Article

An Integrated Sensor Data Logging, Survey, and Analytics Platform for Field Research and Its Application in HAPIN, a Multi-Center Household Energy Intervention Trial

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Abstract: Researchers rely on sensor-derived data to gain insights on numerous human behaviors and environmental characteristics. While commercially available data-logging sensors can be deployed for a range of measurements, there have been limited resources for integrated hardware, software, and analysis platforms targeting field researcher use cases. In this paper, we describe Geocene, an integrated sensor data logging, survey, and analytics platform for field research. We provide an example of Geocene's ongoing use in the Household Air Pollution Intervention Network (HAPIN). HAPIN is a large, multi-center, randomized controlled trial evaluating the impacts of a clean cooking fuel and stove intervention in Guatemala, India, Peru, and Rwanda. The platform includes Bluetooth-enabled, data-logging temperature sensors; a mobile application to survey participants, provision sensors, download sensor data, and tag sensor missions with metadata; and a cloud-based application for data warehousing, visualization, and analysis. Our experience deploying the Geocene platform within HAPIN suggests that the platform may have broad applicability to facilitate sensor-based monitoring and evaluation efforts and projects. This data platform can unmask heterogeneity in study participant behavior by using sensors that capture both compliance with and utilization of the

intervention. Platforms like this could help researchers measure adoption of technology, collect more robust intervention and covariate data, and improve study design and impact assessments.

Keywords: sensors; data loggers; field research; cookstove; household energy; platforms; stove use monitors

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1. Introduction

The collection, storage, and analysis of sensor data is increasingly important for field research. Where traditional observational or survey data may induce behavior changes (a bias known as the "Hawthorne Effect") [1,2] or result in recall or courtesy biases, sensors can provide objective data [1,2]. In this paper, we discuss a novel, sensor-based data logging, surveying, and analytics platform called "Geocene," for deploying data-logging sensors in large fleets. To illustrate the capabilities of this platform, we focus on one case study: the Household Air Pollution Intervention Network (HAPIN) trial. HAPIN—a large, multi-center randomized controlled trial evaluating the impact of a clean fuel intervention on exposure to air pollution and related health impacts among 3200 households—is using the Geocene platform to track cookstove adoption.

Many researchers face technical challenges when seeking to objectively evaluate environmental performance or behavioral indicators using sensors in field-based studies. Often, the novel research questions they want to explore cannot be answered with commercially-available sensor solutions. Most commercial internet-of-things (IoT) devices are vertically integrated platforms to address common consumer needs in developed markets (e.g., FitBit as a step-counting platform). By contrast, researchers often want to use sensors to answer difficult questions about novel subjects (for instance, assessing latrine use in the developing world [3]) for which commercially available, off-the-shelf solutions do not exist. In these cases, researchers can develop their own hardware [4–7] or find creative ways to apply available sensors [8–10].

When no pre-existing solution exists, researchers often utilize a common, generic class of devices called "data loggers" (Figure 1). Data loggers record data about the physical environment and can often be equipped with many different types of sensors. Unlike IoT devices, which typically tend to solve a particular use case for sensing (e.g., counting steps), data loggers record raw sensor data about the world (e.g., recording the raw vibrations caused by stepping)—sometimes for a specific need, but often simply to observe characteristics of the monitored environment [11].

Data loggers are often constrained in other ways, including in the amount of data they can store and the ways in which data are retrieved from the loggers. Most data loggers transfer their data using USB to a computer. The data transferred to the computer is often warehoused as static, comma-separated values (CSV) or as a proprietary, encoded file. It is common for researchers to encode metadata in downloaded file names (e.g., "site-a__house-1__treatment-true__phase-post.csv" or, more cryptically, "a1truepost.csv"). Keys to merge raw sensor data with additional information gathered from surveys are often encoded in the file name. The management and sharing of these data files is commonly accomplished with commercial cloud storage platforms such as Dropbox, Box, or Google Drive. The results of practices like this are large volumes of sometimes poorly organized raw sensor data that must be analyzed with custom analytics.

Research in international development and public health often involves randomized controlled trials or observational studies measuring small effects across hundreds to thousands of subjects [3,5,8,9,12–14]. To measure these effects, data loggers are deployed in similarly large fleets. However, with hundreds or thousands of data loggers, managing data can be a major barrier to successful research.

In our prior work [9,15–17], the operational costs of deploying traditional data loggers, including fieldworker training and compensation, data management and analysis, and interpretation of findings,

outweighed the capital costs of the loggers. Additionally, because of the complexity of supervising field teams to deploy data loggers, quality checks and analytics are often delayed, which can result in errors with metadata, sensor placement, or other issues. These issues might have been managed during deployment if easier review of data was possible.

