring and final visits, these charts were checked for completion. If the households had not consistently tracked people fed, the field staff assisted the households in filling in the charts as accurate as possible. Standard adult (SA) equivalents were determined using FAO standard adult weighting values: <14 years = 0.5, adult female >14 years = 0.8, adult male between 14 and 59 years = 1.0, and adult male >59 years = 0.8 (FAO, 1983). Table 3 shows the range in the number of SA fed in households each day throughout the monitoring period. Due to potential recall bias, these values were not used to calculate fuel use per SA but were used to inform contextual differences in households across districts.

Table 3
Standard adult (SA) equivalent fed per day in households.

SA per day	Taplejung	Panchthar
Before RPN Stove		
Mean (SD)	11.46 (8.85)	3.63 (1.94)
Range	1.00–47.40	0.00–13.90
After RPN Stove		
Mean (SD)	21.99 (19.63)	3.45 (2.74)
Range	1.30–130.50	0.80–27.20

Following the completion of the study, RPN field staff were provided with a survey regarding their feedback on the provided training materials, sensor use, sensor deployment, household training, and data collection. Their responses along with the quality of collected data were used to assess the feasibility of similar studies.

2.3. Equipment preparation and deployment

Before HAPEX sensors were deployed in the field, a span calibration and offset calibration was conducted. The span calibration was conducted by placing all HAPEX sensors in a chamber that was filled with incense smoke. A reference HAPEX, used exclusively for span calibration to prevent drift, was placed in the chamber along with the other HAPEX. The chamber was equipped with a fan to promote uniform PM concentration units (CU). While in the chamber, the HAPEX sensors were exposed to step increases in concentration and their response was recorded. Each HAPEX sensitivity coefficient was then adjusted so that they match that of the reference HAPEX. This process was repeated a second time to confirm that the measured CU reported by each HAPEX was within $\pm 5\%$ of the reference HAPEX. The HAPEX were then manually dusted with an air blower to reduce the amount of accumulated dust on the sensor optics. Finally, the HAPEX offset value calibration was completed by placing the sensors in a zeroing box with an air purifier with zeroing setting turned on. After a few minutes, the HAPEX sensors automatically adjust their offset coefficient so that the recorded value is zero. These two calibrations aim at reducing inter-device variability so that two devices exposed to the same aerosol at the same concentration will report the same measurement.

Before deployment, all FUEL sensors were calibrated using three 2-kg weights for a total of a 6-kg reference weight. FUEL holders used in the FUEL system shown in Fig. 4c were manufactured in the local villages using rice jute sacks and nylon rope. Before installation, household participants were asked to specify their preferred location for the FUEL system to ensure ease of use.

EXACT sensors (Fig. 4a) were fastened to cookstoves using either metallic U-nails, tent stakes, or metallic tape depending on the type of stove being monitored and the household configuration. HAPEX sensors were hung within 1-m of the monitored stove and 1-m above the ground away from any windows or ventilation (Fig. 4b). FUEL systems were installed by hanging the sensors on preexisting support beams. Once installed, all sensors were deployed simultaneously with the launcher. Sensor data were checked and collected during mid-monitoring check-ins to ensure that all sensors were working properly. If a sensor was found to be not functioning, the field staff first attempted to relaunch the sensor; if this was unproductive, the sensor was replaced when possible. Due to limited resources, all sensors were removed from households in between monitoring periods for use in other households, then replaced and relaunched during the following monitoring period.

2.4. Data analysis

2.4.1. EXACT

Identifying stove use events consistently is an area of active research (Ruiz-Mercado et al., 2012; Wilson et al., 2020; Wilson et al., 2020). Accurately and consistently identifying stove use requires that factors regarding cooking duration, cooking patterns, and a stove's thermal capacity be taken into consideration. The EXACT sensors, used for stove use monitoring in this study, contain internal software that identifies stove usage when a temperature threshold is reached. In addition to actual measured temperature, this is also reported as a binary usage metric (1 for stove use and 0 for non-usage) allowing field staff to check for appropriate sensor performance and expected stove use during visits. Although these binary metrics are useful for checking data, a more detailed analysis was performed once complete temperature data were retrieved. Event identification was performed using the "fire-finder" method (Wilson et al., 2020). This method allows for merging cooking

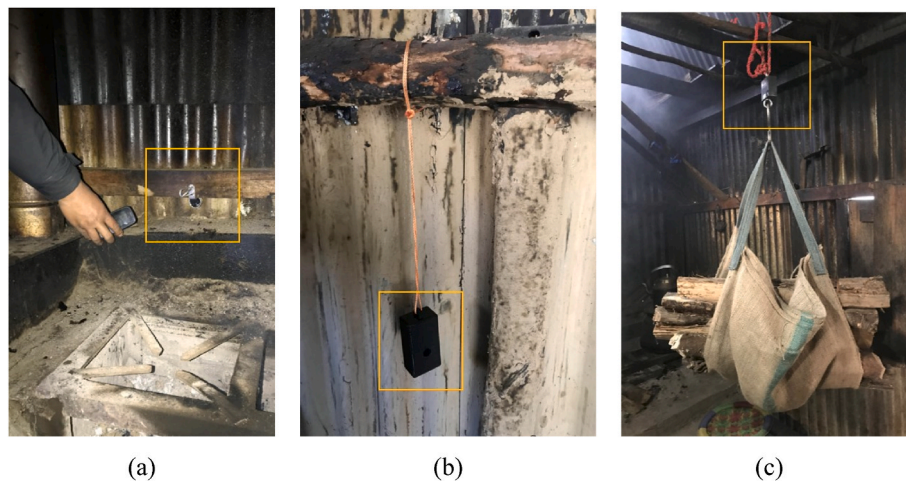


Fig. 4. Household sensor deployment. (a) EXACT, monitoring stove use; (b) HAPEX, monitoring household air pollution; (c) FUEL, monitoring fuel consumption.

events that are too close to each other, removing events that are too short, and detecting the beginning (threshold, high slope) and the end (threshold, low slope, and slowing decreasing temperature) of stove use events. We chose this method because it allows for the detection of the slow cool down of high thermal mass stoves and accurate characterization of cooking time. All parameters (e.g., threshold values, positive slope, and negative slope) were adjusted based on stove type. Stove usage start and stop times were verified manually.

