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Techno-economic comparison of the FUEL sensor and Kitchen Performance Test to quantify household fuel consumption with multiple cookstoves and fuels

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ABSTRACT

Quantifying the impact of improved stoves and fuels designed to combat the health and environmental burdens of traditional cooking is necessary to ensure sustainable outcomes but remains challenging for practitioners. The current standard method to determine household fuel consumption, the Kitchen Performance Test, is costly, time intensive, and subject to error. To address these challenges, the Fuel Use Electronic Logger (FUEL), a sensor-based system that monitors fuel consumption in households was developed. In this study, the accuracy, granularity, and cost of FUEL were compared to that of the standard Kitchen Performance Test through simultaneous testing. Monitoring was conducted over four and five consecutive days in 10 households in Burkina Faso that were each stacking LPG, charcoal, and wood stoves; and in 20 households in Uganda stacking multiple wood stoves, respectively. Results show good agreement between the two methods on an aggregate level, with an overall R^2 value of 0.81, and more varied agreement when comparing fuel consumption on a day-to-day basis. The sample variation was found to generally decrease with increasing monitoring length, pointing to value in monitoring over longer durations afforded by the FUEL. There was no systematic over- or under-prediction of fuel consumption between FUEL and the KPT, suggesting that the FUEL method does not have significant bias relative to the KPT, but the accuracy of the methods relative to the true, "ground truth" household fuel consumption value was not known. There was no agreement between either method with self-reported survey data, further illustrating the unreliability of quantitative survey data. Moisture content and Standard Adult Equivalence measurements were found to be similar whether measurements were taken only on the first and last days of the study period as compared to each day, although this should be evaluated over a longer time period for future studies. Potential errors in each method are discussed and resulting suggestions for developing an effective study with the FUEL system are presented. An economic analysis shows that the FUEL system becomes increasingly economical as monitoring duration increases or new studies are conducted, with a breakeven point at 40 days in this case. Overall, these results point to the viability of the FUEL system to quantify long-term, in-situ fuel consumption with similar accuracy to current methods and the capability for more granular data over longer time periods with less intrusion into households.

1. Introduction

Over 2.8 billion people rely on solid fuels burned in inefficient open fires to meet their cooking and heating needs, resulting in high energy burdens and emission of dangerous pollutants (Bonjour et al., 2013; Lim, 2012; WHO, 2014, 2016). In an effort to alleviate the economic, health, and environmental harms resulting from this traditional practice, hundreds of organizations and governments have been working to disseminate tens of millions of improved cooking stoves and cleaner fuels in recent years (GACC, 2017). While laboratory testing during the design phase of these technologies is common, practitioners have faced challenges in validating the impact of these devices when they are used in real-world households. Although laboratory testing provides best-case scenarios of potential impacts, improved stoves often have less than perfect adoption rates, are used alongside other traditional technologies that reduce benefits, or are used with different fuels or tending

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practices that decrease expected performance. For these reasons, among others, the difference between expected and measured outcomes can be significant. It is therefore necessary to quantify in-situ usage and performance to gain an accurate understanding of project outcomes to inform program implementers and evaluators, funding organizations, and researchers.

Sensor-based methods that reduce the cost and time for monitoring and increase data quality have been used in recent years to monitor both adoption and emissions. However, the process for monitoring fuel consumption has not been automated, despite being a key indicator of a stove's technical performance and can further be used to predict emissions affecting health and climate. Current tools to determine fuel consumption include manual measurements such as the Kitchen Performance Test (KPT) and qualitative or quantitative surveys that rely on imprecise household estimates that can be costly and time-consuming with limited statistical power and known unreliability (Thomas et al., 2013; Wilson et al., 2015). Another method uses cooking duration data from temperature sensors to extrapolate to fuel consumption using an energy flux approach (Graham et al., 2014). While more accurate than survey methods, accurate measurement of cooking duration to correct for cooking events relies on calibrating for different stove types to account for varying heat up and cool down times. To create a more accurate and cost-effective process for monitoring fuel use, researchers at Oregon State University have developed a sensor-based system called the Fuel Use Electronic Logger (FUEL) to enable automated continuous logging of fuel consumption data in a household for up to several months at a time. The design, usability, and technical performance of the FUEL system have been previously evaluated (Ventrella and MacCarty, 2019; Ventrella et al., 2020). The purpose of this paper is to compare the accuracy, cost, and granularity between the FUEL system to the KPT, the current standard method for fuel consumption measurement in the sector. To do so, two studies used both methods simultaneously over four monitoring days to compare the results: one in Uganda with wood stoves in a sample of 20 households, and a second in Burkina Faso in 10 households stacking wood, charcoal, and LPG stoves. Results demonstrate the range of the FUEL's capabilities and applications for practitioners when monitoring a variety of fuel types and stove stacking.

2. Background

Cleaner fuels and cooking devices can increase combustion and heat transfer efficiencies relative to traditional cooking methods, but their in-field performance and adoption rates can vary significantly depending on the design and context. Laboratory and other controlled testing are insufficient to predict real impact because they do not account for adoption rates or local stove usage practices that may decrease stove efficiency, such as using wet wood, over-filling the combustion chamber, or leaving the fire to burn for long periods of time with minimal tending. In addition, stove stacking, in which a household uses multiple stoves or fuel types, is common and must also be accounted for when determining aggregated household fuel use (MacCarty and Bryden, 2017; Masera et al., 2000). Therefore, it is necessary to measure impacts of interventions as used in households to verify project effectiveness. These data can be used to demonstrate impacts to donors to secure results-based financing, monetize savings in the form of carbon credits or averted disability adjusted life years (aDALYs), or if goals are not being met, reevaluate the program or technology design.

There are several existing manual and sensor-based methods that are currently used to monitor in-home stove technical performance and adoption. These techniques can be used to determine metrics such as adoption and usage, stove stacking, fuel consumption, and emissions. A general summary of current tools and their attributes are listed in Table 1. Each of these tools is used to measure various metrics of either in-home stove performance or user adoption, both of which dictate overall stove impact. A more detailed description of the specific tools available is presented in Ventrella et al. (2020).

Fuel consumption is one of the most important metrics of cooking intervention performance. Fuel consumption indicates the time and financial burdens in households and can be extrapolated to emissions that impact health and climate via emission factors. Fuel consumption data can also be used in the carbon market, where fuel savings are translated to mitigated carbon dioxide equivalent ($t_{CO2,e}$) that are traded or sold as carbon credits on the voluntary or compliance market as a source of financing for larger-scale clean cookstove programs (Lee et al., 2013). Fuel consumption can also be used to predict air quality in the home and resulting Averted Disability-Adjusted Life Years (ADALYs) (Johnson et al., 2011; WHO, 2014a, 2014b; Smith et al., 2015; MacCarty et al., 2020). The most commonly used tool for determining fuel use is currently the KPT, discussed in detail in Appendix A. The KPT is challenging due to the labor intensity, disruption to households, and possible errors associated with its application. Because sensors can increase accuracy while decreasing associated monitoring cost and time (Pillarisetti et al., 2014; Ruiz-Mercado et al., 2012), the FUEL sensor has been recently developed as the only existing sensor-based alternative (Ventrella and MacCarty, 2019; Ventrella et al., 2020).