In this paper, we discuss the Geocene platform and illustrate its application in the context of the multi-country HAPIN trial. Geocene attempts to address some of the challenges of deploying sensors for field research. Geocene consists of (1) a sensing platform that accepts multiple sensors for different parameters and includes a Bluetooth radio for communication with mobile devices; (2) inbuilt survey and metadata management; and (3) cloud-based, customizable analysis tools to translate raw sensor data into meaningful study metrics. In prior work [18], a multidisciplinary team of researchers envisioned a "proposed integrated data collection, analysis, and sharing platform for impact evaluation"; the Geocene platform makes significant progress towards realizing many aspects of that vision.

Figure 1. Examples of data loggers, as illustrated by page 1 of Google image search results for "data logger," accessed November 11, 2019.

2. Materials and Methods

We next describe the components of the platform, including hardware and its management using mobile applications, data transfer (from sensors to mobile devices to the web), and data translation and analysis.

2.1. Hardware

Geocene data loggers, called Dots (Figure 2), are designed to operate in harsh environments without access to power or internet-connected networks. Dots are powered by two AAA alkaline batteries, which are available globally. Dots have gasketed seals and are water- and dust-resistant. The onboard non-volatile flash memory in Dots can store 196,000 16-bit samples. At a 5-minute sampling rate, memory fills in 22 months; at a 1-second rate, memory fills in 2.3 days. Because memory is non-volatile, if the logger's battery dies, data is preserved. Depending on the application, Dots can be outfitted with different sensors including temperature, electrical current, electrical voltage, GPS, light, pressure, humidity, or vibration.

Figure 2. Geocene Dot. The left panel is a photograph of a temperature-logging Geocene Dot; the right panel is a schematic of the Dot. The Dot contains a BLE (Bluetooth Low Energy) radio for communication with mobile devices, a button to power on and power off the device, and an LED to indicate device status. The Dot requires two AAA batteries and includes power management, communication, and data processing and storage capabilities.

2.2. Provisioning, Surveying and Metadata Management

Loggers in the Geocene platform perform data collection "missions"—a period of data logging activity performed by a particular data logger and associated with metadata. A narrative description of a mission's metadata might read as follows:

> "Temperature data was collected by the logger named 'ABCD' at a sampling rate of 2 minutes. The logger was installed on a traditional cookstove within home 12345 in the intervention group."

Geocene's platform manages metadata collection using a surveying tool built into the Geocene iOS and Android mobile applications (Figure 3). Before a mission can be started (i.e., before the logger can start recording data), field workers must complete a metadata survey that is associated with the time series data that will be collected by the data logger (Figure 4). The survey contains fields that restrict free data entry and enforce data types (e.g., responses that should be numeric are forced to be numeric). Responses to survey questions are transformed into metadata "tags" that take on a *key:value* format.

For the descriptive example given above, survey questions about cookstove type, intervention group status, and household identifier would be translated into tags like *cookstove_type:traditional*, *intervention_group:true*, and *household_id:12345*. Tags can be used to search and filter data or as covariates for downstream analyses.

The platform also supports narrative "notes" for unstructured metadata. These kinds of metadata can be useful for special cases or caveats that are important to remember for later analysis and data cleaning. Examples of missions, tags, and notes are described in the HAPIN case study below.
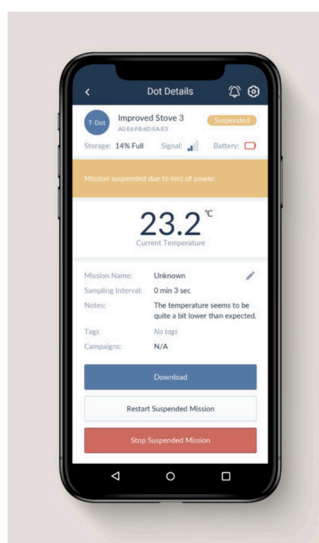
Figure 3. The Geocene mobile application, shown here running on Android.
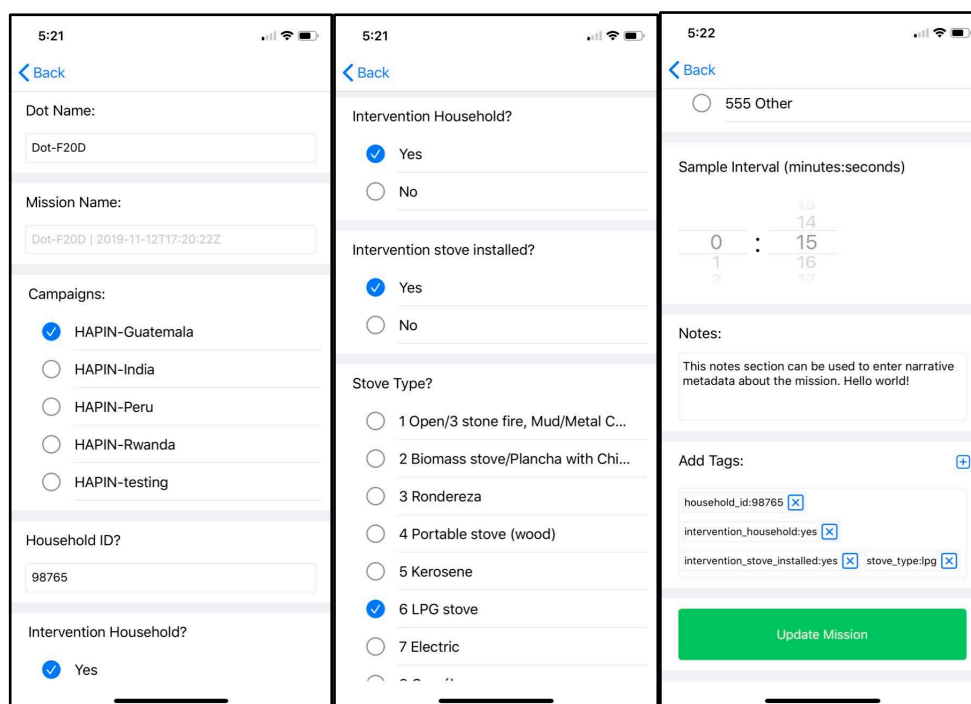
Figure 4. An example of an inbuilt survey in Geocene's mobile application (from the ongoing Household Air Pollution Intervention Network (HAPIN) trial, shown here running on iOS).

