Geospatial-Temporal, Demographic, and Programmatic Adoption Characteristics of a Large-Scale Water Filter and Improved Cookstove intervention in Western Province, Rwanda

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ENVIRONMENTAL HEALTH | RESEARCH ARTICLE

Geospatial-temporal, demographic, and programmatic adoption characteristics of a large-scale water filter and improved cookstove intervention in Western Province, Rwanda

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Abstract: Lowering the global disease burden of preventable disease has been addressed in part by the distribution of health products and behavior change campaigns in low-income countries. Realizing a health impact requires adoption by participants, and the topic of program uptake and sustained adoption has been studied extensively, although an ecological context is largely missing from existing work. This study characterizes self-reported and observed adoption of improved cookstoves and point-of-use water filters among nearly 80,000 households in Rwanda using demographic and programmatic variables from implementer surveys and integration of geospatial and temporal data based on differentiated recipient location. The odds of stove or filter adoption were analyzed using Generalized Estimating Equation logistic regression modeling. Administrative district, rural residency, elevation, social networks, socioeconomic category, family composition, education delivery, technological factors, and use of the accompanying technology in the combined intervention were

ABOUT THE AUTHOR

The Mortenson Center in Global Engineering at the University of Colorado Boulder combines education, research and partnerships to positively impact vulnerable people and their environment by improving development tools and practice. The research featured in this article is based on programs started in Rwanda in 2003 by the University of Colorado Boulder, and was funded by the social enterprise DelAgua Health and the Ministry of Health in Rwanda. This research profiles findings on the determinants of water filter and household cookstove interventions, that can inform further development tools, practice, and programs.

PUBLIC INTEREST STATEMENT

Cogent Environmental Science

Geospatial-temporal, demographic, and programmatic adoption characteristics of a large-scale water filter and improved cookstove intervention in Western Province, Rwanda

Reducing respiratory and waterborne illness in low-income countries through the distribution of household cookstoves and water filters requires adoption by recipients. The environment in which participants live, in addition to individual and social factors, should inform the study of such health behavior and decisions. A large public health program in Rwanda found that use of cookstoves and water filters was related to household location, elevation, social networks, socioeconomics, family size, education, and the technology itself. Environmental data represent objective, current, and vast data sources that can help improve the design and evaluation of health programs. Funders, governments, and implementers should consider the environmental context when conducting and monitoring these programs to contribute to the evidence base for successful interventions and, ultimately, to improve health outcomes.

significantly associated with the odds of adoption of either the stove or filter. Population density, precipitation, anisotropic travel time to services, and timing of the health campaign largely showed no significant relationship with adoption. This research promotes the inclusion of geospatial and temporal data in designing and evaluating other public health interventions by successfully leveraging an ecological explanation of adoption decisions.

Subjects: Behavioral Sciences; Development Studies; Population & Development; Rural Development

Keywords: geospatial; improved cookstove; point-of-use water treatment; public health intervention; adoption

1. Introduction

The global burden of preventable disease, including lower respiratory infections and diarrheal conditions, is disproportionately borne by those living in low socio-demographic index countries (Institute for Health Metrics and Evaluation [IHME] 2015). This disease burden is partially attributed to household air pollution (HAP) from woodfires and contaminated drinking water (Black, Morris, & Bryce, 2003; Ezzati & Kammen, 2001)—features of daily life in low- and middle-income countries. HAP from traditional stoves and other sources contributes to acute lower respiratory infections (ALRI) while microbial contamination from unsafe collection and storage of drinking water increases risk of diarrhea, leading causes of death and disability (IHME 2015). Therefore, important health gains may be achieved through interventions that target risk factors of disease, such as improved cookstoves (ICS) and point-of-use (POU) water treatment. Moreover, advanced combustion stoves are promoted for environmental co-benefits, such as reduced fuel consumption. However, when coverage is insufficient or uptake and sustained adoption of distributed health technologies is not achieved, the impact may not be realized (Brown & Clasen, 2012). Characterizing factors influencing the adoption of these technologies in low-income settings is thus important for implementers, public agents and, ultimately, the populations served.

Considerable research has been conducted describing the determinants of adoption for both ICS and POU water treatment. Family size, number of children in the household, socioeconomic status, and prior experience with ICS and water treatment are conventionally assumed determinants of adoption (Malla & Timilsina, 2014). Family composition is thought to impact household health decisions by influencing the valuation of labor, time, and resources needed to cook and treat water for more people (Lewis & Pattanayak, 2012; Rehfuess, Puzzolo, Stanistreet, Pope, & Bruce, 2014). Socioeconomic status is a common indicator in health services research for the availability of resources and education to expend on acquiring and adopting new products. Positive or negative previous experience with similar health technologies can reinforce perceptions of other health interventions and, thus, intentions to adopt (Hulland, Martin, Dreibelbis, DeBruicker Valliant, & Winch, 2015). Similarly, components of the technologies themselves are important for adoption, especially if a user believes there is a problem with the product affecting function or effectiveness or feels empowered to use more than one health intervention (Hulland et al., 2015; Rehfuess et al., 2014). Programmatic delivery of the health campaign, including timing, quality, and quantity of user education and support, and hardware choices, are also important factors in uptake and sustained adoption (Dreibelbis et al., 2013). However, there is a clear gap in the available literature considering geospatial and temporal variables of intervention adoption.

A consortium of researchers (Puzzolo, Stanistreet, Pope, Bruce, & Rehfuess, 2013; Rehfuess et al., 2014; Stanistreet, Puzzolo, Bruce, Pope, & Rehfuess, 2014) identified 31 factors under seven domains that influence uptake of ICS including fuel and technology characteristics; household and setting characteristics; knowledge and perceptions; finances, taxes, and subsidies; market development; regulation, legislation, and standards; and programmatic and policy mechanisms. Of the 31 factors, only one—geography and climate—is explicitly related to a geospatial perspective. Furthermore, Dreibelbis et al.

(2013) found in their systematic review of eight water, sanitation, and hygiene (WASH) adoption frameworks that behavior change theories focused on individual- and community-level determinants and disregarded the potential effect of the natural or physical environment.

The context in which adoption occurs is a critical component of behavior change theories and often an ecological approach that considers individual, interpersonal, and environmental factors is promoted (Moran et al., 2016). Thus, a spatiotemporal perspective allows for the incorporation of multiple, seemingly disparate datasets into a cohesive framework for evidence-based program evaluation and decision-making (Huerta Munoz & Källestål, 2012). Inclusion of geospatial variables in research analyses has increased with the ability to capture survey respondent location at the household level from global position system (GPS)-connected survey devices, and there are examples of geospatial studies for healthcare access (Aoun, Matsuda, & Sekiyama, 2015), water quality (Kirby et al., 2016), and diarrhea prevalence (Uwizeye, Sokoni, & Kabiru, 2014).

However, using geospatial variables as determinants of adoption of health programs is unexplored, and there are no peer-reviewed publications on the subject known to the authors. This represents an area where previous research that has suggested relationships between the physical and social environment and health behaviors can be expanded. For example, civic and sociopolitical differences among regions of decentralized governments may impact the efficacy of health programs for constituents (Barstow, Nagel, Clasen, & Thomas, 2016). Population density can determine the availability and quality of natural resources, highlight access to public services, or suggest network influences (Bain et al., 2014; Hanlon, Burstein, Masters, & Zhang, 2012). Finer resolution social networks, on a neighborhood scale, may also have an important influence on personal adoption choices (Beltramo, Blalock, Levine, & Simons, 2015; Reich, 2016).

Elevation and precipitation are two important factors for establishing ecological and environmental context and may influence intervention adoption. Program implementers of a distribution of improved wood-fire stoves found householders were less likely to use the stove at higher, cooler elevations, where traditional three-stone fires provided ambient warmth, and during periods of rain, when it was difficult to store dry wood and use the stove outside (Barstow et al., 2014). Other researchers observed that drinking water quality was higher at increased elevations and that extreme rain events were a risk factor for increased contamination (Kirby et al., 2016), knowledge of which could impact households' perceptions of susceptibility to waterborne diseases and prompt changes in the frequency of water treatment. Additionally, a recent study observed increased utilization of surface water over improved water sources after rain events (Thomas et al., 2019).

Household location and ease of travel to main roads and urban centers are a proxy for access to markets, social networks, and information and indicate increased socioeconomic status (Uwizeye et al., 2014), all of which may contribute to intervention adoption rates. However, proximity to services may be more accurately estimated by the amount of time it takes to reach a point of interest than reliance on Euclidean distance (Noor *et al*. 2006), and can be estimated from anisotropic models which account for travel speed through landscapes due to topographic relief and movement through different landcover classes.