To directly monitor fuel consumption in households, FUEL monitors and records time-stamped fuel mass data using a logging load cell. To operate, a household cook is trained to store his or her fuel supply in the bucket- or sling-type fuel holder (Fig. 1), remove fuel as needed for cooking, and refill when empty. These actions result in discrete reductions in weight, which are recorded by the load cell and integrated to determine total wood use over a specified time. The FUEL system has capability to operate in tension for fuels like firewood, charcoal, and agricultural residues; or in compression for LPG, ethanol, or kerosene. If households stack with multiple stoves or fuels, a separate sensor can be installed for each stove or fuel type. An external temperature sensor on the cookstove coupled to the data output generates a continuous temperature profile over the monitoring period, which is used to determine cooking duration and serve as a corroboration for the weight data by verifying that the cookstove temperature is elevated, i.e. "on", when a weight reduction is detected. Details of the two prototype hardware versions are available in Appendix B.

The FUEL has been previously tested for usability and performance in proof-of-concept and pilot testing in Guatemala, Honduras, and

Table 1
Summary of current in-home monitoring tools in the clean cooking and fuels sector.

	Surveys	Kitchen Performance Test	Temperature Sensors	Emissions Sensors	Fuel Sensors
Metrics	Adoption, cooking duration, fuel use	Fuel use	Adoption, cooking duration	Pollutants	Fuel use
Benefits	Relatively inexpensive	Direct measurement of fuel use	Higher objectivity	Direct at-source measurements	Direct at-source measurements
Sources of Error	Survey, recall, social desirability biases	Manual measurement errors	Data loss from broken sensors, accounting for heating and cool-down time	Noise (PM sensors), sensor drift, background pollution	Human error, sensor drift
Data Type	Qualitative, quantitative	Quantitative	Quantitative	Quantitative	Quantitative
Data Collection	Manual	Manual	Automated	Automated	Automated

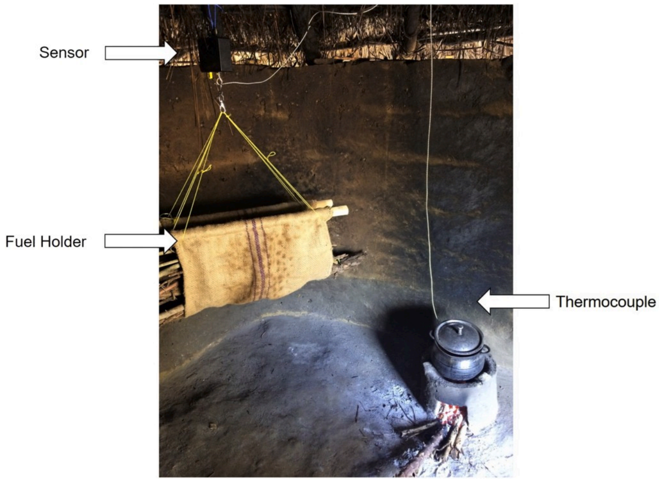

Fig. 1. Fuel system installed in Apac, Uganda (Ventrella, 2018).

Uganda. Results from a study of 85 households in rural Uganda showed that 82% of users consistently engaged with the FUEL systems, and a usability survey revealed that participants in this study context found benefits to using the holder, including drying their fuel wood and keeping it organized (Ventrella and MacCarty, 2019; Ventrella et al., 2020).

There are several factors that can affect the accuracy of measurements reported by the KPT and FUEL methods.

i. Using fuel that was not weighed by the sensor or enumerator (i.e. burning fuel from a non-measured source). In the KPT, this can occur if the household runs out of fuel before the enumerator comes to weigh it. With FUEL, this can occur if fuel is burned without first placing it in the fuel holder.
ii. Not using fuel that was weighed by the sensor or enumerator (i.e. giving fuel away)
iii. Removing fuel from holder and putting it back unused (FUEL only)
iv. Enumerators not accurately weighing the amount of fuel
v. Not accurately accounting for the moisture of the fuel
vi. Not accurately accounting for the number of meals served each day to calculate fuel use per Standard Adult Equivalence (SAE)
vii. Not capturing daily and seasonal variability in number of people served, number of meals cooked, fuel moisture content, or seasonal cooking practice

The goal of this study was to compare the FUEL and KPT in terms of measurement accuracy, granularity, and cost by conducting both methods simultaneously in a sample of households. As the FUEL relies on consistently accurate individual household use of the system compared to the KPT which asks them to only burn fuel manually weighed by trained testers, this comparison can help to identify if the FUEL system is prone to user error. Specific objectives were to compare calculations of daily and aggregated fuel consumption based on both FUEL and KPT data, verify and validate the FUEL analytics algorithm, and determine best-use practices for the FUEL system.

3. Methods

Comparison testing of the FUEL and KPT methods was conducted in Uganda and Burkina Faso using 1st and 2nd generation FUEL sensors, respectively, in July and August of 2018. While the FUEL sensors were deployed, the KPT was simultaneously conducted to directly compare measurements. Both studies had oversight for protection of human subjects by the Oregon State University Institutional Review Board under study number 7257.

3.1. Sample size

3.1.1. Uganda

International Lifeline Fund (ILF), an NGO that works on clean stove and water projects in East Africa, partnered with OSU researchers to conduct the validation study in the Apac district of Uganda with 20 convenience-sampled households over a five-day period. Participants were compensated with a portion of food and a set of dishware. Households in the study sample rely primarily on collected firewood, and the three stove models monitored were all wood stoves. The traditional stove types in the region are the three stone fire (TSF) and locally mudded stove (LMS), and the improved is the ILF rural wood stove (RWS), Fig. 2. Monitoring was primarily focused on households using only the RWS, however several households were stacking with either the TFS or LMS (Table 2). Due to prototype sensor malfunction, the sample included in the analysis was 16 households. With the 1st generation FUEL system, stoves were fitted with wired thermocouples to measure temperature.

3.1.2. Burkina Faso

Nafa Naana, a social enterprise that works on clean stove projects, Entrepreneurs du Monde, and Climate Solutions Consulting also partnered with OSU researchers to conduct a second validation study in Burkina Faso in 10 convenience-sampled households over a four-day period. The fuel/stove types in the area include LPG, charcoal, and wood (Table 3, Fig. 3). The Telia LPG stove is the intervention stove, the Roumde is a slightly improved stove that can be used with either firewood or charcoal, and the traditional stoves include the three stone fire for wood and "Malagasi" rebar brasero for charcoal. EXACT temperature sensors were installed on each stove to record temperature (Lefebvre, n. d.).