2.3. Ongoing In-App Data Collection and Data Management

When a user connects to a Dot via Bluetooth, the user can download the Dot's sensor data. These data transfers take from a few seconds to a few minutes depending on the amount of data in the Dot's memory. The application then displays the downloaded data on an interactive chart. This differs from many traditional data loggers, where data might need to be downloaded to a laptop, then loaded into an application (such as Microsoft Excel) to generate charts—all before data quality can be evaluated. The interactive chart on the mobile application can be immediately used for in-field quality control checks of sensor placement (e.g., for a cooking fire, to ensure that temperature spikes are hot enough to clearly detect cooking on a stove but not so hot that they damage the sensor), participant behavior and/or compliance (e.g., confirmation that a participant is using an intervention cookstove),

or to validate and elaborate participants' survey responses (e.g., a user reported cooking three times yesterday, but the sensor data shows just one single meal—why might this be?).

The mobile application allows the user to edit or add metadata or narrative notes at any time—for instance, to correct a mistake during previous entry or to make notes about changes in the environment that arose between visits.

2.4. Networking and Data Transfer to the Cloud

Dots communicate to Android or iOS mobile applications using Bluetooth Low Energy (BLE). Data is logged continuously and stored locally on the logger. When a phone or tablet running the Geocene app approaches the Dot, data can be transferred from the Dot to the mobile device over BLE. The loggers communicate over BLE rather than cellular, Wi-Fi, or other internet-connected networks to manage cost and power consumption, and, more importantly, because internet-connected networks are weak or absent in many locations where field work is performed. BLE data has a range of 3–100 m, depending on the number of obstacles in the way. However, the 100 m theoretical range of BLE is rarely achieved in practice; with Dots, data can typically be downloaded in real-world contexts from up to 30 m away with clear line of sight, or about 10 m away with a wall or significant obstacle in the way. In practice, field staff can typically download data from just outside homes or structures in which Dots are placed.

After data moves from the logger to the mobile device, the data must be moved to the internet. The Geocene networking topology relies on "sneakernet," a step in the data transfer process where data must be physically moved (i.e., by walking it from one place to another while wearing sneakers) to an internet-connected network (Figure 5).
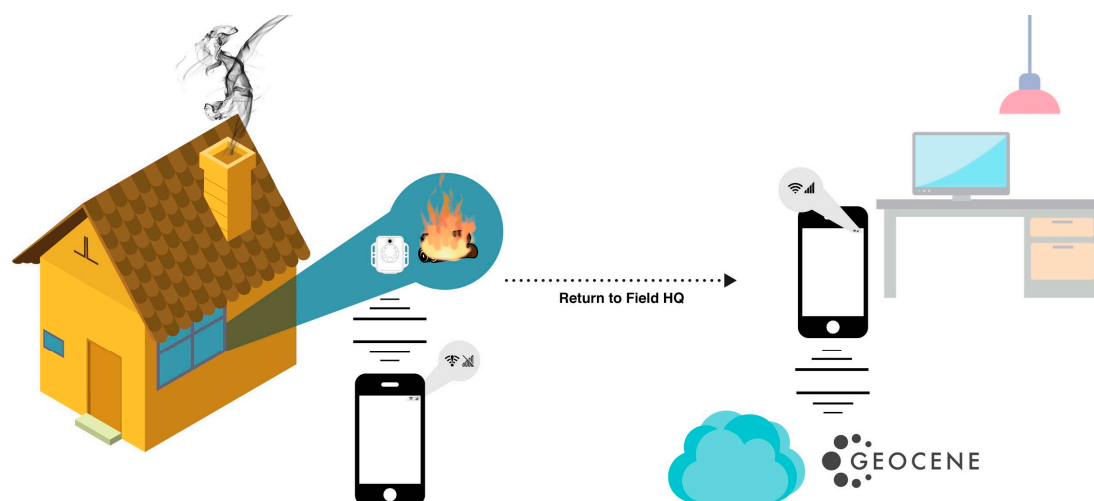
Figure 5. Schematic of Geocene data collection. Fieldworkers either visit households or, in some cases, walk near households. Dots within range are found by the mobile application and data can be downloaded and the Dot relaunched. When fieldworkers return to their field HQ, where they have Wi-Fi and/or cell service, data is transmitted to Geocene's cloud servers for warehousing and processing.