In this study, we investigate one of the largest public health interventions operating in East Africa to date that targets HAP and unsafe drinking water through the distribution of ICS and POU water filters. The design and health outcomes of the project are described elsewhere (Barstow, Clasen, Kirby, & Thomas, 2018; Barstow et al., 2016, 2014), but similar to the state of the field in general, geographic and temporal elements are missing from previous assessments. Here, we focus on the development and description of geospatial and temporal variables while retaining some conventional demographic and programmatic variables to create a referenceable and unifying schema. We demonstrate that geospatial and temporal factors are easily accessible and informative data sources in the evaluation of health behavior and adoption despite being currently underutilized in research and implementation. Additionally, we leverage the unusually large sample size of household level data and longer-term monitoring cycles to contribute evidence of the characteristics of sustained adoption, a better indication of health benefits than initial uptake (Martin, Hulland, Dreibelbis, Sultana, & Winch, 2018). This research seeks to encourage other studies to include a geospatial and temporal perspective in implementation and evaluation when promoting technologies and advocating behavior change and adoption among vulnerable populations.

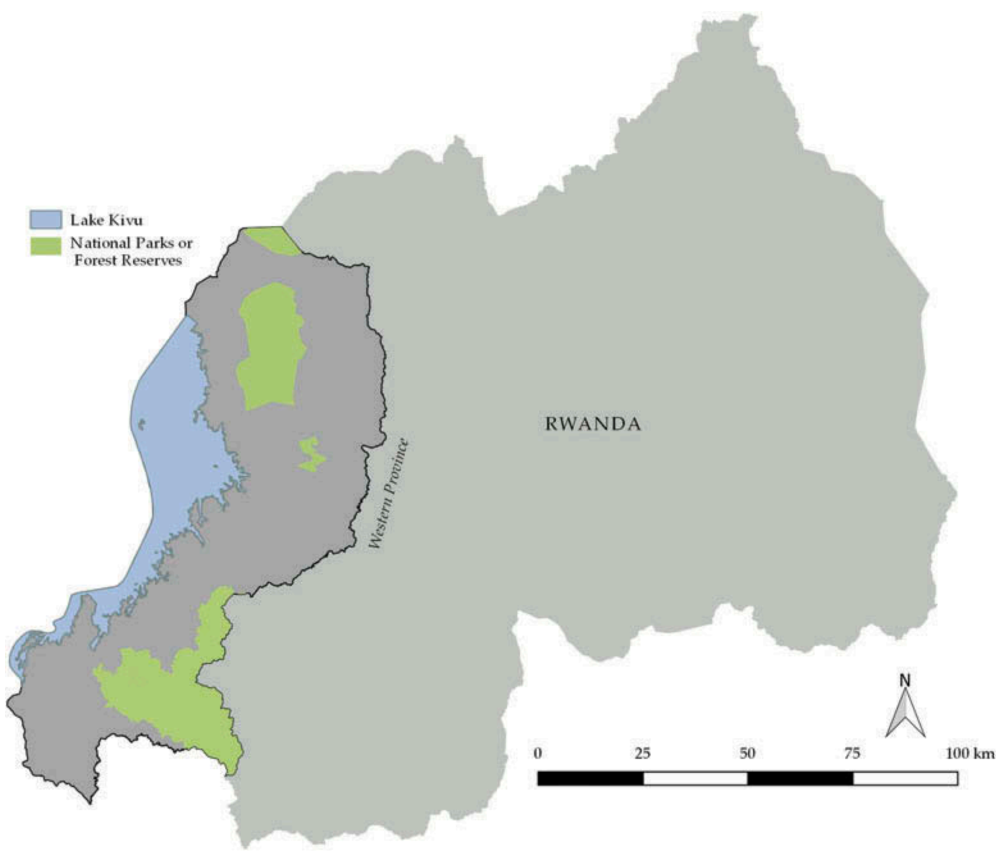
2. Methods

2.1. Study site and participants

Participants were initially enrolled in a large-scale public health intervention conducted by the Rwanda Ministry of Health with the private sector company DelAgua Health which sought to reduce exposure to household air pollution from open-air wood cooking fires and increase access to microbially safe drinking water (Barstow et al., 2016). The *Tubeho Neza* program included a hardware and educational campaign and distributed over 100,000 Ecozoom Dura improved cookstoves and LifeStraw Family 2.0 water filters to the poorest quarter of households—members of the poorest socioeconomic classes, known as *ubudehe* 1 and 2—in Western Province, Rwanda (Figure 1) from September to December of 2014. Local community health workers (CHWs) and leaders also received stoves and filters as part of the program.

Implementers distributed the health technologies at cell-level community meetings and immediately following visited each recipient household to conduct personal demonstration and education. Approximately three to six months later, follow-up visits were performed to reinforce education and collect data on participants and their observed and reported use of the stove and filter. Local CHWs were trained as educators and enumerators of program surveys, which were collected electronically on smartphones at each visit and captured the GPS location of each household.

Figure 1. Western Province, Rwanda, where *Tubeho Neza* distributed improved cookstoves and water filters to nearly 100,000 households in 72 of 96 randomly selected sectors.



2.2. Data sources

In order to determine the effect that environmental and contextual variables had on adoption, we studied self-reported and observational measures of adoption for each technology. Household surveys were conducted from January to April 2015 to assess adoption and reinforce education. Spot checks were included to address the expected over-estimation of self-report. Thus, our four outcomes were binary (yes/no) across (1) participant response to use of EcoZoom stove as primary cooking stove, (2) visual confirmation by enumerator of EcoZoom use for subset of participants who were cooking at time of follow-up visit, (3) participant response to treating water with Lifestraw filter, and (4) visual confirmation by enumerator of presence of water in Lifestraw at time of follow-up visit. A total of 77,417 households, including 11,137 households who contributed to the observational cooking measure, met study eligibility criteria. Independent variables were grouped into geospatial, demographic, and programmatic themes. Based on the availability of data in the programmatic surveys and from external sources, prior evidence, and new hypotheses regarding the effect of geographic and temporal factors, 24 variables were developed.

2.2.1. Geospatial-temporal variables

Administrative district was included from the follow-up survey. Rural-urban classification of resident village, with peri-urban villages being designated as urban, was derived from data provided by the Rwanda Housing Authority (RHA). Proportionally allocated gridded population density projected to 2015 from the 2012 national census, available for download from the Socioeconomic Data and Applications Center (SEDAC) (Center for International Earth Science Information Network [CIESIN], Columbia University 2017), was estimated by sector, categorized into quartiles, and assigned to each resident household. A 100 m buffer was applied around each household's location and the proportion of adopters of each respective technology within the boundary was summarized. On average households had three to four neighbors enrolled in the program within this distance, which compared well to other research that has studied the association between social networks and cookstove adoption and which a sensitivity analysis showed did not impact the mean proportion of adopters significantly compared to other proposed distances in our study. The level of neighborhood adoption was categorized into less than 90% and greater than or equal to 90%; if no fellow program recipients were found within this proximity, the household was recorded as isolated. For each household, the level of adoption among local leaders in their village was likewise summarized as less than 90%, greater than or equal to 90%, or isolated. Generally, adoption of the intervention stove and filter was high, and the proportions of network adopters were highly left skewed; thus, the cutoff was set at 90% to capture distinction between neighborhoods.

Based on household GPS coordinates collected during surveying, elevation was extracted from a digital elevation model (DEM) of Rwanda at 30 m resolution provided by the Shuttle Radar Topography Mission (SRTM) and made publicly available by the Regional Center for Mapping of Resources for Development (RCMRD), 2015 . Households were categorized as being located below 1500 m, between 1500 m and 1999 m, or at or above 2000 m, which represented terciles of the observed distribution of elevations. An estimate of the number of days a household experienced precipitation during the period between when they received a stove and filter and when they were visited for follow-up was calculated by using TAMSAT (2014) satellite-based daily rainfall estimates at 4 km resolution at the household's differentiated location.

2.2.2. Anisotropic variables

Our method followed a parallel workflow to that developed in AccessMod (World Health Organization [WHO], Switzerland, Geneva, version 5.0) and applied by Huerta Munoz and Källestål (2012) and Aoun et al. (2015). We relied primarily on the open-source Geographic Resources Analysis Support System Geographic Information System (GRASS GIS) [GRASS Development Team, Germany, Bonn, version 7.2.0] to implement the workflow in QGIS (QGIS Development Team, version 2.18). Inputs included the SRTM DEM from above, a road network, and landcover in the Western Province, which were co-registered to the same extent, resolution (30 m) and coordinate system (Galls-Peter, an equal-area projection). We used AccessMod 5.0 to overlay the layer containing national, district, and local/feeder roads on the landcover layer given the program's dexterity in merging layers while considering priorities and artifacts. The road layer was obtained from the Center for Geographic Information Systems and Remote Sensing—University of Rwanda (CGIS-UR). We summarized a landcover layer from 2015, made available by the Intergovernmental Authority on Development's Climate Prediction and Applications Center (ICPAC) (2017), into 10 similar classes (Table 1) and resampled it from its original 300 m resolution by nearest neighbor interpolation. A travel friction surface was created with GRASS's *r.recode* function where cell values of the merged landcover layer were reassigned according to the expected walking pace in each respective environments (Table 1) based on estimates suggested by other accessibility models (European Commission Joint Research Centre, 2015; Ray & Ebener, 2008). The time it would take a household member to walk to the nearest health facility, main road juncture, and urban center was determined. The locations of operational provincial, referral, and district hospitals, district pharmacies, health centers, and health posts were determined from a list compiled in 2016 and commissioned by the Rwandan Ministry of Health. National and district roads were extracted from the CGIS-UR road layer, hereafter referred to collectively as main roads. Urban centers were described as the centroids of a collection of strictly urban (i.e. not periurban) contiguous villages in the RHA dataset and named by the researchers based on familiarity with existing towns. Each of these layers was created for the western, northern, and eastern provinces so that household proximity to the nearest point of interest was not artificially constrained to the western province.