3.2. Hardware

Several forms of location-specific hardware were needed for conducting the KPT and for installing the FUEL systems in kitchens.

3.2.1. Uganda

Hardware used to conduct the KPT included a digital scale and a moisture meter to determine wood moisture content. A Brecknell Electro Samson digital scale with a 45 kg capacity ±0.2 kg accuracy and 0.05 kg resolution was used to weigh fuel. A General MMD4E moisture meter with measurement range 5–50%, ±2% accuracy and 1% resolution was used to determine wood moisture content. All data were recorded manually on paper and later entered in Excel for analysis.

Hardware used for the FUEL system included an integrated load cell and thermocouple, SD card data storage, and installation equipment. The 1st generation FUEL system used an off-the-shelf tensile load cell with a 50 kg capacity, 0.1% of full-scale accuracy with two-point calibration (1 and 30 kg), and 0.005% resolution. Type K thermocouples rated at 750 °C with 2 m extensions were used to monitor cookstove temperature and calibrated in ice (0 °C) water and boiling (100 °C) water. The integrated system was powered with two C batteries. The logging rate was programmed to 49 s and decreased to 7 s when a specified weight change was detected, until no additional changes in mass were detected. To attach the thermocouple to the stoves, stainless steel brackets were manufactured. Equipment to install the FUEL system in kitchens included S-hooks and rope. To reduce difficulties in transportation, fuel holders were manufactured in Uganda using recycled burlap sacks (Fig. 4), dowels, and nylon rope local to the area. Data were stored on SD cards as .csv files.

3.2.2. Burkina Faso

For the KPT, a digital luggage scale with a 50 kg capacity and 0.01 kg

Fig. 2. Stove Models (from left to right): Three Stone Fire, Locally Mudded Stove, Rural Wood Stove, Uganda.

Table 2
Sample distribution and stove type, Uganda.

Stove Type	Households	Percentage
RWS	11	69%
TSF and RWS	2	19%
LMS and RWS	3	13%
Total	16	

Table 3
Sample distribution and fuel type, Burkina Faso.

Fuel Type	Households	Percentage
LPG	1	10%
LPG, Charcoal	4	40%
LPG, Wood	1	10%
LPG, Charcoal, Wood	4	40%
Total	10	

Fig. 3. FUEL installation for (from left to right): wood, LPG, and charcoal, Burkina Faso.

resolution was used to weigh fuel. A General MMD4E moisture meter with measurement range 5–50%, ±2% accuracy and 1% resolution was used to determine wood moisture content. All data were recorded on the Kobo Collect smartphone app and later exported to Excel for analysis.

Hardware used for the 2nd generation FUEL included a load cell, IR temperature sensor (EXACT), wireless launcher, SD card data storage, and installation equipment. An off-the-shelf tensile load cell with a 50 kg rated capacity and 10 g resolution was used in each sensor, and each cell was calibrated with a 4 kg reference mass. The measurement rate was programmed to 30 s, with data written to memory one time per minute. The data were stored in the device internal memory and then

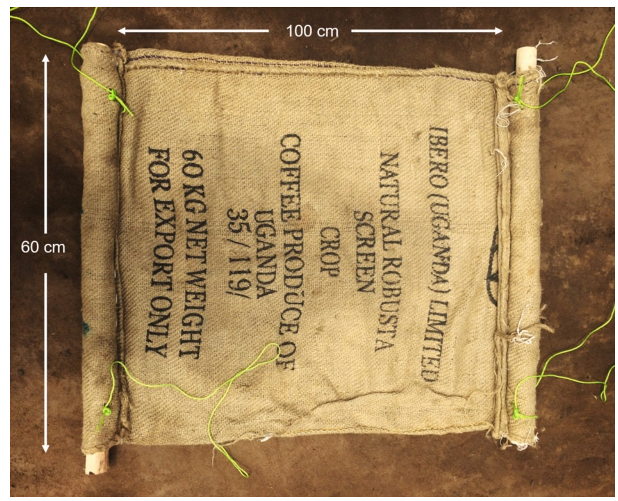

Fig. 4. Fuel holder and dimensions.

downloaded wirelessly to the launcher SD card as a .csv file.

3.3. User training

Training was consistent throughout both studies and was held for both the KPT and FUEL at the same time, prior to the beginning of the study to inform participants of the study requirements. For the KPT, households were informed that they would be visited every day for four days by enumerators to weigh their fuel. In Uganda, participants were then asked to collect approximately enough firewood to last for a four-day period, store in a pile, and collect additional wood as needed. Participants were instructed to store as much fuel as could fit in the FUEL system holder from the larger pile, remove from the holder as needed for cooking, and refill as desired. In Burkina Faso, participants were asked to collect or purchase enough fuel to last for the entire testing duration. Explicit guidance for participants included:

- Maintain as close to normal cooking practices as possible.
- When adding wood, fill holder with as much wood as possible, refill when near empty (helps to reduce noise in data).
- Do not put wood back in holder after removal (including partially burnt wood).
- Wood must be in the holder for at least 30 s before removal.
- All wood used for cooking must be stored in the holder before use in the stove.

3.4. Installation & data collection

While the KPT execution was generally consistent between study locations, FUEL installation differed slightly between Uganda and Burkina Faso.

3.4.1. KPT procedure

The procedure for fuel consumption measurements included weighing fuel and recording moisture content. Participants were visited at roughly the same time each day to maintain a 24-h difference between each daily measurement. Each household was assigned an ID number that corresponded to the FUEL sensor number. Participants were also administered a survey for each monitoring day.

3.4.2. FUEL procedure

3.4.2.1. Uganda. In Uganda, the FUEL systems were hung from pre-existing internal roof supports. Thermocouples were attached to stoves using stainless steel brackets. SD cards were programmed and initiated at the start of the KPT/FUEL monitoring. Following the four-day KPT and FUEL monitoring, SD cards were collected and data uploaded, and

