Improving quality, timeliness and efficacy of data collection and management in population-based surveillance of vital events

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Summary

Electronic data collection (EDC), has become familiar in recent years, and has been quickly adopted in many research fields. It has become commonplace to assume that systems that entail entering data in mobile devices, connected through secure networks to central servers are of higher standard than old paper based data collection systems (PDC). Although the notion that EDC performs better than PDC seems reasonable and is widely accepted, few studies have tried to formally evaluate whether it can improve data quality, and none of these to our knowledge, are in the context of population-based longitudinal surveillance.

This thesis project aims to assess the strength of OpenHDS, a system based on EDC, used in the population-based surveillance of vital events via Health and Demographic surveillance systems (HDSS). HDSS are both sources of vital event data and have the potential to support health intervention studies in the areas where they operate. Setting up and running an HDSS is operationally challenging, and a reliable and efficient platform for data collection and management is a basic part of it. There are often major shortcomings in the data collection and management processes in running HDSS, though these have not been extensively documented.

Recent technological advances, specifically the use of mobile devices for data collection, and the adoption of OpenHDS software for data management, which makes use of best practices for data management, appear to have the potential to resolve many of these issues. The INDEPTH Network and others have invested substantial resources in the roll-out and support of OpenHDS, and there is anecdotal evidence that this has resulted in improvements, but there is considerable demand for compelling evidence.

The Swiss Tropical and Public Health Institute (Swiss TPH) has supported some INDEPTH sites to fully migrate to OpenHDS (Ifakara and Rufiji in Tanzania, Nanoro in Burkina Faso, Manhiça in Mozambique and Cross river in Nigeria) and some are in the migration process (7 sites in Ethiopia: Arba Minch, Butajira, Dabat, Gilgel Gibe, Kersa and Kilite Awlaelo). Some other sites are at different stages of evaluating the possibility of adopting OpenHDS (Navrongo in Ghana, Niakhar in Senegal, Iganga/Mayuge in Uganda, Nouna in Burkina Faso, Birbhum in India etc.) and there is a demand from all of them for evidence of the benefits of adopting this system. Demonstration of the appropriate functioning of the OpenHDS is also highly relevant in the light of recently proposed approaches for comprehensive health and epidemiological surveillance

systems. Such systems will need to satisfy requirements in terms of data availability and integration which are considerable higher than in a classical HDSS.
This project assesses the benefits of OpenHDS in terms of and how the advances in data collection and management translate into improved data quality and timeliness. It asks whether the system architecture of the novel data management system can be further exploited to enable data integration approaches for near time quality control and near time response triggers. It also considers what are the main challenges in implementing such technologies in a new or an existing HDSS.
This entails:

- A description of the new system and of a set of conjectured data management best practices. For each of these best practices there is a literature review to assess if there is evidence to support it and if OpenHDS follow these practices, giving evidence of how this can be feasible and implemented in the field in two different real-life scenarios: the setting up of a new HDSS (Rusinga Island, Western Kenya and Majete Malaria Project, southern Malawi); and the migration of existing HDSSs (Ifakara, Tanzania and Nanoro, Burkina Faso) to OpenHDS. (Chapter 1)
- Describing a novel approach for data collection and management in health and demographic surveillance designed to address the shortcomings of the traditional approach (OpenHDS) and documenting the usage of this system the establishment of a new HDSS (Rusinga) in Chapter 2 and 3.
- Evaluating innovative approaches for quality control measures that are made possible by the novel data system architecture (in particular, use of satellite imagery to assess completeness of populations, using Majete HDSS as an example) in Chapter 4.
- Studying the potential benefits of electronic data collection (compared with paper) in terms of quality, timeliness, and costs by comparing both in a contemporaneous comparison of different systems in 8 villages in Nanoro, Burkina Faso and using historical comparisons of data quality (as assessed by iSHARE2) before and after migration to OpenHDS for a range of INDEPTH sites in Chapter 5.

A series of analyses were carried out to demonstrate that the OpenHDS data system for HDSSs can be implemented in both existing or newly established sites in low- and

middle-income countries, and to test the hypothesis that the system is superior to previous approaches with regard of quality and timeliness of data and running costs of the system. This involved describing the novel approach to data collection and management enabled by OpenHDS, evaluating benefits in terms of quality and timeliness of the data using the OpenHDS mobile electronic data system, and the cost of electronic data collection (OpenHDS) vs. paper. It also involved evaluating the impact on the quality of the data of near-time availability and the potential of the OpenHDS system architecture for data integration for next-generation quality control and surveillance-response applications.