2.5. Cloud Ingress for Dots and Third Party Data Loggers

The mobile application syncs data to the cloud-based web application. This web application communicates with the mobile application and other web services using a REpresentational State Transfer (REST) application programming interface (API). Specifically, the Geocene web app is built on the Django Python REST framework.

Raw sensor data that is synced via the mobile app is first written to Amazon S3. Then, a series of server-based workers import queued raw data into a relational database. Raw logger data from non-Geocene data loggers can also be imported into the platform from a web dashboard (Figure 6).

Figure 6. The import module for non-Geocene data loggers. Currently, the module supports data from a variety of data-logging temperature sensors, including Maxim iButtons, Wellzion SSN-61 Thermocouple loggers, and EME kSUMs.

2.6. Data Warehousing and Viewing

After ingress, all mission metadata and time series data are warehoused in a PostgreSQL relational database. This database serves the Geocene web dashboard via the aforementioned REST API. Backups of this database are made daily and stored as flat objects on Amazon S3.

Geocene's web application includes a dashboard for viewing and editing data. The default dashboard can also be augmented with custom dashboards and email alerts to track relevant program performance indicators and quality control metrics.

2.7. Cloud Analytics: Models and Processors

Geocene's cloud platform includes an analytics module that identifies and summarizes events of interest in time series data (Figure 7). The primary purpose of the cloud analytics engine is to reduce large volumes of raw time series data into summaries of events of interest.

The Geocene cloud analytics system performs analysis on data using "models" and "processors." A model is a function that can detect events in time series data. The simplest example of a model would be a "threshold" model that detects periods that are above, below, or equal to a particular threshold. A model can be customized to meet analytical needs; for example, a threshold model could detect all temperatures below 0 °C. After a model is customized, it is added to a processor, which then analyzes a user-selected subset of missions (e.g., missions tagged "intervention_group:true").

The Geocene analytics framework is built upon the open-source SUMSarizer R library (https://github.com/geocene/sumsarizer/), to which the authors of this paper have contributed substantially. The event detection models available in SUMSarizer and, thus, Geocene, described below.
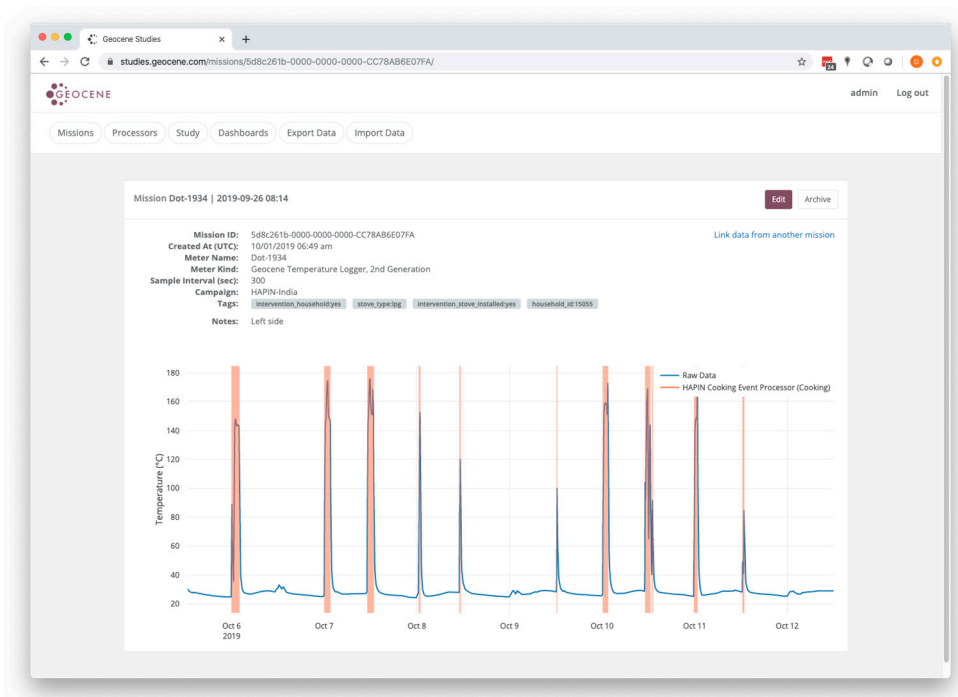
Figure 7. Details of a mission in the Geocene dashboard. Data visualized in the screenshot above includes the raw temperature trace (the continuous blue line) and areas identified as a stove use event (the highlighted orange bars). The plot on this dashboard is zoomable and scrollable, allowing users to focus on areas of interest.