2.4.2. HAPEX

The HAPEX sensors produce a unitless measure of PM concentration in a given space using light scattering technology. Obtaining the concentration (μgm^{-3}) of a specific aerosol requires a gravimetric system to be co-located with the HAPEX sensor to determine the particulate scattering coefficient. Due to limited resources and challenges regarding filter handling, no gravimetric systems were used during data collection in this study. Concurrent work with Climate Solutions Consulting (not yet published), data collected with co-located HAPEX sensors and gravimetric samplers showed a linear relationship with an R squared value above 60%. While this linear relationship will ultimately depend on the aerosol type, the main source of PM emissions in both monitoring periods of this study was biomass from a large stockpile and therefore should have similar compositions. Although the lack of a gravimetric reference adds an additional level of uncertainty to the measured PM levels in each household and phase, limiting direct comparison, the slope of the regression is anticipated to remain similar between the two monitoring periods and allow for comparisons of overall PM concentrations. Subsequently, all PM data presented in this study will be presented as Concentration Units (CU). Although this does not allow for reporting on absolute household $\text{PM}_{2.5}$ levels for comparison to WHO guidelines, it does allow for comparison of the magnitude of HAP before and after the introduction of the RPN stove and correlation with stove usage events as well as fuel usage.

Despite offset calibration before each deployment (zeroing) for the HAPEX sensor, the offset will also drift during deployments. This is due to the accumulation of dust particles on the sensor optics that increase the amount of light that reaches the photodiode. Methods measuring drift before and after often assume that drift occurs linearly which does not appear to be the case when looking at the data. To correct for the offset drift during deployment we used the method documented in (Coffey et al., 2019). This method accounts for the fact the offset drift follows step changes rather than slow and gradual linear change. However, in the absence of PM, and due to measurement noise, it is expected that the HAPEX readings will occasionally read as negative as it oscillates around zero. When the 10-min average fell below zero, the

offset was adjusted back to zero, but the data were not discarded.

2.4.3. FUEL

Household fuel consumption is based on any decreases in weight above a minimum threshold value logged by the FUEL system. The FUEL system will also log any bumps or unintentional tugs which must be accounted for and adjusted to ensure accurate calculations (Ventrella et al., 2020). Fig. 5 shows an example of FUEL system data with a highlighted spike that is assumed to be the result of the system being unintentionally bumped or pulled. Adjusting the inaccurate data was accomplished by comparing surrounding data points. If there was a sudden weight increase that immediately returned to the previous value or fell below it, the value would be adjusted to the previous value. This process was mirrored to adjust for sudden negative changes in weight.

Monitoring household fuel use with the FUEL system requires that we question the degree to which households accept and consistently use the system according to the instructions provided. FUEL system acceptance includes two different aspects: 1) whether the fuel removed from the system was used in a monitored stove and 2) whether all household fuel used was first logged by the fuel system. Although the amount of unmeasured fuel used cannot be reported, fuel changes were associated with stove use events by identifying the time at which fuel was removed and its temporal relation to identified stove use events. Associating logged fuel changes with identified stove use events allows for the calculation of the percentage of a household's stove use with which fuel could be associated. This also allows for obtaining the correlation

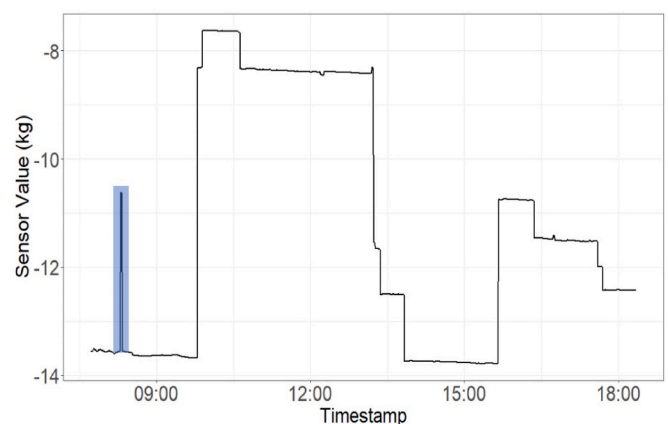


Fig. 5. Fuel data with a highlighted fuel change indicative of the sensor being knocked or tugged highlighted.

between household stove use duration and associable fuel use. Each of these metrics helps inform researchers on study participant behavior patterns regarding the FUEL system and may indicate which household data is suitable for reporting purposes.

3. Results & discussion

Each of the 48 households (22 in the Taplejung district and 26 in the Panchthar district) was monitored for a minimum of 10 full days before and after the introduction of the RPN stove with chimney. Due to both user error and sensor malfunction, not all sensor data was useable for each household. However, since each household contained multiple sensors, households with complete data from a particular sensor type were isolated and analyzed. This resulted in varying sample sizes and should be taken into consideration when viewing results as different results represent different portions of the study group.