We assumed our target population—the lowest income households in Western Province—would use walking as their exclusive mode of transportation as it is unlikely they would have access to bikes, public transportation, or private vehicles.

Anisotropic cumulative cost estimates were obtained from GRASS's *r.walk* program (GRASS Development Team, 2018). GRASS implements Naismith-Langmuir's algorithm to determine the walking time (in seconds) where

$$time = a^{*}dist + b^{*}\Delta alt + c^{*}\Delta alt + d^{*}\ \Delta alt \quad (1)$$

and a is the time in seconds to walk 1 m, *dist* is the horizontal distance covered in meters, and Δalt is the difference in altitude in meters. Additional walking time in seconds per 1 m is included

Table 1. Landcover classes in Western Province, Rwanda and associated travel times

Landcover Class	Percent of land surface	Walking speed (km/hr)	Walking pace (sec/m)
Cropland	49.3	1.67	2.16
Evergreen tree cover and closed deciduous tree cover	18.0	1.00	3.60
Open deciduous tree cover	1.4	1.25	2.88
Mosaic tree and shrub cover	8.9	1.25	2.88
Regularly flooded tree or shrub cover	0.2	1.00	3.60
Shrub or grass cover	0.3	1.67	2.16
Sparse vegetation cover	< 0.1	2.50	1.44
Water bodies (including Lake Kivu)	17.4	1.00[1]	3.60
Urban areas	0.2	5.00	0.72
Roads (any)	4.3	5.00	0.72

[1] Without knowledge of how residents move across rivers, Lake Kivu, or other small water streams, transportation across water was assigned the slowest walking speed so that the estimates were conservative.

for (*b*) uphill slopes, (*c*) moderate downhill slopes between 5 and 12 degrees, and (*d*) steep downhill slopes over 12 degrees. The proposed model coefficients are a = 0.72, b= 6.0, c = 1.9998, and d = −1.9998. Landscape friction costs are accounted for in a, where the value of a is adjusted by landcover class. Movement cost was calculated every 30 m (the resolution of our maps) and iteratively, the path of least resistance, considering knight's moves, was followed outward from points of interest while travel time was added cumulatively with each progression. Maps were created to capture travel time to health facilities, main roads, and urban centers for the province (Figure 2), and a household's estimated travel time was recorded by extracting the value at their individual location.

2.2.3. Demographic and programmatic variables

Family size, number of children in the household, socioeconomic status, and prior experience with improved cookstoves and water treatment were derived from participants' responses in the implementer's follow-up survey. The number of days between distribution and initial education was calculated from time records on the implementer's distribution and first household visit surveys for each household. Measures of the value of the household education visit included the duration of the visit and attending educator quality. CHWs were scored on a nominal scale by supervisors during evaluations in households or advanced training that tested knowledge of messaging; engaging presentation; completion of posters given to households as cues to action; and capability with the smartphone used to record survey answers. Education was organized by sector teams, and the timing of the duration of the campaign in their area—first week, last week, and intervening time between—was included as relative educator experience or burnout could influence a household's adoption. The number of days between the education visit and follow-up visit for each household was included in the analysis to control for adoption attrition. User experience with the stove and filter and dual adoption of the technologies were interpreted from questions asked in the follow-up survey.

A final sample of 77,417 recipient households was used in the analysis after removing records due to missing data, duplicates, inconsistent responses, inaccurate or missing geographic location, required matching across multiple programmatic surveys, and outlying observations (see Additional file 1 for detailed inclusion criteria). A total of 11,137 of the households were cooking at the time of the follow-up visit and contributed to the observational cooking measure of adoption. Table 2 displays the sample population characteristics for each dependent variable and covariate described above.

Figure 2. Estimated walking time (in hours) to nearest (*a*) health facility, (*b*) main road, or (*c*) urban center in Western Province, Rwanda.

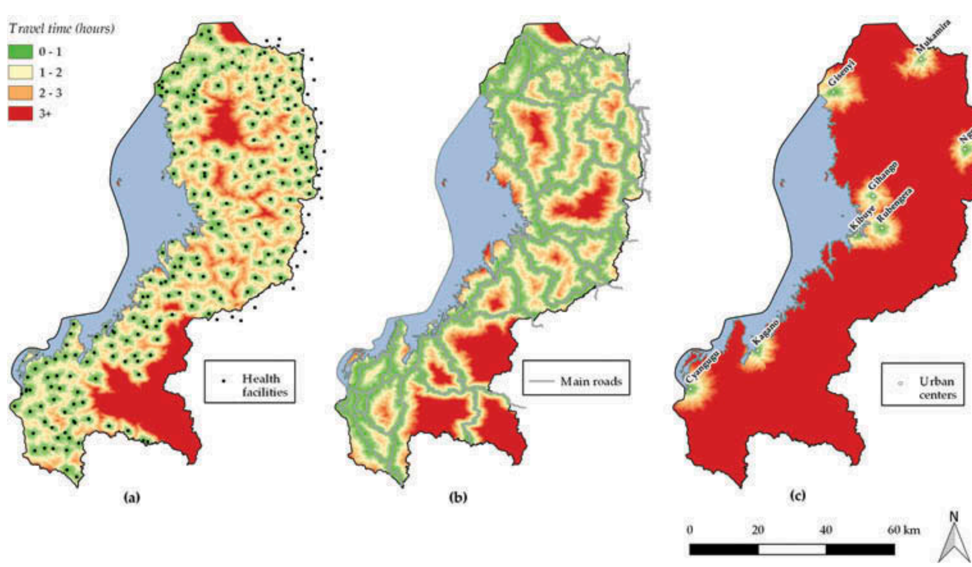


Table 2. Recipient household characteristics and selected variables

			N or Mean[1]	% or SD[1]
Outcomes	*Self reported intervention stove adoption*		72,600	93.8%
	Observed cooking on intervention stove		8561*	76.9%
	Self reported filter adoption		75,334	97.3%
	Observed water in filter		62,092	80.2%
Geospatial-temporal	*District:*	Karongi	10,934	14.1%
		Ngororero	13,000	16.8%
		Nyabihu	7852	10.1%
		Nyamasheke	11,477	14.8%
		Rubavu	8724	11.3%
		Rusizi	12,631	16.3%
		Rutsiro	12,799	16.5%
	Rural village residency		71,211	92.0%
	Population density quartile (per km^2):	1st quartile (242–465)	20,476	26.4%
		2nd quartile (466–585)	18,491	23.9%
		3rd quartile (586–782)	17,745	22.9%
		4th quartile (783–2636)	20,705	26.7%
	Household elevation:	<1500m	5735	7.4%
		1500–1999m	43,328	56.0%
		≥2000m	28,354	36.6%
	Mean number of days it rained		50.2	17.47
	Month of follow-up:	Jan	4471	5.8%
		Feb	40,800	52.7%
		Mar	32,043	41.4%

(*Continued*)

Table 2. (*Continued*)

			N or Mean[1]	% or SD[1]
		Apr	103	0.1%
	Percentage of neighbors adopting stove:	Isolated household	13,070	16.9%
		< 90%	9128	11.8%
		≥ 90%	55,219	71.3%
	Percentage of neighbors adopting filter:	Isolated household	13,070	16.9%
		< 90%	4272	5.5%
		≥ 90%	60,075	77.6%
	Percentage of local leaders adopting stove:	Isolated household	2507	3.2%
		< 90%	10,361	13.4%
		≥ 90%	64,549	83.4%
	Percentage of local leaders adopting filter:	Isolated household	2507	3.5%
		< 90%	2731	3.2%
		≥ 90%	72,179	93.2%
Geospatial—Anisotropic	*Travel time to health facility (min)*		54.05	31.06
	Travel time to main road (min)		54.22	53.94
	Travel time to city center (min)		314.77	159.53
Demographic	*Ubudehe 1 & 2 recipient category*		69,790	90.1%
	Mean family size[2]		4.55	2.10
	Mean number of children in household[3]		0.6	0.77
	Prior experience with ICS		17,764	22.9%
	Prior experience with water treatment		19,810	25.6%

(*Continued*)

Table 2. (*Continued*)

			N or Mean[1]	% or SD[1]
Programmatic	*Experienced user problem with stove*		676	0.9%
	Experienced user problem with filter		939	1.2%
	Education delivery in sector	Within first week	19,867	25.7%
		During middle weeks	46,840	60.5%
		Within last week	10,710	13.8%
	Community health worker (CHW) quality rating	Strong	52,687	68.1%
		Needs improvement	1336	1.7%
		Satisfactory	23,394	30.2%
	Duration of household education (min)[4]		31.37	14.33
	Time between distribution and education (days)		3.27	2.71
	Time between education and follow-up (days)		104.33	26.80
	Adoption of both stove and filter		71,345	92.2%

[1]The number and percentage of applicable households are displayed for categorical variables and the mean and standard deviation of households for continuous variables.