This work demonstrates that OpenHDS is a system that manages data in a standard reference format, using rigorous checks on demographic events, adding the flexibility to introduce entire questionnaires, variables that a longitudinal study could require, and that OpenHDS can take over old demographic surveillance systems with this new real-time low-cost paperless technology opportunity to abandon old fashion research systems, that remain in use in developing countries.

Zusammenfassung

Elektronische Datenerfassung (EDC) ist in den letzten Jahren populär geworden und wurde schnell in vielen Forschungsbereichen eingeführt. Es wird generell angenommen, dass Systeme, welche die Dateneingabe durch mobile Geräte ermöglichen, und die durch sichere Netzwerke mit einem zentralen Servern verbunden sind, eine höheren Datenqualität ermöglichen als papier-basierte Systeme zur Datenerhebung (PDC). Obwohl diese Annahme vernünftig erscheint und weitgehend akzeptiert ist, haben nur wenige Studien überprüft, ob EDC die Datenqualität tatsächlich verbessert. Unseres Wissens war keine dieser Studien im Kontext von populations-basierten, longitudinaler Beobachtungsstudien angesiedelt.

Diese Dissertation beabsichtigt eine Bewertung der Stärken von OpenHDS, einem auf EDC basierendem System, das zur Beobachtung der Bevölkerungsentwicklung in Gesundheits- und Demographie Systemen (HDSS) eingesetzt wird. HDSS sind sowohl eine Quelle für Daten über die Bevölkerungsentwicklung, als auch eine Unterstützung für Studien zu Gesundheitsinterventionen in den Gebieten, in denen sie operieren. Das Einrichten und Betreiben von HDSS sind operationell herausfordernd, und eine zuverlässige und effiziente Plattform für das Erfassen und Verwalten von Daten ist eine grundlegender Voraussetzung. Oft gibt es in HDSS gravierende Mängel in den Prozessen des Erfassens und Managens der Daten, jedoch sind diese weitgehend nicht dokumentiert.

Das Schweizerische Tropen- und Public Health Institut (Swiss TPH) unterstützt einige Standorte des INDEPTH -Netzwerks in der vollständigen Migration zu OpenHDS (Ifakara and Rufiji in Tanzania, Nanoro in Burkina Faso, Manhiça in Mozambique und Cross river in Nigeria) und einige sind im Migrationsprozess (sieben Standorte in Ethiopien: Arba Minch, Butajira, Dabat, Gilgel Gibe, Kersa und Kilite Awlaelo). Andere Standorte sind noch in unterschiedlichen Etappen des Evaluationsprozesses hinsichtlich der Einführung von OpenHDS (Navrongo in Ghana, Niakhar in Senegal, Iganga/Mayuge in Uganda, Nouna in Burkina Faso, Birbhum in India etc.), und es besteht die Nachfrage, die Vorteile der Einführung des Systems unter Beweis zu stellen. Die Demonstration der angemessenen Funktionsfähigkeit von OpenHDS ist auch hochgradig relevant angesichts kürzlich vorgeschlagener Ansätze zum Aufbau umfassender Gesundheits- und epidemiologischer Beobachtungssysteme. Solche Systeme müssen Anforderungen hinsichtlich Datenverfügbarkeit und -integration genügen, die erheblich höher angesetzt werden, als in klassischen HDSS.

Dieses Projekt untersucht mögliche Vorteile von OpenHDS in Bezug auf Verbesserungen in der Datenerfassung und –verwaltung, und wie sich diese in verbesserte Datenqualität und Aktualität übersetzen. Es wird gefragt, ob die Systemarchitektur des neuen Data Management Systems weiter genutzt werden kann, um Ansätze der Datenintegration für die zeitnahe Qualitätskontrolle zu nutzen und zeitnahe Reaktionen zu ermöglichen. Es berücksichtigt auch die grössten Herausforderungen bei der Implementierung dieser Technologien in einem neuen oder bestehenden HDSS.