Of the three sensor types, the EXACT temperature sensors experienced the greatest amount of data loss. Useable EXACT data was recorded for three households after the RPN stove introduction and useable data for both monitoring periods was recorded for only one household. EXACT data loss was caused largely by two main factors. 1) The RPN stove's chimneys are made of reflective metallic material which reduced the ability for the infrared EXACT sensors to detect temperature changes. The EXACT sensors were mounted to the chimneys and no instructions were provided to scuff or blacken out the target surface during training. 2) During remote RPN field staff training, it was not made clear that all stoves that may be used in a household must be monitored to obtain a comprehensive understanding of the household environment. Because of this, we can't report on stove stacking use with any level of confidence. Significantly more HAPEX and FUEL data was collected with 36 and 38 households having complete data before and after the RPN stove introduction, respectively. Only complete sensor data, or data that encompassed the entire 10-day monitoring duration, were included in the analysis.

Due to losses in data, limited metrics can be reported on the usage of the RPN stove with chimney. However, median changes in HAP, as well as logged fuel usage, were analyzed. Complete data were collected from all three sensors in 18 households before the introduction of the RPN stove. With these data, initial methods for cross-sensor data validation and analysis were developed for their use in further studies. The remainder of this section will discuss these methods as well as the changes found in fuel use and HAP following the RPN stove introduction.

3.1. Household air pollution

Table 4 shows the distribution of the average 24-hr PM CU logged in each district during each monitoring period. Due to the non-normal distribution seen within household 24-hr average PM CU values, the median 24-hr average PM CU within each household was chosen to determine the percent change in PM CU after the introduction of the RPN stove. Fig. 6 shows the distribution of these calculated changes within each district. While some households in the Taplejung district (n = 17, median = -45.7%) did experience an increase in median daily average PM, approximately 70% experienced a reduction.

Table 4
Household Average 24-hr PM CU across both districts and monitoring period.

Average 24-hr PM CU	Taplejung	Panchthar	Total
Before RPN Stove	(N = 177)	(N = 272)	(N = 449)
Mean (SD)	586.99 (924.35)	354.01 (415.05)	445.85 (672.95)
Range	6.94-4846.82	5.65-2177.64	5.65-4846.82
After RPN Stove	(N = 169)	(N = 242)	(N = 411)
Mean (SD)	188.7 (205.023)	112.41 (456.09)	143.78 (375.38)
Range	20.42-1082.62	16.32-6891.26	16.32-6891.26

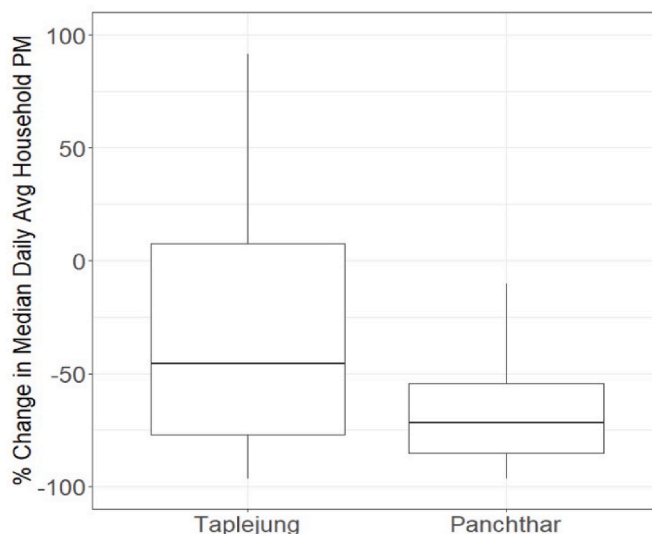


Fig. 6. Percent change in median household 24-h PM during each 10-day sampling period. Taplejung (n = 17, med = -45.7%); Panchthar (n = 19, median = -64.5%); Total (n = 36, median = -61.2%).

Comparatively, all the households in the Panchthar district (n = 19, median = -64.5%) experienced a reduction. A study conducted by Singh et al. (2012) found a similar trend to that observed in the Panchthar district, with an observed 63% reduction in mean values of PM_{2.5} following the introduction of an improved cookstove in Nepal. Although PM_{2.5} was not specifically measured in this study, we hypothesize that reduction in PM_{2.5} would follow the patterns of reduction in PM CU.

The difference in reductions between the two districts was likely due to household context. As explained previously, many of the households in the Taplejung district operate as tea houses serving a range in the number of guests each day. This not only requires longer stove use duration but also may have resulted in more stove stacking. Alternatively, the households in the Panchthar district served a more consistent and smaller number of people in a household each day and may not have needed to use more than a single stove throughout the day to meet their needs. This is likely why there is a more observable and consistent reduction in measured HAP following the introduction of the RPN stove in the Panchthar district.

An unpaired Wilcoxon test was performed to determine whether there was a significant difference between the two populations. Given the small sample size and the uncertainty introduced due to the lack of gravimetric measurements a 90% confidence interval was chosen. The Wilcoxon test with a 90% CI (1.35, 75.83) indicates a statistically significant difference in the median percent change in daily average household PM between the two districts.