2.7.1. Custom Ensemble Machine Learning

Researchers are often able to visually identify important features of data. For instance, temperature peaks from a sensor placed on a stove might represent cooking events and may be easily visually identifiable. Users with fairly large datasets can upload a subset of their data to a web-based application known as TRAINSET, which facilitates rapid labeling of features of interest. In TRAINSET, users click and drag over the portions of the charted data they identify as important events. This creates a labeled training dataset, which is used to train an ensemble machine learning model, which can then automatically identify similar features across the entire dataset.

2.7.2. FireFinder

FireFinder is a deterministic algorithm that is used to detect rises in temperature associated with heat addition events. Most users of SUMSarizer and Geocene use FireFinder to detect cooking events in temperature time series data (Figure 8). FireFinder operates in 7 distinct steps to detect events (using "cooking" events here as an illustrative event example):

1. Assume no points are cooking.
2. Assume all points above a user-set primary threshold are cooking—this is a first pass at identifying periods of stove usage.
3. Assume points with long runs of negative slopes are not cooking, because the stove is cooling off.
4. Assume points with very positive slopes are cooking, because the stove is heating up.
5. Assume points with very negative slopes are not cooking because the stove is quickly cooling off.
6. Ignore points with inter-sample gaps greater than sample interval—these gaps are due to paused missions.
7. Smooth identified events by applying a user-set minimum event length, minimum inter-event gap, and minimum event temperature.
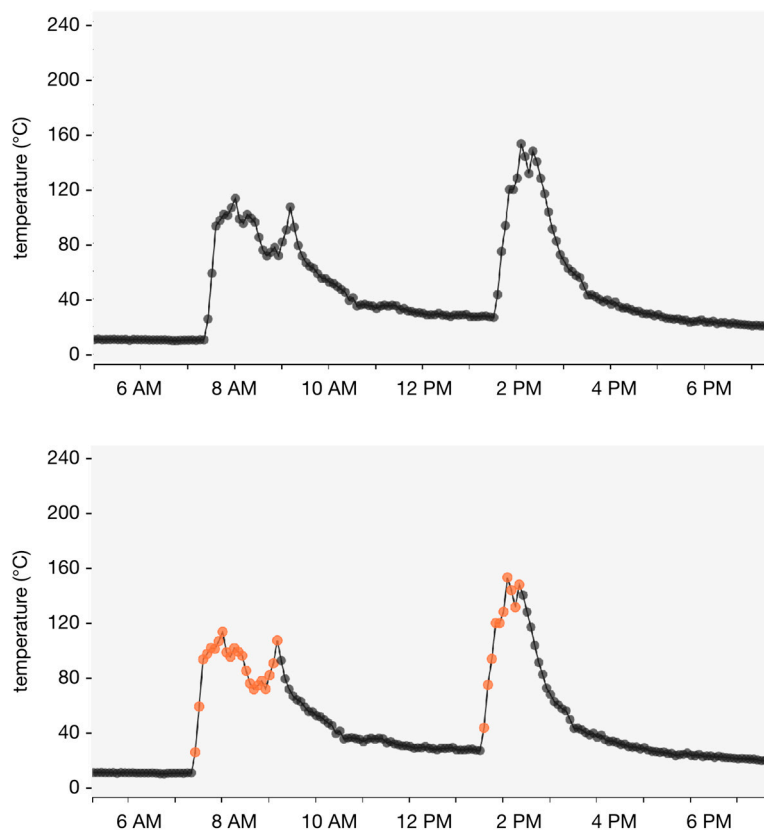
Figure 8. Sample data from a Geocene Dot temperature logger. The top panel includes data prior to analysis with FireFinder; the bottom panel shows the periods FireFinder identified as cooking (in orange).

2.7.3. Threshold

The threshold algorithm is simple: it looks for periods above, below, or equal to a specific user-specified value. These can be particularly useful for detecting sensor errors or out-of-spec environmental conditions, for example, extremely negative or extremely positive temperatures.

2.7.4. Constant

The constant detector looks for a user-specified length of unchanging values, typically indicative of an error.

2.8. Exports

Users can download all of their analyzed data from Geocene as flat-text comma-separated value files that can be opened in Microsoft Excel, R, or other programs to analyze and visualize data. Downloads include a list of missions, mission tags, raw time series metrics, sensor types, and a list of events detected by all processors applied to uploaded data.

2.9. Platform Usage

As of February 2020, the Geocene platform has been used to deploy 12,258 data collection missions with 500 million unique data points. The analytics system has detected about 1.9 million events within that data.