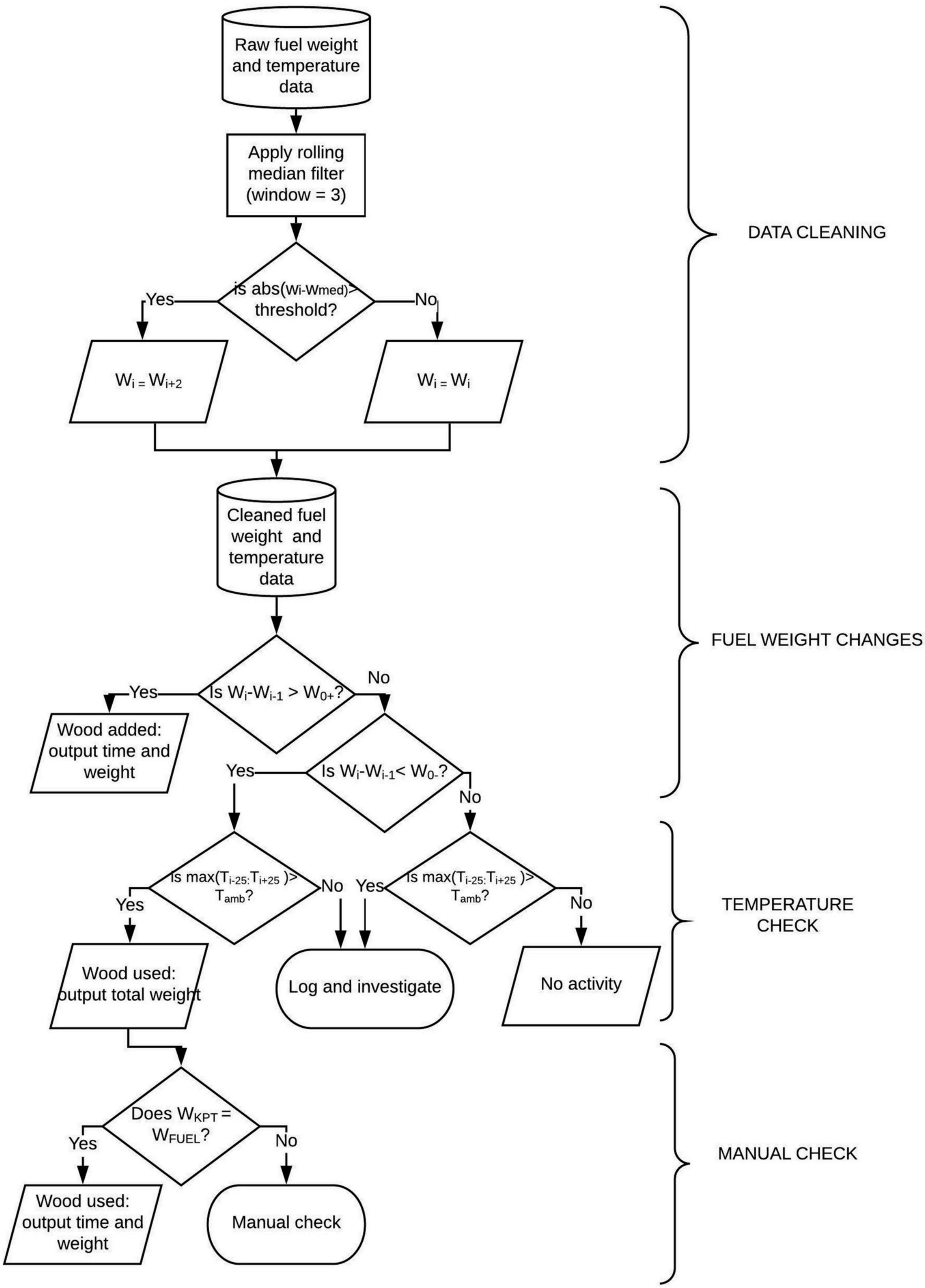

Fig. 5. Algorithm for FUEL data analysis.

the sensors were then re-launched to continue monitoring for an additional 30–45 days. Data from this additional monitoring are presented in Ventrella and MacCarty (2019).

3.4.2.2. Burkina Faso. In Burkina Faso, the FUEL systems required external wooden support for installation, constructed by a local carpenter (Fig. 4). EXACT temperature sensors were attached to stoves using pre-attached stainless steel brackets. A wireless launcher was used to program the logging rate and download logged sensor data after the four-day monitoring period.

3.5. Post processing

Survey and sensor data from the KPT and FUEL were analyzed to determine daily and aggregated fuel consumption for households in both locations, using manual and algorithmic processing. Daily KPT data were entered in an Excel spreadsheet, corrected for average moisture content and analyzed on a daily and aggregated basis. Following FUEL data collection, the sensor data were first cleaned by hand to remove the changes in weight caused by the enumerators removing all fuel from the holder to weigh and then reloading the fuel in the holder during the KPT. Data were then analyzed using the FUEL algorithm, which applies a sensor-specific calibration curve and then integrates mass changes over a specified time, corrects for discrete outliers using a rolling median filter, and corroborates weight data with cookstove temperature, Fig. 5 (Ventrella and MacCarty, 2019). The manual check comparing the KPT to FUEL values was only necessary for the validation study to identify sources of error coming from each method. The 2nd generation FUEL system applies calibration internally. Temperature was not used to corroborate fuel use in the LPG stoves because the LPG tanks were only attached to the FUEL sensors when the enumerators came to weigh them for the KPT. Therefore, temperature would not correspond with decreases in weight. Cooking duration was determined from temperature data by using peak detection and time-window clustering, modeled after a similar method used by Ruiz-Mercado et al. (2012). Peaks were clustered in time windows of 3 h. If a period of time between two temperature peaks was greater than 3 h, the algorithm would consider these as two separate cooking events. These measured cooking duration data were then compared to reported cooking duration per each meal prepared in the past 24 h, collected as part of the KPT survey in Uganda.

3.6. Algorithm verification and validation

The algorithm was verified and validated using a combination of KPT and FUEL data. For verification, fuel use as measured by the FUEL in Burkina Faso was graphed and interpreted manually. The same data set was then run through the algorithm and results were compared and expected to be the same. To validate the algorithm, both daily and aggregated fuel consumption data from the FUEL sensors calculated using the algorithm were compared to the KPT measurements of fuel consumption. To test the data cleaning function, FUEL data were analyzed with and without cleaning and also compared to the KPT measurements.

4. Results

Results of daily and aggregated fuel consumption measured by the FUEL as compared to the KPT, as well as analysis of moisture content variation, reported versus measured cooking duration, and algorithm verification are presented.

4.1. FUEL versus KPT fuel usage

A comparison of daily and aggregated fuel consumption measured by FUEL versus the KPT for all fuel types in each study location is shown. 1:1 trendlines are shown for Fig. 7, and the slope and y-intercept of each best fit line are reported, and R^2 values are reported for best fit lines.

The first row in Fig. 6 shows a comparison of charcoal fuel as measured by FUEL versus the KPT in Burkina Faso, aggregated over the monitoring period and daily, with reported R^2 values of 0.9567 and 0.1642, respectively. Values for the aggregated measurements agreed within 6.9% on average. Data from three charcoal stoves were not included in the analysis due to noise. It is unclear what contributed to this low correlation in the daily measurements.