*A subset of 11,137 households were cooking at the time of the follow-up visit, while the other three outcomes considered the full sample of 77,417 households.

2.3. Analysis
All data extraction, variable development, and analysis were conducted in R program (R Core Team, Vienna, Austria, version 3.4.1). Bivariate logistic regression analysis using robust Wald's tests adjusted for administrative cell clusters proceeded between each of the four outcomes and all of the independent variables. Simultaneous multiple logistic regression using Generalized Estimating Equations (GEE) was conducted and adjusted odds ratios with robust cluster-adjusted standard errors were reported. All variables were included in the models regardless of significance suggested during preliminary analysis because there is little existing theoretical or applied precedence for the effect geospatial and programmatic variables have on health technology adoption by vulnerable populations. Moreover, we were interested in how these variables responded in the presence of the traditional demographic variables we had available to us in this study.

3. Results
Tables 3 and 4 show the adjusted odds ratios for the stove and filter outcomes, respectively. The models for self-reported ICS adoption, observed ICS use, self-reported filter adoption, and observed filter use were able to distinguish between adopters and non-adopters 77.8%, 73.6%, 83.5%, 62.2% of the time, respectively. The following summary focuses on the observed results except where they differ substantially from the self-reported measures.

3.1. Factors associated with improved cookstove adoption
Several geospatial, demographic, and programmatic variables were significantly associated with reported primary use and observed cooking of the ICS after adjusting for all variables. There was significant variation in the odds of adoption between districts (Table 3) although rural householders had greater odds of reported and observed (OR 1.47, 95% CI 1.04–2.09, $p = 0.03$) stove adoption than households in urban villages controlling for geographic region. Increasing elevation decreased the odds of routine use of the improved cookstove, with lower odds of observed adoption in households at or above 2000 m (OR 0.63, 95% CI 0.40–0.97, $p = 0.04$) compared to households below 1500 m.

Although there was no significant difference in odds of stove adoption between *ubudehe* 1 and 2 recipients and local leaders, whether leaders adopted the stove was significantly associated with individual household adoption, with odds of adoption being lowest among households where less than 90% of the CHWs and local leaders in their village reported using the stove for both the reported and observed (OR 0.58, 95% CI 0.49–0.69, $p < 0.01$) measures. A similar pattern was observed for the influence of neighboring recipients (OR 0.45, 95% CI 0.39–0.53, $p < 0.01$). The difference in odds from high-adoption networks attenuated for isolated households in regards to peer influence (OR 0.69, 95% CI 0.60–0.79, $p < 0.01$) and became indistinguishable when considering leader influence.

Family composition was also associated with stove adoption. An increase in odds of reported adoption was observed for each additional household member (OR 1.08, 95% CI 1.06–1.10, $p < 0.01$) and for each additional child (OR 1.11, 95% CI 1.06–1.16). When considering observed stove use, family size had an opposing effect on adoption with each additional member decreasing the odds of adoption (OR 0.92, 95% CI 0.89–0.95, $p < 0.01$) while the number of children under the age of five in the household was no longer significantly related to adoption. Technology factors dampened the odds of both reported and observed adoption, including prior experience with any improved cookstove (OR 0.74, 95% CI 0.66–0.84, $p < 0.01$) and perception of a functional problem with the stove (OR 0.27, 95% CI 0.18–0.41, $p < 0.01$).

3.2. Factors associated with filter adoption variables
There was some evidence that the resident district had an effect on household filter adoption, but the effect was not uniform (Table 4). Population density was not a significant factor for self-reported adoption, but living in the highest density sector appeared to reduce the odds of observed filter use over the odds in households living in the lowest density sector (OR 0.70, 95% CI 0.54–0.89, $p < 0.01$). At higher elevations, households were less likely to be observed adopting

Table 3. Multivariate logistic regression models for self-reported and observed ICS adoption

			Self-reported stove adoption			Observed stove adoption*		
			Adj OR (95% CI)		*p* Value	Adj OR (95% CI)		*p* Value
Geospatial-temporal	*District:*	Karongi	REF			REF		
		Ngororero	1.91	(1.49–2.45)	**< 0.01**	2.89	(2.16–3.87)	**< 0.01**
		Nyabihu	1.76	(1.39–2.22)	**< 0.01**	2.43	(1.72–3.45)	**< 0.01**
		Nyamasheke	2.50	(1.92–3.27)	**< 0.01**	2.03	(1.39–2.98)	**< 0.01**
		Rubavu	2.35	(1.64–3.35)	**< 0.01**	2.05	(1.22–3.43)	**< 0.01**
		Rusizi	1.89	(1.37–2.61)	**< 0.01**	1.61	(1.03–2.53)	**0.04**
		Rutsiro	1.62	(1.29–2.03)	**< 0.01**	1.48	(1.08–2.04)	**0.02**
	Rural village residency		1.27	(1.04–1.55)	**0.02**	1.47	(1.04–2.09)	**0.03**
	Population density quartile (per km2):	1st quartile (242–465)	REF			REF		
		2nd quartile (466–585)	0.89	(0.72–1.10)	0.28	0.69	(0.52–0.91)	**< 0.01**
		3rd quartile (586–782)	1.09	(0.88–1.35)	0.42	0.88	(0.65–1.19)	0.41
		4th quartile (783–2636)	1.20	(0.88–1.64)	0.25	1.47	(0.92–2.36)	0.11
	Household elevation:	<1500m	REF			REF		
		1500–1999m	0.48	(0.35–0.67)	**< 0.01**	0.72	(0.50–1.04)	0.08
		≥2000m	0.40	(0.28–0.58)	**< 0.01**	0.63	(0.40–0.97)	**0.04**
	Days of rain (per additional 7 days)		1.06	(0.96–1.16)	0.25	1.04	(0.92–1.18)	0.53
	Month of follow-up:	Jan	REF			REF		
		Feb	1.14	(0.90–1.44)	0.28	1.15	(0.85–1.55)	0.35
		Mar	1.22	(0.93–1.60)	0.16	1.40	(0.96–2.04)	0.08
		Apr	3.51	(1.14–10.80)	**0.03**	3.10	(0.67–14.32)	0.15
	Percentage of neighbors adopting technology:	≥ 90%	REF			REF		
		< 90%	0.41	(0.35–0.47)	**< 0.01**	0.45	(0.39–0.53)	**< 0.01**

(*Continued*)

Table 3. (*Continued*)

			Self-reported stove adoption			Observed stove adoption*		
			Adj OR (95% CI)		***p* Value**	**Adj OR (95% CI)**		***p* Value**
		Isolated household	0.76	(0.70–0.84)	**< 0.01**	0.69	(0.60–0.79)	**< 0.01**
	Percentage of local leaders adopting technology:	≥ 90%	REF			REF		
		< 90%	0.37	(0.34–0.41)	**< 0.01**	0.58	(0.49–0.69)	**< 0.01**
		Isolated household	0.64	(0.53–0.78)	**< 0.01**	1.06	(0.69–1.63)	0.78
Geospatial—Anisotropic	*Travel time to health facility (per 1 hr increase)*		0.99	(0.88–1.12)	0.92	1.07	(0.91–1.26)	0.40
	Travel time to main road (per 1 hr increase)		0.97	(0.89–1.06)	0.50	0.97	(0.87–1.08)	0.60
	Travel time to city center (per 1 hr increase)		1.00	(0.97–1.03)	0.94	1.01	(0.96–1.05)	0.74
Demographic	*Ubudehe 1 & 2 recipient category*		1.00	(0.89–1.12)	0.95	0.86	(0.73–1.02)	0.08
	Family size (per 1 additional member)		1.08	(1.06–1.10)	**< 0.01**	0.92	(0.89–0.95)	**< 0.01**
	Children under 5 in household (per 1 additional child)		1.11	(1.06–1.16)	**< 0.01**	1.05	(0.99–1.12)	0.10
	Prior experience with similar technologies		0.83	(0.76–0.90)	**< 0.01**	0.74	(0.66–0.84)	**< 0.01**
	Programmatic	*Experienced user problem with technology*		0.15	(0.12–0.18)	**< 0.01**	0.27	(0.18–0.41)
< 0.01								
	Education delivery in sector	During middle of campaign	REF			REF		
		Within first week	1.19	(1.01–1.41)	**0.04**	1.22	(0.99–1.51)	0.07
		Within last week	0.99	(0.83–1.17)	0.90	1.18	(0.91–1.53)	0.20
	Community health worker (CHW) quality rating	Strong	REF			REF		

(*Continued*)

Table 3. (*Continued*)

			Self-reported stove adoption			Observed stove adoption*		
			Adj OR (95% CI)		*p* Value	Adj OR (95% CI)		*p* Value
		Needs improvement	1.23	(0.89–1.70)	0.21	1.53	(0.92–2.55)	0.10
		Satisfactory	1.10	(1.00–1.20)	**0.04**	1.01	(0.87–1.18)	0.85
	Duration of household education (per additional 10 min		0.98	(0.95–1.01)	0.17	0.99	(0.95–1.02)	0.46
	Time between distribution and education (per additional 1 day)		0.99	(0.98–1.01)	0.26	0.98	(0.95–1.00)	0.09
	Time between education and follow-up (per additional 1 week)		0.94	(0.89–1.00)	0.05	0.93	(0.86–1.00)	0.06
	Adoption of both stove and filter		9.08	(7.85–10.51)	**< 0.01**	3.10	(2.73–3.53)	**< 0.01**

Bolded numbers indicate statistical significance < 0.05.
*A subset of 11,137 households were cooking at the time of the follow-up visit while self-reported adoption considered the full sample of 77,417 households.