3. HAPIN: A Case Study

3.1. Overview

The Household Air Pollution Intervention Network (HAPIN) trial is an ongoing randomized controlled trial (RCT) enrolling 3200 households in Guatemala, India, Peru, and Rwanda. HAPIN is evaluating the impact of cooking with liquefied petroleum gas (LPG) versus traditional biomass-fueled stoves on birth outcomes in pregnant women, pneumonia and stunting in infants, and blood pressure in older adult women [19]. Mixed use of traditional and clean cooking fuels is common in household air pollution intervention studies [8,9,15,20]. Models estimate that even occasional use of biomass fuel can lead to high average exposures to harmful household air pollution [21]. With the goal of achieving as much compliance with exclusive LPG use as possible among intervention households, HAPIN is using the Geocene platform to monitor stove use and reinforce the use of LPG and abandonment of biomass-fuelled stoves among intervention participants.

The study protocol has been reviewed and approved by the institutional review boards (IRBs) or Ethics Committees at Emory University (00089799), Johns Hopkins University (00007403), Sri Ramachandra Institute of Higher Education and Research (IEC-N1/16/JUL/54/49) and the Indian Council of Medical Research, Health Ministry Screening Committee (5/8/4-30/(Env)/Indo-US/2016-NCD-I), Universidad del Valle de Guatemala (146-08-2016/11-2016) and Guatemalan Ministry of Health National Ethics Committee (11-2016), Asociación Beneficia PRISMA (CE3571.16), the London School of Hygiene and Tropical Medicine (11664-5), the Rwandan National Ethics Committee (No.357/RNEC/2018), and Washington University in St. Louis (201611159). The study has been registered with ClinicalTrials.gov (Identifier NCT02944682).

Data loggers and related analysis routines used to evaluate cookstove adoption are often referred to as part of the Stove Use Monitoring System (SUMS). Stove use monitoring in HAPIN enables field teams to respond to non-compliant intervention households who use their traditional stoves. It also provides objectively quantified metrics of stove use for incorporation in statistical models and other analyses.

About 3800 (30%) of all Geocene missions belong to HAPIN. HAPIN's globally-distributed field staff have synced approximately 155 million unique data points from these missions. HAPIN has deployed Geocene's cloud analytics to detect 330 thousand events of various kinds ranging from cooking, excessive probe temperature, and probe errors (Figure 9). Each day, HAPIN syncs about 500 thousand new data points to the platform, and the analytics detect about 1000 new events daily.
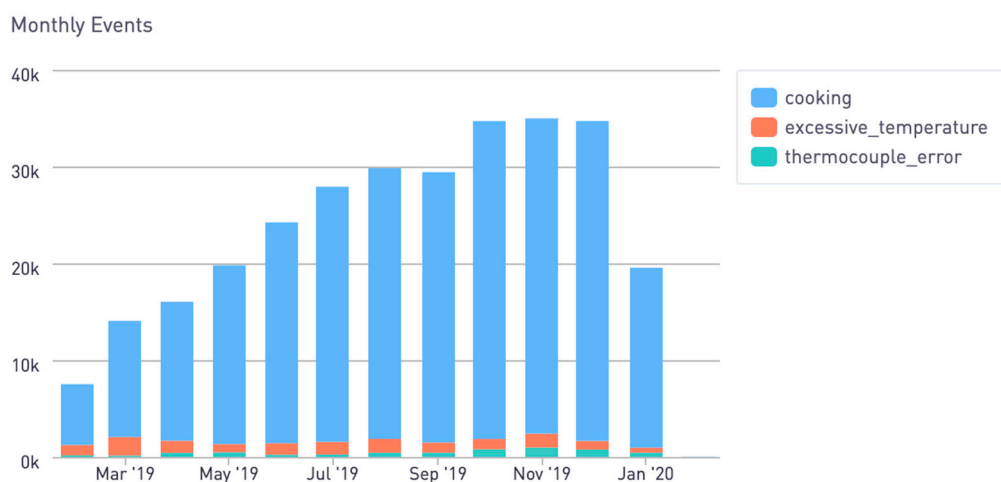
Figure 9. Events detected by Geocene cloud analytics per month for the HAPIN trial.

3.2. Hardware and Provisioning, Surveying, and Metadata Management

Previous studies of household air pollution interventions relied primarily on Maxim iButton temperature data loggers [8,13,15], which have limited memory and temperature sensing ranges, or low-cost thermocouple data-loggers [16,20]. The Geocene Dots used in HAPIN use k-type thermocouples. K-type thermocouples have a theoretical range of about −200 °C to 1250 °C, but depending on build quality and environmental considerations, usable temperature ranges can be much more limited. The high temperature range of thermocouples enables HAPIN field staff to place Dots' sensing elements close to the combustion zone of traditional and LPG cookstoves to detect greater temperature increases when the stove is lit during cooking. Field staff place the probe in a location where cooking will induce a temperature spike of at least 100 °C, but no more than 400 °C. Although well-made thermocouples can reach temperatures of >1000 °C, surpassing 400 °C regularly can significantly degrade their useful lifetime; therefore, the HAPIN team aims for maximum temperatures of 400 °C to ensure probes will last for the duration of the trial.

When installing Dots, HAPIN field staff answer a common set of questions about each deployment on handheld tablets using the inbuilt survey (Figure 4). These include data on the specific stove type on which the Dot is installed, the household ID, the type of household (intervention or non-intervention), and other metadata that can subsequently be used to filter and subset data. For example, trial investigators can examine data by country, by intervention status, and/or by stove type.