The second row of Fig. 6 shows a comparison of LPG fuel as measured by FUEL versus the KPT in Burkina Faso, aggregated over the monitoring period and daily, with reported R^2 values of 0.9834 and 0.8148, respectively. Values for the aggregated measurements agreed within 7% on average. Negative numbers for the daily values indicate a measurement error in the KPT due to the resolution of the scale, temperature drift, and relatively low mass change for LPG usage (see Appendix B). Data from two LPG stoves were not included in the analysis due to missing data.

The comparison of wood fuel as measured by FUEL versus the KPT in Burkina Faso, aggregated over the monitoring period and daily, had reported R^2 values of 0.9878 and 0.9519, respectively. Values for the aggregated measurements agreed within 12% on average.

The final row of Fig. 6 shows a comparison of wood fuel as measured by FUEL versus the KPT in Uganda, aggregated over the monitoring period and daily, with reported R^2 values of 0.7916 and 0.1085, respectively. Values for the aggregated measurements agreed within 15% on average.

Overall, in Burkina Faso, aggregated measurements between the KPT and FUEL were in good agreement, with R^2 values over 0.96. However, there was less correlation when comparing daily measurements of the KPT and FUEL. This was likely due to people removing more fuel from the holder for FUEL than was needed for cooking on a single day and using it the next day. Daily LPG may have the highest R^2 value because it requires the least user compliance in comparison to wood and charcoal, which can both be removed or re-added to the FUEL holder.

In Uganda, aggregated fuel as measured by the KPT was in fairly good agreement with FUEL, with an R^2 value of 0.7916. The agreement may be lower than in Burkina Faso because of differences in fuel collection and use of the fuel holder between the two locations. In Burkina Faso, households initially gathered enough fuel to last for the entirety of the monitoring period and were thus not required to refill the holders as needed, thereby minimizing human interaction and potential measurement error. Each household in Burkina Faso also only had one or less of each type of stove. In comparison, the participants in Uganda were asked to collect their own wood and refill the holder as needed, necessitated because they used much higher quantities of wood than in Burkina Faso since it was the sole fuel type in that community. Increased fuel gathering can result in a higher chance of user/enumerator error, and therefore fuel measurements for both the KPT and FUEL system have greater uncertainty. In addition, several households used two wood stoves and were asked to choose fuel from the holder that corresponded with the correct stove, which could have also resulted in higher error.

There was low agreement when comparing daily measurements of the KPT and FUEL, again most likely due to participant usage patterns. For example, a household might remove more fuel than needed for one meal, and use it later, as was observed with a participant in Burkina Faso. This kind of usage habit could result in inaccurate daily measurements if the fuel was not used until the next monitoring day.

4.2. Combined results

Fig. 7A shows a normalized comparison of all fuels as measured by FUEL versus the KPT in both study locations, aggregated over the monitoring period, with a reported R^2 value of 0.8052 and average difference of 18%.

Fig. 7B shows a normalized comparison of all fuels as measured by

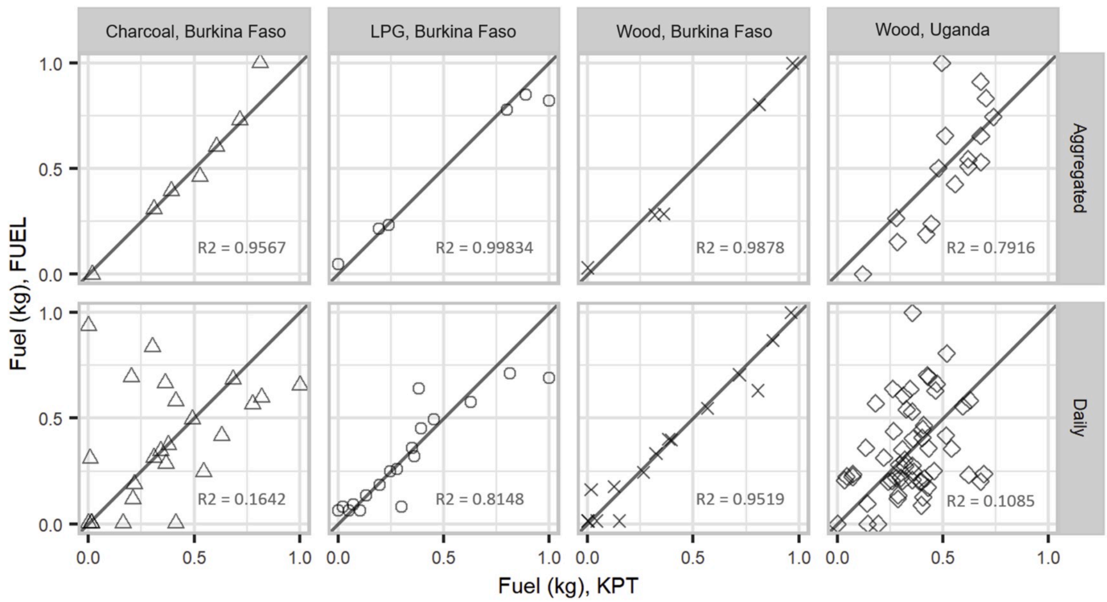

Fig. 6. FUEL versus KPT in Burkina Faso and Uganda aggregated over the monitoring period and daily for all fuel types. Slope (m) and y-intercept (b) for all graphs: 1) Aggregated, Burkina Faso, 1a) charcoal: m = 1.160, b = −0.3833 ; 1b) LPG: m = 0.8479, b = 0.0761,1 c) wood: m = 1.019, b = −0.2252; 2) Daily, Burkina Faso, 2a) charcoal: m = 0.4154, b = 0.615, 2b) LPG: m = 0.7757, b = 0.0442, 2c) wood: m = 1.0185, b = −0.2252; 3) Aggregated, Uganda, wood: m = 1.2954, b = −10.454; 4) Daily, Uganda, wood: m = 0.4549, b = 4.1965.