Table 4. Multivariate logistic regression models for self-reported and observed filter adoption

			Self-reported filter adoption			Observed filter adoption		
			Adj OR (95% CI)		p-value	Adj OR (95% CI)		*p* Value
Geospatial-temporal	*District:*	Karongi	REF			REF		
		Ngororero	1.67	(1.24–2.24)	**< 0.01**	1.26	(1.03–1.55)	**0.02**
		Nyabihu	1.66	(1.19–2.31)	**< 0.01**	1.45	(1.14–1.85)	**< 0.01**
		Nyamasheke	1.39	(1.04–1.87)	**0.03**	1.46	(1.19–1.78)	**< 0.01**
		Rubavu	3.10	(2.08–4.62)	**< 0.01**	2.01	(1.56–2.59)	**< 0.01**
		Rusizi	1.27	(0.84–1.91)	0.25	1.20	(0.91–1.58)	0.20
		Rutsiro	1.27	(1.00–1.62)	0.05	0.94	(0.78–1.14)	0.56
	Rural village residency		1.19	(0.94–1.51)	0.15	1.03	(0.88–1.21)	0.69
	Population density quartile (per km2):	1st quartile (242–465)	REF			REF		
		2nd quartile (466–585)	0.91	(0.71–1.16)	0.43	0.93	(0.78–1.11)	0.43
		3rd quartile (586–782)	0.81	(0.60–1.09)	0.16	0.87	(0.71–1.07)	0.20
		4th quartile (783–2636)	0.81	(0.58–1.13)	0.21	0.70	(0.54–0.89)	**< 0.01**
	Household elevation:	<1500m	REF			REF		
		1500-1999m	0.63	(0.39–1.01)	0.06	0.53	(0.40–0.70)	**< 0.01**
		≥2000m	0.47	(0.29–0.76)	**< 0.01**	0.48	(0.36–0.65)	**< 0.01**
	Days of rain (per additional 7 days)		0.99	(0.87–1.12)	0.84	1.08	(0.99–1.18)	0.09
	Month of follow-up:	Jan	REF			REF		
		Feb	1.27	(0.97–1.66)	0.08	1.00	(0.84–1.19)	1.00
		Mar	1.19	(0.87–1.62)	0.28	1.13	(0.91–1.41)	0.26
		Apr	2.50	(0.30–20.61)	0.39	0.70	(0.36–1.37)	0.30
	Percentage of neighbors adopting technology:	≥ 90%	REF			REF		
		< 90%	0.41	(0.33–0.50)	**< 0.01**	0.62	(0.57–0.68)	**< 0.01**
		Isolated household	0.77	(0.67–0.87)	**< 0.01**	0.92	(0.88–0.98)	**< 0.01**

(*Continued*)

Table 4. (*Continued*)

			Self-reported filter adoption			Observed filter adoption		
			Adj OR (95% CI)		p-value	Adj OR (95% CI)		*p* Value
	Percentage of local leaders adopting technology:	≥ 90%	REF			REF		
		< 90%	0.31	(0.26–0.37)	**< 0.01**	0.71	(0.60–0.83)	**< 0.01**
		Isolated household	1.05	(0.78–1.40)	0.76	0.93	(0.79–1.09)	0.37
Geospatial—Anisotropic	*Travel time to health facility (per 1 hr increase)*		0.97	(0.84–1.12)	0.69	0.99	(0.90–1.08)	0.76
	Travel time to main road (per 1 hr increase)		0.94	(0.86–1.01)	0.11	0.93	(0.86–1.02)	0.12
	Travel time to city center (per 1 hr increase)		1.08	(1.03–1.13)	**< 0.01**	1.03	(1.00–1.06)	0.06
Demographic	*Ubudehe 1 & 2 recipient category*		0.56	(0.46–0.68)	**< 0.01**	0.65	(0.60–0.70)	**< 0.01**
	Family size (per 1 additional member)		1.15	(1.11–1.18)	**< 0.01**	1.06	(1.04–1.07)	**< 0.01**
	Children under 5 in household (per 1 additional child)		1.00	(0.93–1.08)	0.96	0.96	(0.94–0.99)	**0.01**
	Prior experience with similar technologies		1.26	(1.10–1.45)	**< 0.01**	1.29	(1.22–1.36)	**< 0.01**
Programmatic	*Experienced user problem with technology*		0.04	(0.03–0.05)	**< 0.01**	0.14	(0.12–0.16)	**< 0.01**
	Education delivery in sector	During middle of campaign	REF			REF		
		Within first week	0.78	(0.66–0.91)	**< 0.01**	0.92	(0.81–1.04)	0.20
		Within last week	0.80	(0.63–1.02)	0.07	0.92	(0.80–1.06)	0.26
	Community health worker (CHW) quality rating	Strong	REF			REF		
		Needs improvement	0.66	(0.47–0.93)	**0.02**	1.17	(0.98–1.40)	0.09
		Satisfactory	0.87	(0.77–0.98)	**0.03**	0.96	(0.90–1.03)	0.26
	Duration of household education (per additional 10 min)		1.07	(1.02–1.11)	**< 0.01**	1.02	(1.00–1.05)	0.09
	Time between distribution and education (per additional 1 day)		0.98	(0.96–1.01)	0.12	0.99	(0.97–1.00)	0.06
	Time between education and follow-up (per additional 1 week)		1.02	(0.94–1.10)	0.65	0.96	(0.91–1.02)	0.16
	Adoption of both stove and filter		9.07	(7.79–10.57)	**< 0.01**	–	–	–

Bolded numbers indicate statistical significance < 0.05.

the filter. The odds were significantly lower in households between 1500 and 2000 m for reported and observed (OR 0.53, 95% CI 0.40–0.70, $p < 0.01$) adoption and at 2000 m and above (OR 0.48, 95% CI 0.36–0.65, $p < 0.01$) for confirmed use.

Recipient socioeconomic category significantly impacted the odds of adoption, irrespective of outcome measure. *Ubudehe* 1 and 2 households had lower odds of observed use compared to local leader recipients (OR 0.65, 95% CI 0.60–0.70, $p < 0.01$). Perceived adoption by neighboring recipients was a significant factor for individual household adoption, despite attenuating when considering the observational outcome measure. In low adoption networks, households had almost half the odds (OR 0.62, 95% CI: 0.57–0.68, $p < 0.01$) of filter adoption than in households where most neighbors reported adoption. Isolation, or having no fellow recipients within 100 m, was again protective compared to observing peers not adopting the filter and nearly displayed no difference from high adoption networks when filter adoption was spot-checked (OR 0.92, 95% CI 0.88–0.98, $p < 0.01$). Depressed adoption by local leaders reduced the odds of adoption by other households compared to villages where almost all of the leaders adopted the filter, although the relationship was closer to parity with observed adoption (OR 0.71, 95% CI 0.60–0.83, $p < 0.01$). Adoption by isolated households was not significantly different from households in communities with high leader adoption.

Additional family members increased the odds of adoption (OR 1.06, 95% CI 1.04 −1.07, $p < 0.01$), while each additional child under age five significantly lowered the odds of having water in the filter at the time of the visit, although the effect size was nearly null (OR 0.96, 95% CI 0.94–0.99, $p = 0.01$) and was insignificant for self-reported adoption. Prior experience with treating drinking water increased the odds of observed use (OR 1.29, 95% CI 1.22 −1.36, $p < 0.01$) and was comparable to the odds of self-reported use. Experiencing a problem with the filter severely decreased the odds of both self-reported and observed (OR 0.14, 95% CI 0.12–0.16, $p < 0.01$) adoption.