3.3. Date Warehousing and Viewing

Given the large sample size of the trial (3200 households across 4 countries; 800 per country, 400 each in control and intervention arms), approximately 3140 Geocene temperature loggers will be in use for periods of approximately 18 months. A team of roughly 50 HAPIN investigators and field staff have been trained to provision and deploy these data loggers and download data from them every two weeks. Dot data are synced using the sneakernet networking topology: field workers collect data in the field using handheld tablets and synchronize the data with the cloud upon return to their Wifi-equipped offices (Figure 9).

3.4. Analytics

Stove use monitoring in HAPIN serves multiple purposes. During the trial, FireFinder is parameterized to be very sensitive to temperature increases from Dots on traditional stoves to flag all potential traditional stove uses. The sensitive parameters applied to FireFinder result in a high false-positive rate, but this is desirable for the use case of reducing the rate of false negatives to near-zero levels. In the HAPIN context, a false negative cooking event would mean a participant was using their cookstove, but HAPIN staff could not detect this use in the data. Field staff use this data to visit flagged households and provide behavioral change guidance to encourage exclusive LPG use.

Additionally, HAPIN uses several mechanisms to ensure data quality. First, constant and threshold detectors identify Dots with thermocouple or other errors. Study staff visit flagged households to either re-position, repair, or replace the Dot probes or entire Dots. Second, a dashboard and weekly email highlight households with missing metadata, such as household identifiers, stove type, intervention installation status, and/or county location.

Finally, HAPIN uses a modified version of FireFinder to create summary data by household on the frequency and duration of traditional stove use. These data will be used in statistical models to estimate the influence of stove usage on exposure to household air pollutants, among other analyses [19].

3.5. Administration

To help improve data quality and increase accountability, HAPIN uses custom dashboards and email alerts through the Geocene platform. Site leaders receive weekly email alerts with screenshots of

dashboards listing households with traditional stove use (Figure 10), Dots with technical problems, and missions with missing or corrupt metadata.
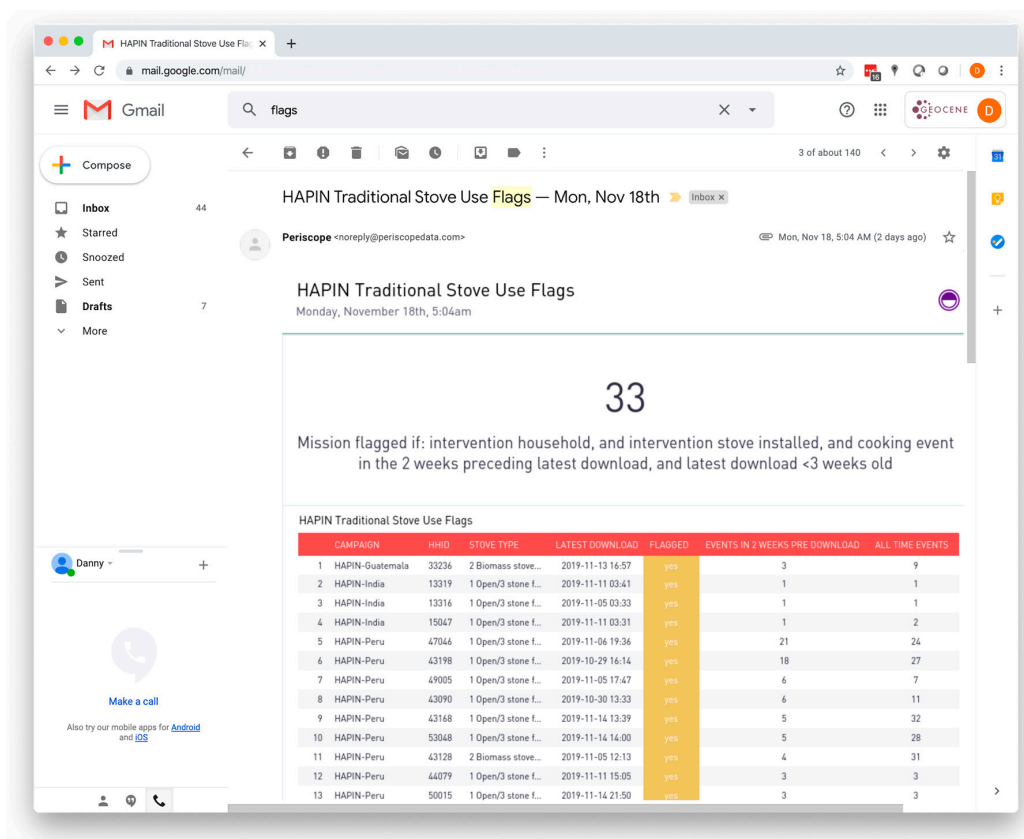

Figure 10. A weekly email alert about non-compliant households in the HAPIN trial.