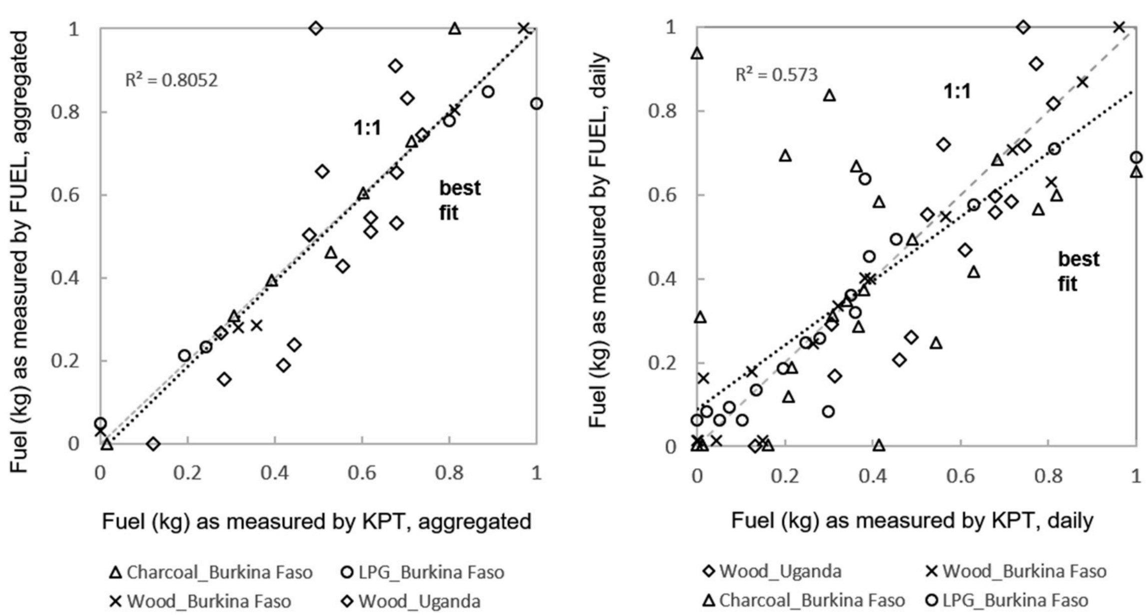

Fig. 7. FUEL versus KPT normalized, all stove types and locations, with data (A) aggregated, m = 1.0222, b = −0.0187 and (B) daily, m = 0.7618, b = 0.0899.

FUEL versus the KPT in both study locations on a daily basis, with a reported R^2 value of 0.573.

Figs. 7A and B indicate that there is no systematic over predicting or under predicting by FUEL. Since the data are not biased in one way or another, this suggests that there is no consistent mode of user error, such as not putting fuel in the holder.

4.3. Algorithm verification & validation

To verify the algorithm, aggregated fuel consumption of wood stoves in Burkina Faso as measured by FUEL and calculated using the FUEL algorithm was compared to aggregated fuel consumption when the FUEL data were graphed and interpreted by hand (Appendix D). The reported R^2 value of this verification was 0.9941.

For validation of the data cleaning algorithm which removes outlier points not caused by intentional fuel removal and decreases in weight not corroborated with a corresponding increase in temperature, aggregated fuel as measured by FUEL was compared to fuel measured by the KPT with and without data cleaning (Appendix D). Results show that with no cleaning, the reported R^2 value was 0.5992 and with cleaning, 0.7916. Note that all data presented in Figs. 6 and 7 was after cleaning.

Verification and validation results showed that the data cleaning and temperature corroboration algorithms have appropriate thresholds and work as intended. Applying a median filter to smooth weight outliers with a set threshold value improved the R^2 value, indicating that the algorithm is working well. More work is needed to validate the

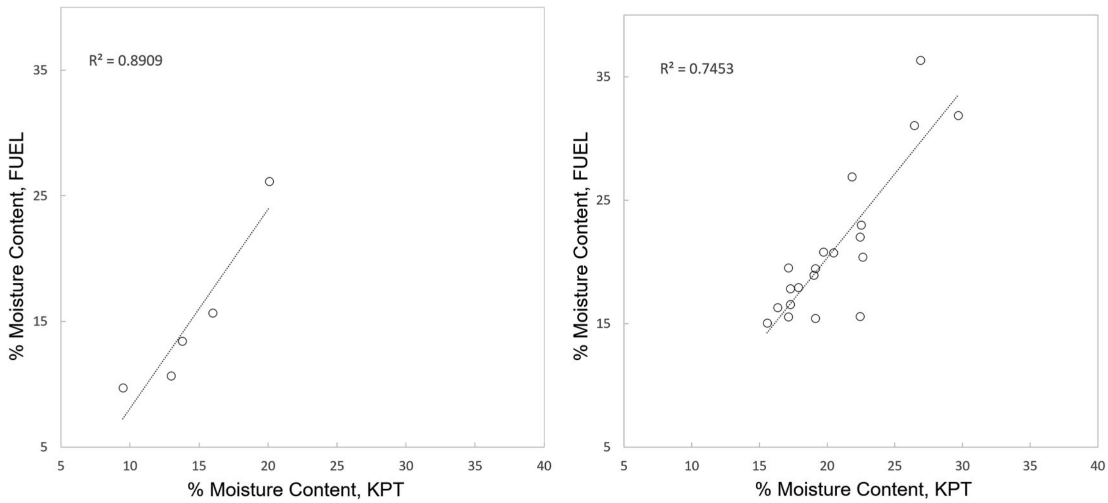

Fig. 8. Percent moisture content for first and last day of monitoring (FUEL) versus all days (KPT) with data from (A) Burkina Faso, m = 1.5838, b = −7.7696 and (B) Uganda, m = 1.3641, b = −6.9579.

algorithm for cooking duration.

4.4. Moisture content

Moisture content readings for KPT compared to FUEL were characterized by comparing the difference between taking moisture content readings every day (KPT) versus the average of the first and last day of monitoring (FUEL), to represent what would happen in practice for a monitoring session with FUEL exclusively (Fig. 8). Results for Burkina Faso reported an R^2 value of 0.8909, while in Uganda, the reported R^2 value was 0.7453.

In Burkina Faso, the average moisture content across households for all four days was 15.1 ± 1.2% as compared to 14.5 ± 1.0% for moisture content measured only on days 1 and 4. In Uganda, the average moisture content across households for all four days was 20.6 ± 3.8% as compared to 21.07 ± 6.1% for moisture content measured only on days 1 and 4. This indicates that there was not a significant difference between average household moisture content for all four days (KPT) versus the first and last days (FUEL), and suggests when using the FUEL, it is sufficient to measure wood moisture content on the days of installation and system removal. However, these results may vary for longer monitoring durations, especially if there are seasonal variations within the monitoring period. Taking moisture content readings in intervals throughout the desired monitoring time could capture potential variations. The higher R^2 value for moisture content in Burkina Faso could be attributed to a more stable climate in the region or during that monitoring period, or a more accurate and consistent moisture meter.