Households visited during the first week of their respective CHW team's deployment had decreased odds of self-reported adoption (OR 0.78, 95% CI 0.66–0.91, $p < 0.01$) compared to households visited during the middle of the campaign, although this relationship was not shown in observed filter use. Odds of reported filter use were lower for households visited by a CHW not rated as a strong educator, with the households visited by poorly rated CHWs having the lowest odds (OR 0.66, 95% CI 0.47–0.93, $p = 0.02$). CHW quality was not associated with observed adoption. The longer an educator spent in a household during the initial visit, the higher the odds of reported adoption for each additional 10 min (OR 1.07, 95% CI 1.02–1.11, $p < 0.01$) which did not have a significant impact on observed adoption. Travel time to health facility and to main road were not significantly associated with adoption, but there was evidence to suggest that higher travel times to the nearest urban center increased the odds of self-reported adoption (OR 1.08, 95% CI 1.03–1.13, $p < 0.01$) although this relationship was also insignificant for observed adoption.

In summary, key findings included similarities and differences between factors affecting each technology and discrepancies between self-reported and observed measures. Adjusted models showed that residential district, higher elevation, perceived adoption in social networks, and technical difficulties with the product were associated with the adoption of either the stove or filter. However, CHW interaction, recipient category, and prior experience had a singular impact on filter use while living in a rural area only impacted stove adoption. Family composition had an inconsistent relationship with self-reported and observed stove adoption. Gains in filter adoption with increased CHW interaction were not congruent from self-reported to observed use. Population density, number of days of rain, month of follow up, time between distribution and education, and time between education and follow-up, and travel time to services were not significant determinants of cookstove or filter adoption. Buy-in of the combined intervention strongly impacted the adoption of one intervention product when the household also reported adopting the other intervention product; though the impact of the combined intervention attenuated with observed adoption, it remained strong (OR 3.10, 95% CI: 2.73–3.53, $p < 0.01$).

4. Discussion

4.1. Geospatial-temporal variables

Rwanda has undertaken a major decentralization policy since 2000 to improve good governance and service delivery by the local government. Provinces and district boundaries were restructured over this period, having a potentially profound impact on cultural identity, citizen participation, and services delivery (Ministry of Local Government, 2012). Sustained differences in the odds of adoption between districts after accounting for other geospatial variables in our study support the conclusion that there are likely other shared attributes specific to districts that were not quantified, such as political, social, or even other environmental characteristics. It is worth studying the relationship between administrative units more closely in further research as Rwanda continues to decentralize.

Rural residency only affected the odds of stove adoption. The observed higher odds of ICS use by residents of rural villages compared to urban residents could be due to an increased ability to gather wood over purchasing it, depressed charcoal use, or an inability to purchase wood or competing cookstoves regardless of supply because of unavailability of markets and lowered financial resources, features common in rural communities. The odds of filter adoption were not different in rural and urban areas, perhaps because there is little to no difference between access to required externalities after initial accrual of the product in contrast to those that exist to use the stove as the quantity of water demanded by the filters does not change in relation to this program as does the amount of fuelwood the stove demands. While non-significant in the presence of district and urban-rural status, an increasing population density trend suggested increased odds of stove adoption and decreased odds of filter adoption. Likely, fuelwood is scarcer in areas with more competition for resources, acting as a driver to use the fuel-efficient stoves. In a nationally representative sample in Rwanda, household drinking water quality increased at higher population densities (Kirby et al., 2016) and if households perceive their water to be cleaner they may have less health incentive to treat it before consumption (Trent et al., 2018).

The odds of stove and filter adoption were lower at higher elevations. This aligns with expectations from previous studies. In contrast, our data failed to show that precipitation impacted adoption in this study. However, there are many ways to conceptualize precipitation and we chose an indicator measure due to limitations of the TAMSAT data (Maidment et al., 2017), whereas an estimate of the amount of precipitation may have been more instructive at suggesting water availability, source, and subsequent water treatment. Furthermore, proximate timing and severity of rainfall may be more relevant to water treatment behavior than an aggregate measure over a longer period of time, particularly for observed use (Kirby et al., 2016). Finally, the implementer purposefully avoided Rwanda's heaviest rainy season from March to May to facilitate distribution and household visits as well as included messaging on how to use the technologies during rainy periods. The non-significance of precipitation on the adoption of this health campaign may simply be an indication of successful program design.

Adoption, as reported by a neighbor or leader, was operationalized in the models regardless of whether the household's self-reported or observed outcome was of interest; thus, this variable studies how the *perception* of adoption by associates affects individual reported and actual adoption. In this study, peer and local leader networks had a similar effect on individual household adoption. The highest odds of adoption were among households where 90% or greater of their local leader or peer network reported adopting the technology. Interestingly, having no network to observe increased individual adoption compared to having a low adoption network. The effect of negative feedback in networks, or the positive effect of self-reliance in the absence of one, should be studied further as our data suggests this may have a substantial impact on individual adoption decisions. Furthermore, implementers designed the program to leverage the existing role of CHWs and elected local officials as thought leaders in their communities to encourage adoption by other households. However, since the impact of peer and leader networks on individual adoption was very comparable, our study did not show that local leaders had an outsized role as change agents.

In this study, access to health facilities, main roads, and urban centers were largely insignificant and had null effects on adoption with an exception being the positive association between self-reported filter adoption and travel time to the nearest urban center. This is consistent with our finding that the odds of observed filter use were lower in the highest density sectors. Reasons to explain this association include increased product choice in urban areas and perceptions of higher water quality in built environments, or perhaps it was a spurious observation. On the whole, either access to services is not a good predicator of stove and filter adoption or not well modeled by walking time.

4.2. Demographic variables

We found that households recognized as members of the most at-risk population—*ubudehe* 1 and 2—had lower odds of adopting the filter than households that received those products because of their involvement with promoting the health program—the CHWs and local-elected officials. Recipient category did not affect stove adoption in a similar way. The filter hardware is more complex and its performance less obvious in near time—compared to the stove, which immediately reduces the amount of fuelwood and smoke with each use—so having a better understanding of risk factors for disease, such as drinking contaminated water, could serve to improve adoption of the filter. Local leaders, especially CHWs, are more likely to have this knowledge and may more readily recognize non-health related incentives such as social responsibility, possibly leading to increased behavior change.

Households with more members, including more children, had greater odds of reporting stove use but could be less likely to actually use the stove based on the odds of observing households cooking on the intervention stove at the time of the visit. Improved cookstoves often require more active tending, cooking time, and smaller dishes compared to traditional three-stone fires; thus, larger families may find it difficult to cook efficiently and adequately on the EcoZoom stove. Furthermore, households with more members, and children, may not value the time spent collecting wood, one of the main incentives of improved cookstoves which use less firewood, since more people are expendable to perform the task. Finally, there was a significant decreasing trend in the proportion of households reporting exclusive use of the ICS as family size increased (χ_1^2 = 36.1, p-value < 0.01), suggesting families are stove stacking when there are more members to feed. A detailed survey on a small subset of participants enrolled in this health program previously found no correlation between household size and stove stacking behavior (Barstow et al., 2016).

Households with more members also had higher odds of filter adoption according to both self-report and observation, although the odds attenuated when studying households who had water in their filter at the time of the visit. The number of young children was not significantly related to reported use but decreased the odds of observed filter use. Larger families and caretakers with more children, i.e. non-contributing family members, may find it hard to supply the proper quantity of treated water for their families. As households report higher use than is observed by spot-check of both technologies, this could indicate self-report bias.

Prior experience with improved cookstoves decreased the odds of adoption of this program's distributed stove. Conversely, prior experience with treating water increased the odds of filter adoption. The most widely available improved cookstoves in Rwanda are locally made ceramic, rock, or metal rocket design stoves that are not actually effective at reducing the amount of fuelwood or pollution (Global Alliance for Clean Cookstoves, 2018). Experience with one of these stoves could understandably make households skeptical of other products promoted as improved cookstoves. Water treatment campaigns and products, on the other hand, have successfully entered the household goods market in Rwanda (Nzabonimpa & Karangwa, 2012). Positive experiences with water treatment previously could have benefited filter adoption by forming water treatment habits, increasing the agency of caretakers, and motivating users to reduce susceptibility to waterborne illness.

4.3. Programmatic variables

Proper use of the filter is more complex and requires more steps than implementing the improved cookstove, which may explain why higher quality and more attentive CHWs had a greater impact on filter adoption than stove adoption. However, since the described relationships were only significant when studying self-reported measures, the program's targeted messaging could have better primed householders' responses, but not necessarily changed health behavior.

Perceiving a problem with either technology strongly discouraged households from adoption, and was more detrimental to filter adoption than stove adoption. As our inclusion criteria removed those products that appeared to have a legitimate malfunction, we see that perception of a problem is strong enough to discourage use all together. Interestingly, experiencing a problem with either technology actually increased the odds of observed use when compared to self-reported adoption. Households who were likely to report a functional problem with the stove may be more frequent and invested users while if the filter has malfunctioned, the water seen in the container may not reflect recent usage. The implementers learned that the ICS was still useful as a cooking stove despite complaints while households were more likely to definitively discontinue use of the filter either because of actual mechanics or the perception of complexity and unfamiliarity. This indicates that programs that address user questions and troubleshooting, such as through a call line or regular promotional visits, are essential for program success.