3.2. Stove usage

One of the challenges of stove usage monitoring with temperature sensors is accurately identifying the beginning and end of a discrete stove use event. This can be made even more complicated if a sensor is placed incorrectly and less variation in temperature is captured. However, analyzing HAP data along with stove temperature provides an interesting opportunity to more accurately identify discrete cooking events. When a stove use event is initiated, there is a predictable spike in PM CU within a household that precedes a rise in stove temperature. Using this information, it is possible to verify and adjust stove use initiation times and represent the stove event more accurately. Elevated levels of PM CU, indicative of a stove use event, may also be used to identify PM that has no corresponding stove temperature change indicating an external polluting source (e.g., trash burning). Fig. 7a

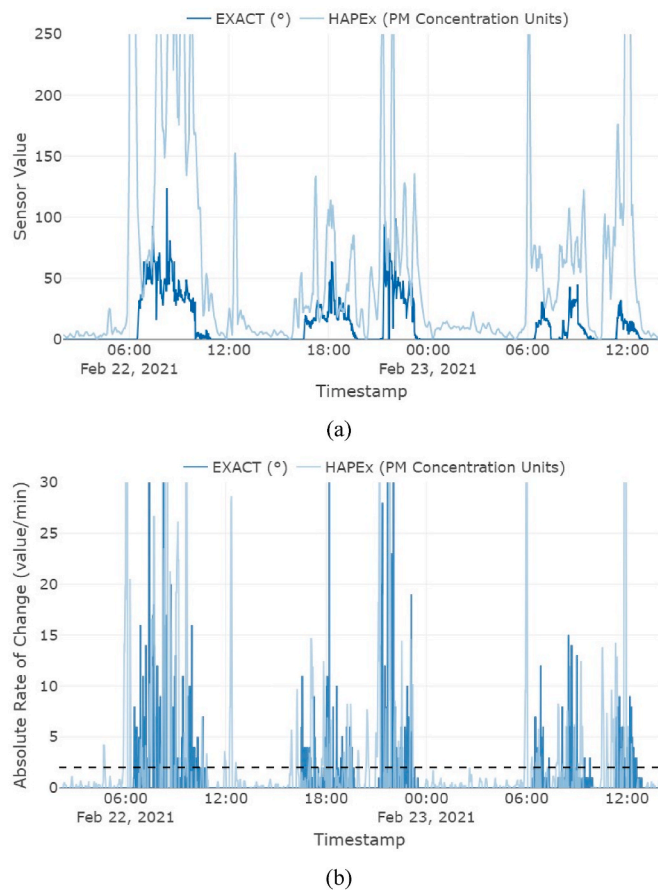


Fig. 7. Household 2 Baseline PM CU (HAPEX) and stove temperature (EXACT) sensor agreement. (a) Direct sensor values; (b) Absolute rate change in sensor values. The household median absolute PM CU rate of change (2.0 CU/min) is indicated with the dashed horizontal line. The axes in both plots have been truncated to highlight areas of interest.

illustrates this by showing an example of the relationship between a household’s stove temperature and HAP data collected before the introduction of the RPN stove.

The magnitude and fluctuation of PM CU differ depending on the stove and fuel in use as well as the household ventilation and stove use practices (Sharma and Jain, 2019). This makes correlating household PM CU and stove use events difficult when addressing more than one household based on fixed thresholds. Despite the impact of differing contexts, it is still expected that household PM CU will look different during periods of stove use and periods of non-use. Based on cooking patterns observed in this study, we identified that households were spending more time in 24 h not using their stove than they were using it. This observation coupled with the near-constant flux of measured household PM CU meant that the median rate of absolute change should represent a period of non-stove use in a household. It then follows that stove use events could be identified by periods when the absolute rate of change in PM CU exceeds the household’s absolute median rate of change value. It should be noted that this method may not be valid in settings where the household stove is used for longer durations as is common for heating purposes. Fig. 7b illustrates the relationship between the absolute rate of change in both household stove temperature and PM CU as well as the household median absolute rate of change in PM CU.

By determining the median absolute rate of change in household PM CU it is possible to identify potential stove use events and flag elevated PM CU that occur without any corresponding rise in stove temperature. This was accomplished using the following method modeled after the

Fire-Finder algorithm used for stove use identification.

1. Assume no data points occurred during stove use.
2. Assume all PM data points with an absolute rate change greater than the median absolute household PM rate change have occurred during stove use.
3. Merge all assumed events that are separated by non-use periods shorter than the minimum inter-event threshold.
4. Delete all use events shorter than the minimum event time threshold.
5. Flag any events that do not have a corresponding stove temperature increase during the duration of the event.

Fig. 8 provides an example of the outcome of this method.

Although this algorithm is useful in determining the appropriate start of a cooking event and identifying potential extraneous PM events, it may not be as effective at precisely and reliably determining the end of active stove use duration. Household PM CU often remains elevated for long periods after the active stove use has subsided, especially if the fire is allowed to smolder. This can result in the algorithm incorrectly identifying multiple events as one or identifying the end of the cooking event long after active cooking has subsided, so additional exploration of this method is required.

3.3. Fuel usage

The change in household fuel consumption during an intervention is an important impact metric, particularly for carbon credits and other results-based financing. Accounting for differences in fuel moisture on normalized fuel use per the KPT procedure (Bailis et al., 2007) was accomplished by taking the average moisture level during each visit and adjusting the fuel using two different methods. The first method involved applying the average of all moisture readings in each household during a single monitoring period universally to all fuel use during that period. The second method involved applying moisture values to fuel based on their temporal proximity to fuel removal (i.e., fuel changes were assigned whichever moisture reading was recorded closest to its removal whether it was before or after). Fig. 9 shows the effect of each of these methods on the change in total logged household fuel use, as well as the change in average daily logged household fuel use, after the introduction of the RPN stove. Each of these metrics is further broken down into the total change in weight (kg) as well as the percent change between the two monitoring periods.