4.5. Standard Adult Equivalence

Similarly to moisture content, it is also illustrative to compare the SAE based on daily measurements or average of start and end period in the case of an exclusive FUEL monitoring session when an enumerator does not need to visit the household every day (Fig. 9). In Burkina Faso, the SAE recorded on all four days agreed with the SAE for days one and three within an average of 0.5% and had a pooled standard deviation of 0.037 for the 10 households. In Uganda, the SAE recorded on all four days agreed with the SAE for days one and four, within an average of 1% and had a pooled standard deviation of 0.0995 SAE. The reported R^2 value was 0.8592. The comparison of SAE as recorded on all four monitoring days, as per the KPT, and SAE recorded on the first and last day, as per the FUEL, showed close agreement, suggesting that taking the average at the beginning and end of a FUEL monitoring session should be sufficient. Higher variation might be found with longer

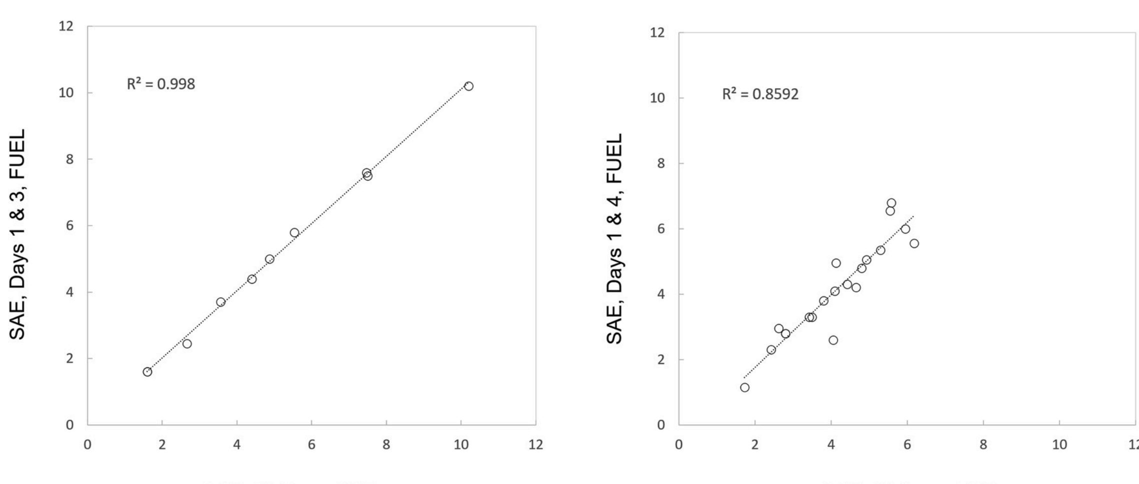

Fig. 9. Average Standard Adult Equivalence for first and last day of monitoring (FUEL) versus all days (KPT) with data from (A) Burkina Faso, m = 1.0113, b = −0.0106 and (B) Uganda, m = 1.1111, b = −0.4633.

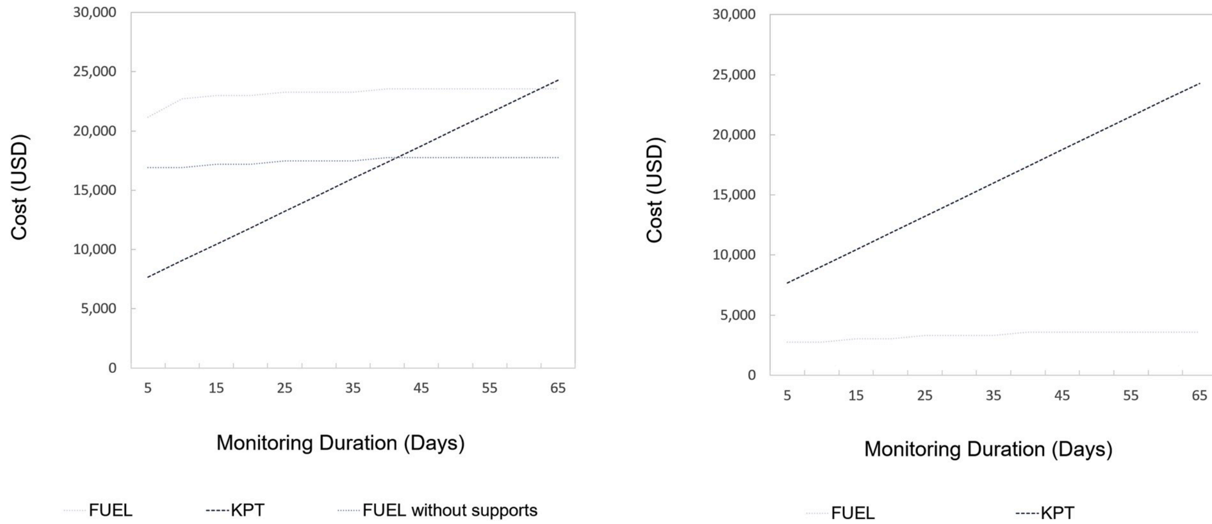

Fig. 10. Cost versus Monitoring Duration, FUEL and KPT, with projections for (A) 1st study and (B) subsequent studies.

monitoring durations and should be further investigated in future studies.

4.6. *Monitoring duration*

An analysis of the coefficient of variation (COV) of average daily fuel use per capita was conducted for each monitoring day to help inform future study design and sample size calculations. A cumulative average over each consecutive day was taken to control for potential user error in FUEL. Table 4 shows the household-level average daily fuel use, standard deviation, and COV for each fuel type for the KPT and FUEL, and the overall R^2 to assess the fit between FUEL and the KPT. The trend shows that the COV generally decreases with increasing monitoring length, with an overall average reduction of 43% for the FUEL and 36% for the KPT, suggesting that conducting fuel use monitoring over a longer duration will capture more variability than 1–2 days. This is corroborated with similar findings from a study that found that conducting a KPT for 7 days decreased the COV by about 56% (Berrueta et al., 2008).

Analysis of the effects of monitoring duration on average daily fuel consumption results was conducted with the data from Uganda, where FUEL sensors were set to monitor for up to 45 days (Ventrella and MacCarty, 2019). Daily average fuel consumption was calculated over durations of 4, 10, 15, 20, and 25 days and compared to the average fuel consumption over 30 days. Results showed that the standard deviation decreased from 1.20 kg over a four-day monitoring period to 0.093 kg for a 25-day monitoring period, and the average percent error also decreased from 72% to 6.5%, respectively, suggesting that results will be more indicative of actual long-term fuel use with increased monitoring duration.

4.7. *Sources of error*

4.7.1. *FUEL*

During manual interpretation of the FUEL data, there were several sources of error observed. Diurnal drifts in weight of up to 200 g were recorded, likely due to temperature effects that were not yet corrected in this version of FUEL (see Appendix B). In one household, firewood was removed early and used slowly over time for three cooking events. In another household, firewood was removed from the holder and then replaced with no cooking event taking place. These events were identified by the algorithm due to the corroboration check between temperature and weight changes.

4.7.2. *KPT*

Errors were also observed for the KPT. Negative LPG consumption recorded by the KPT shows that the scale used in the KPT is also subject to temperature drift, as well as noise from the scale oscillating during manual weighing. In at least one instance, a human error seems to have occurred where the weight of wood was recorded as 4.09 kg instead of 4.9 kg.

Table 4
Aggregated analysis.