In the first three weeks after deploying alerts on missing metadata, the total number of missions with missing or corrupt metadata dropped from 501 to 200; in other words, 60% of all known data quality errors were fixed within the first household visit after the system was established. The HAPIN team was able to use these alerts to address operational errors early, improving the ease and quality of later analysis.

3.6. Field Benefits and Challenges

The ability to download Dot data over Bluetooth (and without Wi-Fi or cellular network access) has greatly facilitated fieldwork. Field staff are able to download data from outside a participant's house, even when participants are not home, preventing the need for multiple household visits. Also, the Geocene platform's ability to program missions and download data without Wi-Fi allows the HAPIN team to collect data from many participants who live in areas without Wi-Fi or cellular signal. However, challenges have arisen when updates to the Geocene mobile applications were not fully downloaded prior to leaving for the field, resulting in incomplete metadata.

Achieving correct placement of the thermocouple probe, that is, to achieve temperatures greater than 100 °C and less than 400 °C during cooking, is consistently difficult given the heterogeneity in stove construction and structure. Staff struggle to position probes correctly at installation, but are able to use the provided dashboard to identify households where probes have excessive temperatures, and in those homes, move the probes. Additionally, in some contexts, where stoves are either outdoors or portable, there have been challenges in hanging and protecting the logger body. HAPIN teams fashioned protection out of sealable plastic containers, dust bins, and PVC pipes to protect these outdoor Dot installations.

Due to the high sensitivity of the FireFinder algorithm, some households are incorrectly flagged as cooking with their traditional stoves when the stove was not actually used. Mis-flags are often due to outdoor probe positions that are heated by strong direct sunlight, or other temperature sources in kitchens such as hot pots placed on traditional stoves to cool or for storage. Field staff sometimes make visits to falsely flagged households to reinforce exclusive LPG use when this reinforcement is not necessary; however, this precaution is necessary to avoid missing households who are using their traditional stove.

Given that Dots can hold many months of data, field teams initially did not delete data from the Dot after downloading. However, downloads took up to several minutes when there was a large accumulation of data on the Dot. Thus, field teams started deleting data after downloading to reduce time in participant homes. However, after clearing the Dot, the data exist only on the tablet that made the download, which runs the risk of data loss if there are any problems with the tablet or the downloaded data. Occasionally, data downloaded from a Dot does not sync properly with the cloud, but this is largely due to situations where the field worker who originally started the mission never synced the mobile device that originated the mission. Finally, the Geocene application interface is currently only available in English, which causes difficulty for field teams in other countries who often do not speak English. Although staff were able to learn how to program the Dots using the English prompts, they often have trouble interpreting and responding appropriately to warning and error messages.

4. Discussion and Conclusions

Experiences deploying Geocene in the HAPIN trial suggest that the platform has overcome many of the challenges with previously available data loggers for field research. The ability to download over Bluetooth with mobile applications avoids the need to remove data loggers from their installation location to connect the device to the computer. The surveys allow more accurate collection and storage of metadata. Real-time data processing allows for continuous review and responses by field staff to ensure data quality. The data analysis and summary dashboards also facilitate the process of calculating desired indicators from raw data, which can be viewed by globally-dispersed investigators.

However, several challenges remain with the Geocene platform. Achieving correct positioning of the thermocouple probe and adequate protection of the data logger body requires piloting and adjustment based on differing local conditions. Also the algorithm used to flag events of interest may not always correctly capture targeted events. For example, highly sensitive algorithms may falsely flag non-cooking events, while less sensitive algorithms may fail to flag actual cooking events. Field teams must also balance the desire to limit download times by deleting data after each download with the risk of losing data if problems occur with the downloaded file or tablet before synchronization with the cloud. Issues with language and data synchronization have also proven challenging. We anticipate that similar initial challenges may exist for others who use the platform, whether for cookstove adoption monitoring or other sensor-based needs.

Our experiences with deployment suggest several potential improvements. Providing localization of the mobile application (i.e., translation into other languages) and addressing data synchronization issues would facilitate the use of the platform in global field settings. Also, capturing and sharing guidance on probe placement, Dot installation, and algorithm considerations could help research teams deploying the platform for the first time. Lastly, further expanding the compatibility of Geocene with other data loggers could enable teams who already have experience using (or have data from) other types of devices to use the platform for data analysis.

The Geocene platform has the potential to not only ease data collection and improve data quality in research studies, but could also be applied by programs seeking to monitor use of their product. For example, government programs promoting adoption of clean fuel stoves could use the Geocene platform to monitor use of the clean fuel stoves given to households through the program. This would enable implementers with limited analysis capability to quantify the impact of their program and make

adjustments as necessary. Additionally, it would provide programs with more objective data than could be derived from surveys alone. Facilitating the ability of researchers and program implementers to easily monitor behaviors could improve the impact of promoted technologies, which in turn can improve air quality, health, quality of life, or other outcomes among users.

Conflicts of Interest: Coauthor Daniel Wilson is cofounder of Geocene Inc.

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