When considering the first method of fuel adjustment, household data suggest a median average daily reduction in fuel use of 24.5% and 8.1% for households in the Taplejung and the Panchthar district respectively. The differing magnitudes of fuel savings between the two districts are likely due to the impact of household context. With

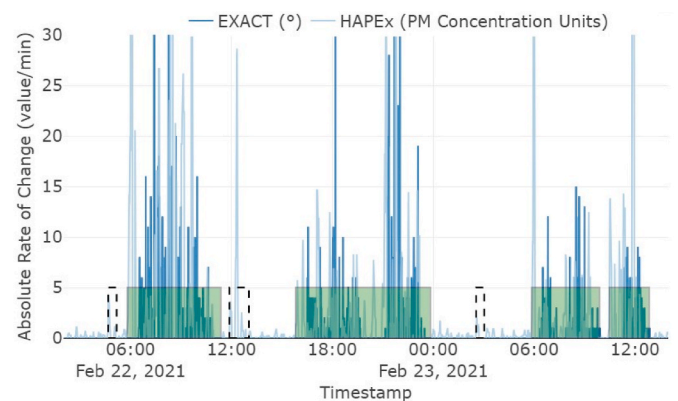


Fig. 8. Stove usage event identification using household HAPEX data. Shaded green boxes indicate the identified events and dashed boxes indicated flagged events that had no corresponding temperature change.

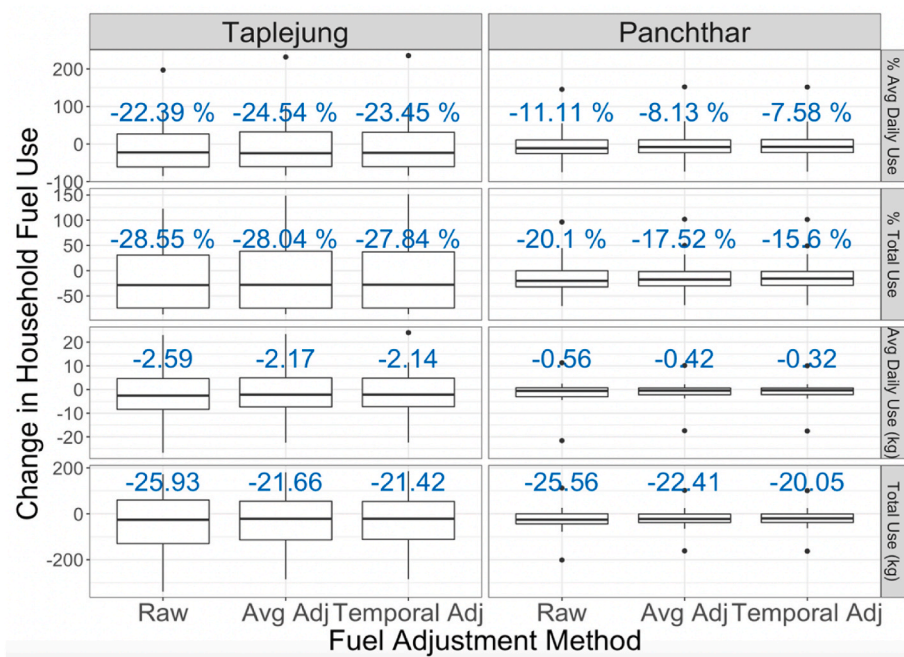


Fig. 9. The change in logged total and average daily fuel use in households was reported as a change in weight (kg) and percent change (%) between the two monitoring periods. “Raw” is fuel weight data with no moisture adjustments. “Avg Adj” are fuel weight data adjusted with the average household fuel moisture content during each monitoring period. “Temporal Adj” are all fuel data adjusted with the household fuel moisture content that was recorded closest to the time of fuel removal. The blue numbers represent the median value for each set of data. The number of households included in the data analysis, Taplejung = 15, Panchthar = 23.

households in the Taplejung district serving greater numbers of people on average, therefore using their stoves more, they were more likely to benefit from larger fuel savings due to economy of scale. However, households in the Panchthar district served fewer, but a more consistent number of people, therefore using their stoves less but more consistently. It follows that the Panchthar households would have smaller overall fuel savings as well as a smaller range of observed savings than those seen in the Taplejung district. A study conducted by Johnson et al. (2013) using KPT to determine the impacts of an improved stove in Nepal showed a similar trend. Their findings suggested a 30% (kg/SA/day) reduction in fuelwood use when comparing households that used an improved stove to those that did not.

It should be noted that this analysis assumed that all fuel changes were representative of actual fuel use in households. The following sections will explore ways to assess a household’s level of acceptance of the FUEL system and whether a household’s FUEL data is likely to be representative of actual fuel usage.

3.3.1. FUEL system acceptance

A household’s level of acceptance and consistent use of the FUEL sensor in terms of how closely they followed instructions for use, dictates how closely their logged fuel use is expected to represent their actual fuel use. To determine this, two questions must be investigated.

1. Were the logged fuel changes representative of fuel that was used in the household and was that fuel used in a monitored household stove?
2. Was all fuel that was used in the monitored household stove first logged by the FUEL sensor?

The first question was addressed by associating fuel changes with identified stove use events within a household. If an event is identified during or directly following the removal of fuel from the FUEL holder, then it was assumed to have been used during that event. A high percentage of fuel removals associated with stove usage events indicates that there was likely good compliance with the instructions regarding when to remove fuel. The second question was addressed with a similar method focused on household stove use time. A household with a high percentage of stove use time with associable fuel was assumed to have

regularly removed fuel from the holder for use on a monitored stove. Whereas a low percentage may be the result of many factors including, but not necessarily limited to, fuel being used that was not first placed in the FUEL holder.