The timing of program visits did not appear to affect adoption, which may again indicate successful program design. Responsive education was achieved by this program as 94% of households were visited no later than one week after receiving products. Households that were visited for follow-up later than others had no decreased odds of adoption, suggesting that sustained adoption of technologies over 3 months was achieved.

Finally, implementing the health program as a combined intervention—distributing and promoting both improved cookstoves and water filters—was beneficial to improving adoption of either technology on its own. The effect size for both technologies is substantial, but greatly reduced, when considering the more objective measures, suggesting reporting bias. Moreover, similar magnitude of adoption between stove and filter self-reported measures indicates bias, meaning that the same households that were compelled to report adoption, regardless of their actual use, did so for the stove and filter equally.

Our own outcomes of interest used two measurement types, but it is important to acknowledge the limitations of each approach. Self-reported surveys are commonly affected by respondent and courtesy bias, but spot check measurements such as observing cooking practices, visually assessing a stove for wear, and confirming the presence of water in a filter or storage container could also be prone to reactivity. Furthermore, as given above, proxy indicators may also be subject to bias and misclassification. The fidelity of self-reported outcomes has been improved by focusing on near-time events, such as in the previous 48 h (Sinha et al., 2016), which advocates for improved questionnaire design and the development of responsive variables, many of which could be geospatial. These considerations highlight the need to collect objective data and include external data sources where possible to improve descriptions of adoption during targeted health interventions.

We performed simultaneous multiple regression because there were few prior hypotheses to guide our study. Consequently, we did not differentiate variables nor undertake variable selection, and our models may not be parsimonious. However, our sample size of over 70,000 participants preempts overfitting. A large sample size also helps mitigate bias and misclassification by certain respondents or enumerators, and we assumed that our outcomes and covariates were correctly specified in general. Although only a fraction of participants were cooking at the time of the follow-up visit and informed the observed stove adoption model, the sample size of this subset was above 10,000 and greater than other existing health interventions and their implementation analyses. In fact, *Tubeho Neza* is one of the largest distributions of cookstoves and water filters ever conducted in East Africa and provides a unique opportunity to study health behavior on a large geographic scale and define fine-resolution outcomes. Nonetheless, the generalizability of results is limited outside Western Province, Rwanda, but implementers should look for similarities in other contexts and certainly the nature of the analysis, with geospatial, demographic, and programmatic descriptors, should be emulated. Here, we have reported on correlation of several factors and not presumed causation, which is appropriate for a cross-sectional study. Experimental, especially longitudinal, study designs would reinforce conclusions, more directly deliver programmatic feedback, and be useful in exploring how spatiotemporal variables may affect acute and sustained adoption differently. Another limitation was the restricted resolution of some of the geospatial variables, including population density at sector-level and precipitation every 4 km, but our approach incorporated the most localized data available, relying particularly on household GPS coordinates, and we expect data will continue to become more specific over time and with technological advances. Finally, when assigning shared variables to individual units, there is concern about committing an ecological fallacy, where inferences made about a group are taken to describe each individual within that group whether merited or not. However, this was avoided in this study in part by incorporating household-level data and developing variables at unique geographic locations when possible.

5. Conclusions

Respiratory infections and diarrheal diseases—large contributors to the global disease burden—are being addressed by distributions of improved cookstoves and point-of-use water filters which necessitate acceptance by recipients. In this study, we had the unique ability to elucidate adoption factors associated with self-reported use and observed use. Effect sizes characteristically attenuated from the self-reported adoption models to observed adoption, which suggests households exaggerated their adoption practices in response to the implementer's survey. However, some comparisons between reported and observed adoption factors imply there are underlying mechanisms of participant perception and health decisions not yet understood.

Moreover, the unique contribution of this study was its demonstration of the integration and importance of geospatial and temporal variables on individual adoption decisions. Accompanying behavior change campaigns have heretofore lacked an appropriate focus on environmental factors, whereas our study has provided a suggestion of how impact analyses can proceed with diverse geospatial variables and advocated for an ecological approach to analysis and implementation of public health programs. The increase in GPS-connected devices and improved resolution of geodata, including satellite imagery, population censuses, and networks, make it possible to extract data from global repositories, conduct variable development relevant to local settings, and be more explicit about considering the context in which people make health decisions. These types of data and analyses may prove to be an important source of information for dissemination and implementation science, which stresses engagement and relevancy within local settings. Additionally, it could lead to dynamic program implementation that proactively targets vulnerable areas for increased program inputs based on current environmental circumstances.

There is an existing disconnect between program design and population health outcomes in many development projects because monitoring and evaluation of these programs have largely not transcended the quantification of inputs, i.e. the number of cookstoves and filters distributed or the number of households reached. Funders, governments, and populations should demand more outcome and evidence-driven programs, and international standards and policies are beginning to reflect this movement toward the use of near-time, objective, and combined methodologies to find and support demonstrated success in health promotion. High-resolution geospatial and temporal information will be an integral source of data in this new era of monitoring and evaluation.

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Competing Interests
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Author Contributions
CB and ET were responsible for the design and data collection of the initial intervention described. KF, CN, MK, and ET conceived of the present research and contributed to the experimental design. KF performed variable development and analysis with the supervision of the other authors and drafted the manuscript. All authors were involved in revisions and critical discussion, and read and approved the final manuscript.

Availability of data and material
All data used in the production of the analysis and results presented are available upon request from the lead and corresponding authors.

Consent for publication
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References

Aoun, N., Matsuda, H., & Sekiyama, M. (2015). Geographical accessibility to healthcare and malnutrition in Rwanda. *Social Science & Medicine*, *130*, 135–145. doi:10.1016/j.socscimed.2015.02.004

Bain, R., Cronk, R., Hossain, R., Bonjour, S., Onda, K., Wright, J., … Bartram, J. (2014). Global assessment of exposure to faecal contamination through drinking water based on a systematic review. *Tropical Medicine & International Health*, *19*(8), 917–927. doi:10.1111/tmi.12334

Barstow, C., Clasen, T., Kirby, M., & Thomas, E. (2018). Health, livelihood, and environmental impacts of the distribution of a carbon-credit-financed, large-scale water filter and improved cookstove programme in Rwanda. *The Lancet Planetary Health*, *2*, S31–S32. doi:10.1016/S2542-5196(18)30116-5

Barstow, C. K., Nagel, C. L., Clasen, T. F., & Thomas, E. A. (2016). Process evaluation and assessment of use of a large scale water filter and cookstove program in Rwanda. *BMC Public Health*, *16*, 584. doi:10.1186/s12889-016-3237-0

Barstow, C. K., Ngabo, F., Rosa, G., Majorin, F., Boisson, S., Clasen, T., & Thomas, E. A. (2014). Designing and piloting a program to provide water filters and improved cookstoves in Rwanda. *PloS One*, *9*(3), e92403. doi:10.1371/journal.pone.0092403

Beltramo, T., Blalock, G., Levine, D. I., & Simons, A. M. (2015). Does peer use influence adoption of efficient cookstoves? Evidence from a randomized controlled trial in Uganda. *Journal of Health Communication*, *20* (Suppl 1), 55–66. doi:10.1080/10810730.2014.927034

Black, R. E., Morris, S. S., & Bryce, J. (2003). Where and why are 10 million children dying every year? *The Lancet*, *361*(9376), 2226–2234. doi:10.1016/S0140-6736(03)13779-8

Brown, J., & Clasen, T. (2012). High adherence is necessary to realize health gains from water quality interventions. *PloS One*, *7*(5), e36735. doi:10.1371/journal.pone.0036735

Center for International Earth Science Information Network (CIESIN), Columbia University. (2017). *Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 10*. Palisades, NY, USA: NASA Socioeconomic Data and Applications Center (SEDAC).

Dreibelbis, R., Winch, P. J., Leontsini, E., Hulland, K. R., Ram, P. K., Unicomb, L., & Luby, S. P. (2013). The Integrated Behavioural Model for Water, Sanitation, and Hygiene: A systematic review of behavioural models and a framework for designing and evaluating behaviour change interventions in infrastructure-restricted settings. *BMC Public Health*, *13*, 1015. doi:10.1186/1471-2458-13-1015

European Commission Joint Research Centre. (2015). Travel time to major cities: A global map of accessibility [online]. Retrieved from http://forobs.jrc.ec.europa.eu/products/gam/sources.php

Ezzati, M., & Kammen, D. M. (2001). Indoor air pollution from biomass combustion and acute respiratory infections in Kenya: An exposure-response study. *The Lancet*, *358*(9282), 619–624. doi:10.1016/S0140-6736(01)05777-4

Global Alliance for Clean Cookstoves. (2018). Clean cooking catalog [online]. *Clean Cooking Catalog*. Retrieved from http://catalog.cleancookstoves.org/

GRASS Development Team. (2018). Geographic Resources Analysis Support System (GRASS 7) r.walk manual [online]. *Open Source Geospatial Foundation Project*. Retrieved from https://grass.osgeo.org/grass72/manuals/r.walk.html

Hanlon, M., Burstein, R., Masters, S. H., & Zhang, R. (2012). Exploring the relationship between population density and maternal health coverage. *BMC Health Services Research*, *12*, 416. doi:10.1186/1472-6963-12-416

Huerta Munoz, U., & Källestål, C. (2012). Geographical accessibility and spatial coverage modeling of the primary health care network in the Western Province of Rwanda. *International Journal of Health Geographics*, *11*, 40. doi:10.1186/1476-072X-11-40

Hulland, K., Martin, N., Dreibelbis, R., DeBruicker Valliant, J., & Winch, P. (2015). *What factors affect sustained adoption of safe water, hygiene and sanitation technologies? A systematic review of literature*. London: EPPI-Centre, No. 2303.