Dieses Projekt beinhaltet das Folgende:

- Eine Beschreibung des neuen Systems und einer Reihe bewährter Verfahren im Datenmanagement. Für jedes dieser Verfahren erfolgt eine Literaturauswertung, um zu bewerten, ob sie unterstützt werden, und ob OpenHDS diesen Verfahren folgt, sofern der Nachweis besteht, wie sie ermöglicht, und implementiert werden können im Rahmen zweier unterschiedlicher Anwendungsszenarien: a) im Aufbau eines neuen HDSS (Rusinga Island, westliches Kenya und Majete Malaria Project, südliches Malawi); und b) in der Migration von existierenden HDSSs (Ifakara, Tanzania und Nanoro, Burkina Faso) zu OpenHDS (Kapitel 1).
- Die Beschreibung eines neuen Ansatzes für die Erhebung und Verwaltung von Daten in der Beobachtung von Gesundheit und Demographie, der darauf ausgerichtet ist, die Mängel in den traditionellen Ansätzen anzusprechen und den Nutzen dieses Systems im Aufbau eines neuen HDSS (Rusinga) in Kapitel 2 und 3 zu dokumentieren.
- Eine Bewertung innovativer Ansätze in zur Qualitätskontrolle, die durch die neue Datensystemarchitektur ermöglicht werden (insbesondere die Nutzung von Satellitenbildern zur Erfassung der Population am Beispiel des Majete HDSS) in Kapitel 4.
- Die Untersuchung der potenziellen Vorteile der elektronischen Datenerfassung (verglichen mit Papier) hinsichtlich Qualität, Verfügbarkeit und Kosten, in einer zeitgleichen Gegenüberstellung der verschiedenen Systeme in acht Ortschaften in Nanoro, Burkina Faso und über einen historischen Vergleich der Qualität der Daten (wie von iSHARE 2 bewertet) vor und nach der Migration in OpenHDS für eine Reihe von INDEPTH Standorte in Kapitel 5.

Eine Reihe von Untersuchungen wurden durchgeführt, um zu testen, ob das OpenHDS Data System für HDSSs in bestehenden oder neu geschaffenen Standorten in Ländern

mit niedrigen und mittleren Einkommen implementiert werden kann. Weiter wurde untersucht, ob das System besser als bisherige Ansätze ist hinsichtlich der Qualität und Aktualität der Daten und die laufenden Kosten des Systems. Dies beinhaltet die Beschreibung des durch OpenHDS ermöglichten neuartigen Ansatzes für die Erfassung und die Verwaltung von Daten, die Bewertung allfälliger Vorteile in Bezug auf die Qualität und die Aktualität der Daten, und die Kosten der elektronischen Datenerfassung (OpenHDS) gegenüber Papier. Es beinhaltet auch die Bewertung der Auswirkungen auf die Qualität der Daten hinsichtlich der zeitnahen Verfügbarkeit und das Potenzial der OpenHDS Systemarchitektur für die Datenintegration mit neuen Systemen zu Gesundheitsüberwachung.

Diese Arbeit zeigt auf, dass OpenHDS seinem Referenz-Datenformat die rigorose Überprüfungen demographischer Ereignisse ermöglicht und darüber hinaus die Flexibilität besitzt, ganze Fragebogen mit Variablen einzuführen, die eine Langzeitstudie benötigen könnte, und dass OpenHDS mit seiner neuen Echtzeit-, preiswerten, und papierlosen Technologie das alte demographische Beobachtungssystem ablösen kann.