Fig. 10 illustrates household acceptance of the FUEL system in the 18 households from which complete data for HAPEx, EXACT, and FUEL sensors were retrieved before the introduction of the RPN stove. The level of acceptance is reported as the percentage of a household’s total logged fuel changes that could be associated with identified stove use events as well as the percentage of total identified stove use duration with associable fuel changes. Because participants were told to remove fuel directly before its use, a 30-min window before the identified start of stove use events was used for fuel association. Stove use events were

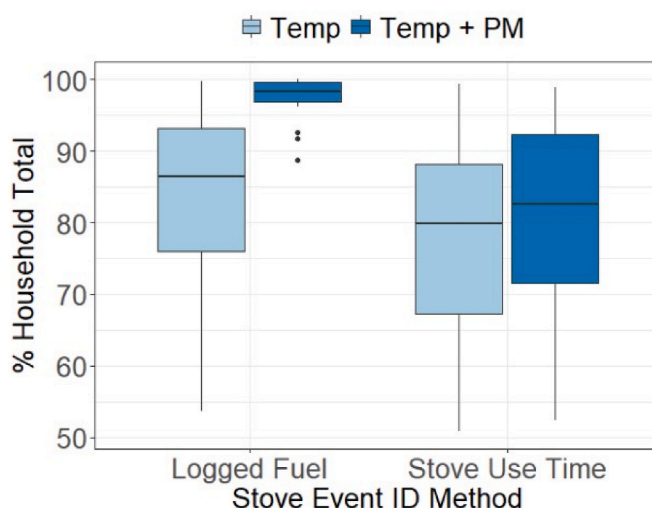


Fig. 10. Percentage of total logged household fuel and stove use duration that could be associated with one another before the introduction of the RPN stove (n = 18). “Temp” refers to stove use being identified only through temperature sensors. “Temp + PM” refers to stove use events adjusted using household PM data. Median Logged Fuel (Temp = 86.4%, Temp + PM = 98.2%); Median Stove Use (Temp = 79.8%, Temp + PM = 82.6%).

identified first using only household stove temperature data (illustrated with the light blue box plots) and then the event's starting point was adjusted using HAP data as described in the previous section (illustrated with the dark blue box plots). By using HAP data to adjust identified stove use event start times, the percentage of logged household fuel use that was associable with stove use increased over 11%. This is primarily due to the earlier identification of stove use start times which allows for more logged fuel removals to be associated with stove events. However, this method does not increase the number of identified stove use events, only their duration. Meaning that unless very few stove use events in a household had associable fuel, to begin with, we would not expect a large increase in the percentage of total stove use with associable fuel. Indeed, the results showed an increase in the median percentage of total stove use time with associable fuel of less than 3% after times were adjusted with HAP data.

Although understanding the percentage of logged fuel that was associable with stove use events provides important insight into user behavior, the remainder of this section will be referring to the percentage of stove use time with associable fuel as FUEL acceptance. A household with a lower than ideal level of FUEL acceptance likely engaged in one or both of the following behaviors:

1. Fuel was used without it first being logged through the FUEL system.
2. Too much fuel was removed for any given stove use event and then used in subsequent events. This would result in some stove use events having large amounts of associable fuel and others with little or none.

Although these are both behaviors that are anticipated to occur at some level when asking a participant to alter their routine in this way, it is important to be able to identify when these behaviors are likely happening in households so that data can be reported as accurately as possible. If a household engages in the first of these behaviors, it would be reason to exclude their data from the final analysis due to their logged fuel usage likely not being representative of their actual fuel use. However, households who engaged in the second behavior followed instructions regarding the use of the FUEL system and their fuel usage data is likely representative of actual use.

Calculating the correlation between the duration of a household's stove use event and their associable fuel use can provide insight into how consistently fuel is being removed (i.e., Does the amount of fuel removed make sense for the duration of stove use time?). Due to

differences in firepower needed for different tasks it is not expected that there will always be a high correlation. However, a household correlation of at least $r(n) = 0.5$ (where n represents the number of identified stove use events) would indicate a low-level positive correlation between the two values indicating some level of consistent use. Comparing a household's r -value and the level of FUEL acceptance may provide a method of discerning which household data should be used in reporting, which need further investigation before they are included, and which household data should not be included in the final reporting.

Fig. 11 shows the relationship between a household's level of FUEL acceptance and their r -value for stove use duration and fuel use. For this example, a minimum FUEL acceptance level was set to 75%, but this value may be modified given a study's parameters and context. Households falling in quadrant A (shaded green) were households whose data showed both high acceptance levels and an acceptable correlation between the duration of stove use events and fuel association. It is likely that these households appropriately and consistently removed fuel from the FUEL system when using their monitored stove and require no extra investigation for inclusion in the final reporting. Households falling in quadrant B (shaded orange) showed high levels of FUEL acceptance but a low correlation between the duration of stove use and fuel association. It is likely that these households either regularly removed too much fuel during stove use events and then used the left-over fuel and some extra in subsequent events or did not consistently use their stove resulting in a varying need for fuel for a given duration. Households that fall into quadrant C (shaded orange) show lower than ideal levels of FUEL acceptance but high correlation values indicating that the households likely consistently removed too much fuel for a given event and then used the left-over fuel in subsequent events without needing to remove more fuel from the system. Households that fall into either quadrant B or C should have their data investigated further to determine whether their data is likely to be representative of their actual fuel use. Finally, households falling in quadrant D (shaded red) likely engaged in behavior that fell outside of the FUEL system instruction and should not be included in the final reporting.