Institute for Health Metrics and Evaluation (IHME). (2015). *GBD compare*. Seattle, WA: IHME,University of Washington. Retrieved from: http://vizhub.healthdata.org/gbd-compare

Intergovernmental Authority on Development's Climate Prediction and Applications Center. (2017). Rwanda Land Cover 2015 [online]. *ICPAC Geoportal*. Retrieved from http://geoportal.icpac.net/

Kirby, M. A., Nagel, C. L., Rosa, G., Iyakaremye, L., Zambrano, L. D., & Clasen, T. F. (2016). Faecal contamination of household drinking water in Rwanda: A national cross-sectional study. *Science of the Total Environment*, *571*, 426–434. doi:10.1016/j.scitotenv.2016.06.226

Lewis, J. J., & Pattanayak, S. K. (2012). Who adopts improved fuels and cookstoves? A systematic review. *Environmental Health Perspectives*, *120*(5), 637–645. doi:10.1289/ehp.1104194

Maidment, R. I., Grimes, D., Black, E., Tarnavsky, E., Young, M., Greatrex, H., … Alcántara, E. M. U. (2017). A new, long-term daily satellite-based rainfall dataset for operational monitoring in Africa. *Scientific Data*, *4*, 170063. doi:10.1038/sdata.2017.63

Malla, S., & Timilsina, G. R. (2014). *Household cooking fuel choice and adoption of improved cookstoves in developing countries: A review*. Washington, DC: World Bank, Policy Research Working Paper No. 6903.

Martin, N. A., Hulland, K. R. S., Dreibelbis, R., Sultana, F., & Winch, P. J. (2018). Sustained adoption of water, sanitation and hygiene interventions: Systematic review. *Tropical Medicine & International Health: TM & IH*, *23*(2), 122–135. doi:10.1111/tmi.13011

Ministry of Local Government. (2012). *National decentralization policy*. The Republic of Rwanda, Kigali, Rwanda.

Moran, M. B., Frank, L. B., Zhao, N., Gonzalez, C., Thainiyom, P., Murphy, S. T., & Ball-Rokeach, S. J. (2016). An argument for ecological research and intervention in health communication. *Journal of Health Communication*, *21*(2), 135–138. doi:10.1080/10810730.2016.1193918

Noor, A.M, Amin, A.A, Gething, P.W, Atkinson, P.M, Hay, S.I, & Snow, R.W. (2006). Modelling distances travelled to government health services in kenya. *Tropical Medicine And International Health*, *11*(2), 188–196. doi:10.1111/tmi.2006.11.issue-2

Nzabonimpa, J. P., & Karangwa, G. (2012). Rwanda (2010): MAP study evaluating the coverage, quality of coverage, and market penetration of condoms and Sur'Eau in Rwanda. doi:10.1094/PDIS-11-11-0999-PDN

Puzzolo, E., Stanistreet, D., Pope, D., Bruce, N., & Rehfuess, E. (2013). *Factors influencing the large-scale uptake by households of cleaner and more efficient household energy technologies*. London: EPPI-Centre.

Ray, N., & Ebener, S. (2008). AccessMod 3.0: Computing geographic coverage and accessibility to health care services using anisotropic movement of patients. *International Journal of Health Geographics*, *7*(1), 63. doi:10.1186/1476-072X-7-63

Regional Center for Mapping of Resources for Development (RCMRD). (2015). Rwanda SRTM 30 meters [online]. Retrieved from http://geoportal.rcmrd.org/layers/servir%3Arwanda_srtm30meters

Rehfuess, E. A., Puzzolo, E., Stanistreet, D., Pope, D., & Bruce, N. G. (2014). Enablers and barriers to large-scale uptake of improved solid fuel stoves: A systematic review. *Environmental Health Perspectives*, *122*(2), 120–130. doi:10.1289/ehp.1306639

Reich, B. (2016). *The diffusion of innovations in social networks*. University College London, Job Market Paper, London, United Kingdom.

Sinha, A., Nagel, C. L., Thomas, E., Schmidt, W. P., Torondel, B., Boisson, S., & Clasen, T. F. (2016). Assessing latrine use in rural India: A cross-sectional study comparing reported use and passive latrine use monitors. *The American Journal of Tropical Medicine and Hygiene*, *95*(3), 720–727. doi:10.4269/ajtmh.16-0102

Stanistreet, D., Puzzolo, E., Bruce, N., Pope, D., & Rehfuess, E. (2014). Factors influencing household uptake of improved solid fuel stoves in low- and middle-income countries: A qualitative systematic review. *International Journal of Environmental Research and Public Health*, *11*(8), 8228–8250. doi:10.3390/ijerph110909256

TAMSAT. (2014). Rainfall estimates [online]. Retrieved from https://www.tamsat.org.uk/data/rfe/

Thomas, E. A., Needoba, J., Kaberia, D., Butterworth, J., Adams, E. C., Oduor, P., … Nagel, C. (2019). Quantifying increased groundwater demand from prolonged drought in the East African Rift Valley. *Science of the Total Environment*, *666*, 1265–1272. doi:10.1016/j.scitotenv.2019.02.206

Trent, M., Dreibelbis, R., Bir, A., Tripathi, S. N., Labhasetwar, P., Nagarnaik, P., … Brown, J. (2018). Access to household water quality information leads to safer water: A cluster randomized controlled trial in india. *Environmental Science & Technology*, *52*, 5319–5329. doi:10.1021/acs.est.8b00035

Uwizeye, D., Sokoni, C. H., & Kabiru, C. W. (2014). Prevalence and correlates for diarrhoea in the mountainous informal settlements of Huye town, Rwanda. *SpringerPlus*, *3*. doi:10.1186/2193-1801-3-745

Additional File 1: Inclusion Criteria

Table A1. Restrictions performed on datasets

Programmatic Surveys	Distribution *n* = 102,318 (households)	Education *n* = 102,480 (households)	Follow-Up *n* = 101,836 (households)
Restrictions	1. Remove non-consents and respondents under the age of 18 years old; Constrain to intervention dates; Constrain to Western Province; Remove duplicate household identification numbers (IDs); Match households across surveys on household IDs, n = 83,794 2. Constrain to households with unique existing GPS coordinates and accuracy less than 10 m, n = 82,867 (−927) 3. Constrain household education to 0–2 hours, n = 82,184 (−683) 4. Constrain time between distribution and household visit to less than one month, n = 81,029 (−1155) 5. Constrain to households where stove and filter are present at both household and follow-up visits and spot-checks recorded, n = 79,834 (−1195) 6. Constrain to households where stove and/or filter did not need replacement at follow-up; otherwise retains households that reported experiencing a problem with stove or filter and those households where technologies could be repaired by CHW during visit, n = 78,201 (−1633) 7. Removed due to missing CHW quality evaluation, n = 77,820 (−381) 8. Removed due to inconsistent geographic location, n = 77,797 (−23) 9. Removed due to extreme family size (over 20 people), extreme number of children under age 5 (over 10 children), or discrepancy where number of children under age 5 in household was greater than or equal to family size, n = 77,417 (−380)		

Table A2. Comparison of selected variables before and after restriction

		Original follow-up survey; *n* (%)		Follow-up survey after restrictions; *n* (%)	
District	*Rusizi*	16,339	(16.0)	10,934	(14.1)
	Nyamasheke	13,937	(13.7)	13,000	(16.8)
	Karongi	14,713	(14.4)	7852	(10.1)
	Ngororero	17,922	(17.6)	11,477	(14.8)
	Nyabihu	10,671	(10.5)	8724	(11.3)
	Rutsiro	16,880	(16.6)	12,631	(16.3)
	Rubavu	10,550	(10.4)	12,799	(16.5)
	Non-western	824	(0.8)	0	(0.0)
Recipient category	*Ubudehe 1 & 2*	89,483	(87.9)	69,790	(90.1)
	Local official	10,043	(9.9)	7627	(9.9)
	Non-western	1973	(1.9)	0	(0.0)
	Unknown	337	(0.3)	0	(0.0)
Outcomes	*Self-reported Ecozoom as primary stove*	92,669	(91.0)	72,600	(93.8)
	Observed cooking on intervention stove at time of follow-up visit	10,738	(75.0)	8561	(76.9)
	Self-reported water treatment with Lifestraw	95,896	(94.2)	75,334	(97.3)
	Observed water in filter compartment at time of follow-up visit	78,570	(77.2)	62,092	(80.2)

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