Abbreviations

API	Application Programming Interface
CAB	Community Advisory Board
CBR	Crude Birth Rate
CDC	Centers for Disease Control and Prevention
CDR	Crude Death Rate
COMREC	College of Medicine Research Ethics Committee
CRUN	Clinical Research Unit of Nanoro
CRVS	Civil Registration and Vital Statistics
DB	Database
EDC	Electronic Data Collection
FWM	Fieldworker Manager
FWs	Fieldworkers
GPS	Global Positioning System
HDSS	Health and Demographic surveillance systems
HRS	Health Registration System
ICIPE	International Centre of Insect Physiology and Ecology, Nairobi, Kenya
IDMP	INDEPTH Data Management Programme
IHI	Ifakara Health Institute, Dar es Salaam, Tanzania
INDEPTH	International Network for the Demographic Evaluation of Populations and their Health
IRS	Indoor Residual Spraying
IRSS	Institut de Recherche en Sciences de la Sante
KEMRI	Kenyan Medical Research Institute
KML	Keyhole Markup Language
LE	Life Expectancy
LLIN	Long Lasting Insecticidial Nets
LMIC(s)	Low- and middle-income countries
LSHTM	London School of Hygiene & Tropical Medicine
MDA	Mass Drug Administration
M&E	Monitor and Evaluation
MMP	Majete Malaria Project
MoH	Ministry of Health
MVR	Majete Wildlife Reserve
NGO	Non-Governmental Organizations
OBT	Odour Baited traps s
ODK	Open Data Kit
PDA	Personal Digital Assistant
PDC	Paper Data Collection
RBM	Roll Back Malaria
RDBMS	Relational Database Management System
RMP	Rusinga Malaria Project
SOP	Standard Operating Procedure
S&R	Surveillance and Response
Swiss TPH	Swiss Tropical and Public Health Institute
TFR	Total Fertility Rate
UN	United Nations

USM	University of Southern Maine
VGI	Volunteered Geographic Information
WHO	World Health Organization
WURC	Knowledge, Innovation and Technology Group, Wageningen University and Research Centre, Wageningen, The Netherlands
ZAC	Africa Centre for Health and Population Studies

Introduction: Description of the system

1. History of Health and Demographic surveillance systems, data systems, and advances in data collection: using database servers and electronic data capture

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Working paper

Abstract

Background

Health and Demographic surveillance systems (HDSS) can be a powerful source of health information in geographic zones where a civil registration and vital statistics system are not in place. HDSSs also play an essential role in supporting health intervention studies in such areas (1). Setting up and running an HDSS is operationally challenging, and a reliable and efficient platform for data collection and management is a basic part of it. The data collection and management processes of HDSS have not been extensively documented. This article reviews how, historically, HDSSs have tried to address issues arising during the setup and running of these operation. Recent Information Communication Technology (ICT) advances, specifically the use of mobile devices for data collection, and the adoption of data management best practices can potentially resolve many of these issues.

Implementation

We describe the OpenHDS system, for data collection and management of HDSS designed to address the shortcomings of conventional approaches, and document the usage of this system in two different real-life scenarios: the setting up of a new HDSS (Rusinga Island, Western Kenya and Majete Malaria Project, southern Malawi); and the migration of existing HDSSs (Ifakara, Tanzania and Nanoro, Burkina Faso) to OpenHDS.

We start by describing a set of conjectured data management best practices, and for each of these best practices we proceed with a literature review to assess if there is evidence to support it and if OpenHDS follow these practices, giving evidence of how this can be feasible and implemented in the field.

Conclusions

OpenHDS is a system that manages data in a standard reference format, transferrable to different settings, using rigorous checks on data entry and demographic events, adding the flexibility to introduce entire questionnaires and variables that a longitudinal study could require. OpenHDS can substitute for older demographic surveillance systems that do not properly address data management best practices, with a new technology that is real-time and paperless, replacing outdated data systems in use today in low-income countries.

Keywords

Health and demographic surveillance system, Mobile data collection, Data management platform, Best practices for data management.

Background

Vital statistics and the need for health planning

Vital statistics are defined as the statistics on births, deaths, and relationships between two individuals (marriages and divorces). They represent essential information for health policy makers to assess population changes and evaluate the success of intervention programs. Civil registration, a governmental system through which authorities collect vital episodes which take place in their populations, usually represent the most prevalent approach of gathering data on these events.

The UN has considered important vital statistics to set objectives and make social and economic plans in a country and made recommendations on Civil Registration and Vital Statistics (CRVS) since 1953; civil registration is defined as "the continuous, permanent, compulsory and universal recording of the occurrence and characteristics of vital events […] provided through decree or regulation in accordance with the legal requirements of each country."(2) A well-functioning CRVS system is made of three components:

- A component for the notification registration of vital events, which aside from births and deaths can take into account neonatal deaths, marriages, and divorces. Collecting these events creates records that represent personal legal documents used by citizens to demonstrate fact over these events (e.g. age and identity)
- A component should be able to produce verified transcriptions of these documents, as needed by citizens
- A component able to produce and disseminate vital statistics from the data produced by the civil registration system.