3.3.2. Further investigation of household data

It is possible to determine whether a household's logged fuel is likely representative of actual fuel use through visual investigation. Fig. 12 shows data for a household in each of the four quadrants depicted in Fig. 11. The duration of identified events (left y-axis) in each household is shown with the dark bars representing verified stove use events and

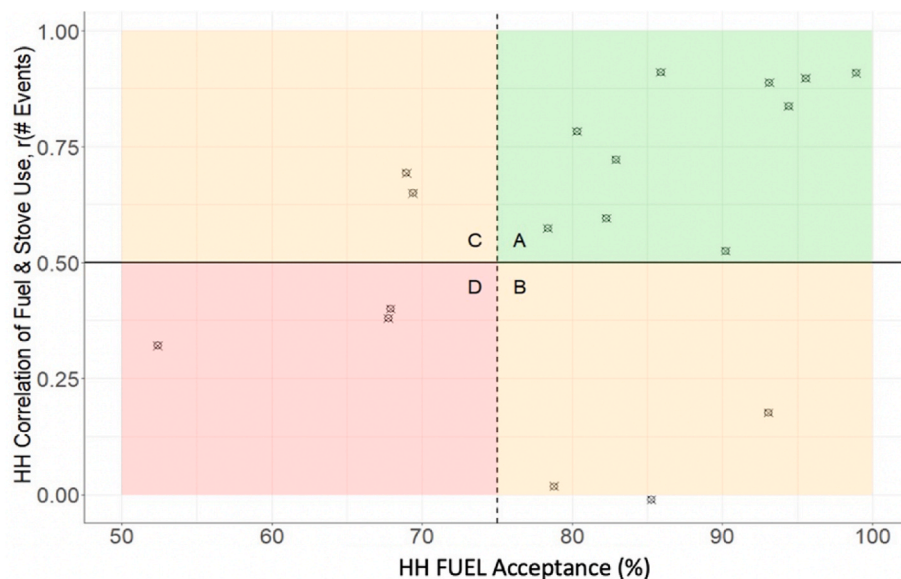


Fig. 11. The relationship between household FUEL acceptance in terms of the percentage of household stove use duration with associable fuel and the Pearson's correlation between duration and logged fuel use. The vertical dashed line represents the variable level of desirable acceptance (set here to 75%). The solid horizontal line represents a minimum r -value of 0.5 representing a low positive correlation. Quadrant A (shaded green) represents households, due to high levels of acceptance and r values, likely used the FUEL system as instructed. Quadrants B and C (shaded orange) represent households with either a high percentage of stove use events with associable fuel or r values but lower than ideal levels in the other. These household data need further investigation before inclusion in the results. Quadrant D (shaded red) indicate households with both low correlation values and lower than ideal acceptance levels indicating likely inaccurate FUEL data.

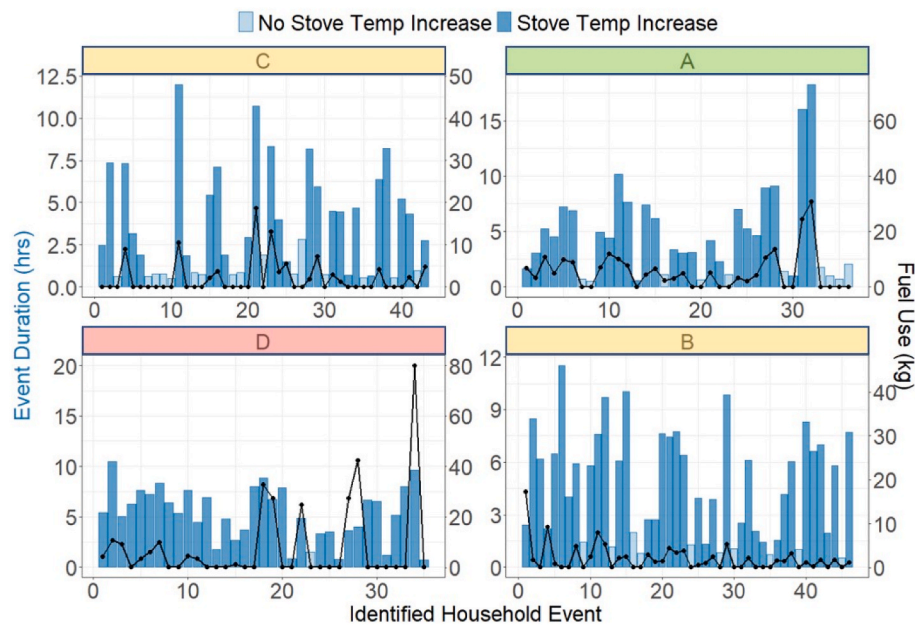


Fig. 12. Further investigation of household data from each of the four quadrants. Identified event duration (left y-axis) and associable fuel use (right y-axis). Dark blue bars indicate stove events with temperature verification, light blue bars indicate periods of raised household PM levels with no corresponding stove temperature increase. Quadrant A is represented by household 6 (stove use acceptance = 95.5%, $r = 0.90$), Quadrant B is represented by household 3001 (stove use acceptance = 85.2%, $r = -0.01$), Quadrant C is represented by household 20 (stove use acceptance = 69.4%, $r = 0.65$), and Quadrant D is represented by household 3020 (stove use acceptance = 52.4%, $r = 0.32$).