Location	Fuel	n days	FUEL			KPT			DAILY	AGG
			AVE	SD	COV	AVE	SD	COV	R^2	R^2
Uganda	Wood	1	2.18	1.96	0.90	2.57	1.16	0.45	0.1085	0.7916
		2	2.23	1.30	0.58	2.47	1.05	0.43		
		3	2.24	1.07	0.48	2.31	0.94	0.41		
		4	2.24	0.87	0.39	2.14	0.73	0.34		
Burkina Faso	Wood	1	0.26	0.21	0.84	0.22	0.20	0.88	0.2374	0.9858
		2	0.31	0.15	0.48	0.33	0.12	0.36		
		3	0.24	0.13	0.55	0.25	0.11	0.45		
Burkina Faso	LPG	1	0.05	0.05	1.07	0.06	0.08	1.30	0.8148	0.9834
		2	0.06	0.03	0.50	0.06	0.04	0.63		
		3	0.06	0.03	0.54	0.06	0.04	0.66		
Burkina Faso	Charcoal	1	0.17	0.15	0.84	0.21	0.17	0.81	0.1642	0.9567
		2	0.12	0.08	0.62	0.17	0.12	0.72		
		3	0.16	0.10	0.59	0.16	0.09	0.58		

4.8. KPT versus FUEL cost

Fig. 10A shows a cost analysis between the FUEL and KPT with a sample size of 50 stoves for increasing monitoring duration based on data from Burkina Faso. Cost data factor in the cost of sensors, installation equipment, KPT scales, supplies, and field staff-related expenditures. If an external structural support for the FUEL system installation is not needed, the breakeven point where the KPT cost begins to exceed the FUEL is after 40 monitoring days. If supports are needed as they were in Burkina Faso where there were not sufficient roof beams in place, the breakeven point will increase to 60 monitoring days. However, if a second, third, etc. study is implemented later on and sensors and installation equipment are a sunk cost, the cost of the FUEL will be less than the KPT regardless of the monitoring duration, and with increasing gains as duration increases, Fig. 10B.

5. Discussion

5.1. FUEL best practices

Results showed that the FUEL sensor worked optimally for certain monitoring conditions and fuel types. For example, the FUEL was more accurate when there was less reloading of the fuel holders, such as when monitoring LPG or when households gathered enough fuel that the holder did not have to be reloaded during the study, as in the Burkina Faso study. In conditions where households use a large amount of fuel, minimizing human-holder interaction could be achieved by increasing the size of the fuel holder to hold more fuel at a time. It was also noted it could be more accurate and easier to measure LPG using a compressive scale, under development, as it would require less structural support and effort than hanging the tank from a tensile scale.

In the planning stages of a fuel usage or savings study, researchers or practitioners should gather location-specific information to better understand the context of where the monitoring will occur. This includes:

- Data on all cookstove and fuel types in the study community to determine how many sensors are needed per household.
- Indication of whether cooking occurs indoors, outdoors, or both to decide where to install the FUEL system and what materials are needed.
- Typical kitchen size and available space for system sizing, sturdiness of roofing or other available structures for installation, and availability of local materials for manufacturing the fuel holders on-site to reduce shipping costs and time and design a holder that is more contextually and culturally integrated.

Longer monitoring duration offered by the FUEL is expected to provide increased statistical power and more effectively capture daily variability in households. Analysis of the effects of monitoring duration on average daily fuel consumption results showed that the standard deviation decreased from 1.20 kg over a four-day monitoring period to 0.093 kg for a 25-day monitoring period, and the average percent error also decreased from 72% to 6.5%, respectively (Ventrella and MacCarty, 2019). Additional monitoring days in a household with FUEL adds only the cost of several brief household check-ins, unlike the KPT which requires more extensive, daily site visits, so longer monitoring is encouraged. This may be especially helpful during the initial stove technology uptake and learning phase to capture behaviors resulting in adoption or rejection.

User training should also be implemented prior to conducting a study to ensure that the system is used correctly. This includes briefing participants on the purpose and functionality of the FUEL system, providing explicit instructions on use, and eliciting and answering clarifying questions following the session. Use instructions should include:

- Remove fuel from holder in small amounts as needed for cooking.
- Refill the holder with fuel when close to empty.
- Ensure all fuel remains in the holder for at least 1 min before removal.
- Do not put any fuel back into the holder after removal, including partially burned or unburned fuel after cooking – save for the next cooking event.

5.2. Limitations

One consideration of this study is that there is no official "ground truth" of 100% accurate fuel consumption measurements in the study, since both the FUEL and KPT methods have potential sources of error previously discussed. This is addressed by referring to the study as a 'comparison' rather than a validation and acknowledging the potential sources of error in both methods. The intention was to compare the most common and currently accepted method of measuring fuel use with the new FUEL method. The small sample size was a further limitation of this study.

Another concern is that both survey and sensor-based methods have been found to have inherent biases, and the presence of a sensor system or visiting enumerator may modify typical usage behavior. A four-week study in Rwanda measured the difference in usage patterns of sensor-monitored water filters and cookstoves between groups that were and were not aware that the sensors were being used. The study found that while there was a significant difference between the water filter groups, there was no significant difference in usage between open and blind groups with cookstoves (Thomas et al., 2016). However, usage for all groups decreased over the four-week monitoring period, suggesting the value in longer-term monitoring. Overall, behavioral reactivity should be taken into consideration when conducting a sensor-based study.

The installation process for FUEL was not trivial, as the fuel holders were heavy and difficult to transport. In Burkina Faso, kitchen roofing structures were not available, which necessitated field staff to construct free-standing supports and cost unanticipated time and money. A possible solution is for field staff to give participants their sensor and holder during the training session and then visit each kitchen for installation. Fully understanding the context before study implementation can help to prevent these unanticipated outcomes, but more work is needed on ways to streamline and simplify the installation process.

6. Conclusion

Two studies were conducted to assess the viability of the FUEL sensor as compared to the KPT. On an aggregate level, FUEL was found to perform well and was comparable to the KPT, with no systematic over- or under-prediction between the two methods. The correlation on a daily basis was lower than the aggregated data, which could be due to several sources of error in either the FUEL or the KPT, such as if time between household visits was slightly longer than the intended 24 h. A cost analysis found that the breakeven point between the KPT and FUEL costs for one study was 40 monitoring days if extra infrastructure materials are not needed for FUEL. However, for any following studies where the purchase price of the FUELs is a sunk cost, the cost for monitoring with FUEL will be well below that of the KPT for any monitoring duration, suggesting long-term cost gains when using the FUEL.

It is hoped that the FUEL can be used in future studies to measure long-term fuel consumption and savings in households. Additional future work may include additional studies with alternative fuels, determining fuel savings as compared to a baseline stove, and conducting further validation by directly observing fuel usage in several households over a period of days to then compare to the FUEL and KPT.

Declaration of competing interest

The authors have a conflict of interest because they manufacture and sell sensors like the ones in this study.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.deveng.2020.100047.

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