light bars representing extraneous PM events (i.e., events with no corresponding stove temperature increase). Additionally, the amount of fuel use logged during each event (right y-axis) is represented with the black line. As anticipated the household in quadrant A seems to be consistently removing fuel before or during each stove use event. Alternatively, the household in quadrant D shows inconsistent fuel removal with some occasionally large fuel removals making their FUEL data unreliable. The quadrant B household shows consistent removal of fuel during stove use events, but the amount of fuel removed does not seem to consistently correspond to the duration of stove use. Although it is possible that fuel was used from another source, the consistency in fuel removal points to the use of left-over fuel from previous stove use events and/or inconsistent stove tending due to the different needs of the user. The large spikes in fuel use seen in the quadrant C household often align with longer-duration stove use events and are often followed by shorter events with very little or no fuel removal. These data support that the household likely took too much fuel for a given event and then followed instructions regarding the use of left-over fuel in subsequent stove use events. Both the households shown in quadrants B and C likely have FUEL data that is reasonably representative of their actual fuel use and can be included in results regarding overall changes in fuel use. However, their data may not be suitable for more granular analysis such as fuel use per day or meal.

In each of the example households shown in Fig. 12 the relatively short duration of extraneous PM events and the lack of fuel use during the events indicate that they are likely due to an external source. This should be accounted for in the analysis regarding stove contribution to HAP. Alternatively, if a household's data showed multiple instances of elevated PM levels with associable fuel, further investigation should be done into the positioning of the stove use monitor as well as whether the household is actively engaging in unmonitored stove stacking.

3.4. Feasibility of remote training for local capacity building

The feedback provided by the RPN field staff responsible for sensor deployment and data collection indicated that they felt the remote training materials provided were sufficient and that all necessary information was included. However, it was indicated that occasional launcher and sensor malfunctions prolonged time spent in the field and increased the difficulty of sensor deployment and data collection. Lack of explicit instructions on installation of the EXACT sensors on chimneys

and miscommunication regarding continued monitoring of traditional stoves resulted in extensive but preventable loss of stove temperature data, however, there were few other errors in sensor deployment or data collection. Although further development of supporting resources, specifically regarding the EXACT sensor, is needed, the novel nature of this monitoring method along with the limited number of errors supports the feasibility of this system for capacity development.

3.5. Limitations

In this study, the ability to report on stove usage was limited by sensor malfunction and incorrect sensor placement. The lack of a gravimetric system co-located with the HAPEx sensors allowed only for reporting relative changes in household PM CU rather than the absolute magnitude of specific aerosols such as $PM_{2.5}$. Although we can report on the changes in total logged fuel use, it is possible that fuel was used that was not captured by the system. Additionally, using this system prohibits reliable documentation of the number of people fed in each household during each day of monitoring. This data is often a crucial part of reporting standardized fuel savings in households and may need to be taken into consideration during future study designs.

4. Conclusions

The households monitored in this study experienced a median reduction of 61.2% ($n = 38$) in their daily average PM levels following the introduction of the RPN stove with chimney, with households in the Taplejung district ($n = 17$, median = 45.7%) experiencing lower median reductions than those in the Panchthar district ($n = 19$, median = 64.5%). Both districts experienced a reduction in logged fuel use with the households in Taplejung experiencing a median total reduction of 24.53% ($n = 15$) and households in the Panchthar district experiencing a median total reduction of 8.13% ($n = 23$). Validation of this study's results should be pursued through the study of the RPN stove in households of different contexts, throughout different seasons, and for a longer duration to ensure that these results represent real-world stove outcomes. Additionally, these differences should also be considered with estimating expected impacts at the population scale.

Based on both the RPN field staff feedback as well as the quality and quantity of resulting study data, further development of the sensor suite training material is needed before it can be reliably implemented by

individuals with limited prior experience. However, as is common in sensor-based stove monitoring, temperature sensors were the main source of data loss and corruption. It is anticipated that further stove studies involving the sensor suite and continual development of the training material will produce a robust and reliable tool capable of building local capacity for household stove monitoring projects.

Through cross-sensor analysis, household PM CU data was used to clarify the beginning of stove usage events and flag rises in PM CU without a corresponding increase in stove temperature. The confounding effects of PM resulting from external sources have been a challenge to stove monitoring projects to date (Ni et al., 2016; Thornburg et al., 2022). Development of this cross-sensor analysis method provides promising potential for the identification and exclusion of these external sources from analyses. Furthermore, it was found that fuel use logged by the FUEL sensor could be validated with either or both temperature and PM CU data. This research shows that the presence of multiple types of sensors in a household provides extended insight on multiple key stove performance metrics while also providing a means for verifying metrics from single sensors, thus increasing confidence in the results reported.

4.1. Future work

Further development of methods regarding household stove use verification with household PM CU data is needed to reliably identify cooking events and associated PM contributions. We anticipate that these methods will be implemented into a user-friendly analytics platform allowing for data upload, management, and analysis with minimal input from the user. With further development, we hope that this suite of sensors, potentially paired with additional existing sensors such as gravimetric pump and filter systems, may be used to support results-based financing in future studies.

All up-to-date user manuals for the individual sensors and the sensor suite can be found on the Climate Solutions Consulting website. The training materials used in this study are continually being updated as new sensors and study locations are developed and feedback from projects is received. We anticipate that the materials will likely need iterations and adjustments with each new study site and research objectives.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: One or more authors of this paper declare a conflict of interest due to their involvement with the manufacture and sale of the integrated suite of sensors described herein.

Data availability

Data will be made available on request.

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