The World Health Organization (WHO) has released a tool to provide standard reviews of country practices CRVS practices (3). This WHO Guidance Tool can be a very efficient way to assess the quality of CRVS operations; it identifies areas for intervention within the system to improve the collection process.

In many LMICs in Africa, Asia and Oceania the vital registration and statistics systems have serious deficiencies.(4) . Among other consequences, this frequently leads to a very poor quality of population-based health statistics, despite the urgent need for reliable epidemiological and demographic data to inform policy (5). Health Demographic Surveillance Systems (HDSS) have been created to address this gap.

History of Health Demographic Surveillance Systems (HDSS)

A Demographic Surveillance Systems (DSS) is a community-based information system that collects longitudinal data on core demographic events (births, deaths, and migration) together with key health indicators at regular intervals within a defined geographical area (Figure 1.1). DSSs have been put in place either to overcome CRVS deficiencies, or as a basis to conduct clinical trials, or as more general purpose platforms for population-based research (e.g. district health service delivery research, research related to epidemics) (6,7) . They are mostly run by non-government organizations or sometimes institutes associated with the Ministry of Health (MoH).

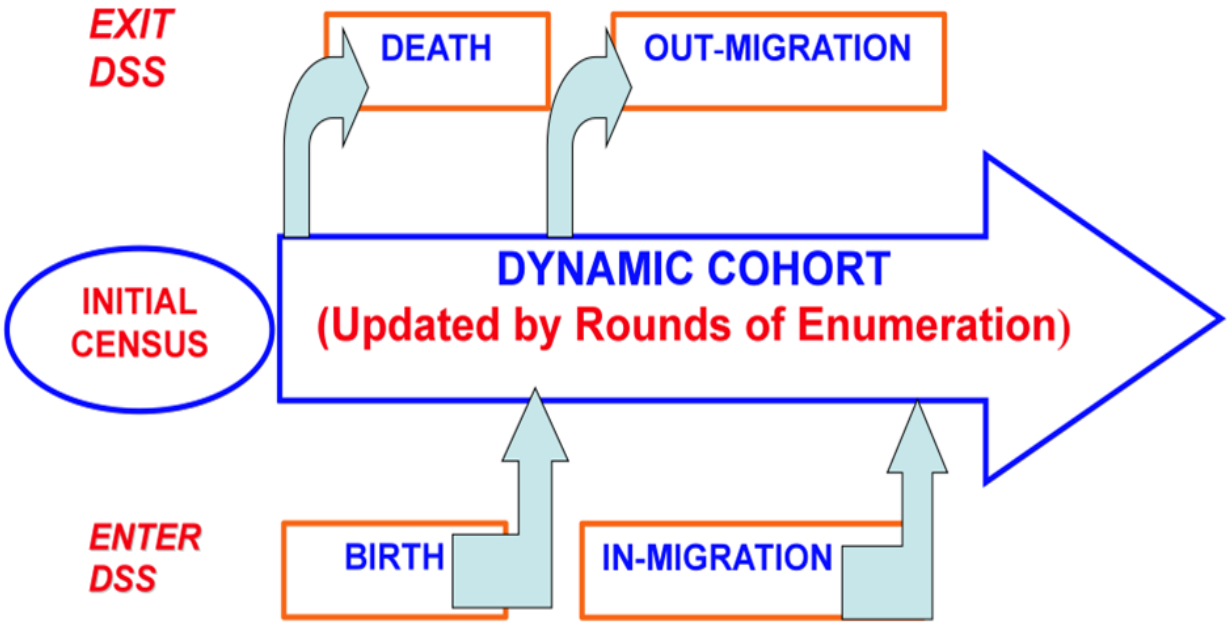


Figure 1.1: Schematic of an HDSS (source INDEPTH Network).

The DSS of Matlab (8) in Bangladesh, which began in 1963 was the first example of a structured data system gathering demographic and health data on target population samples. As part of the research program of the International Centre for Diarrheal Disease Research, it is acknowledged as the biggest and longest-running DSS in the world, it has made major contributions to global health research and development(9). Evaluation of the potential of leveraging the experience of Matlab for research platforms in Africa began in the late 1980s (9). This was the starting point of a project that led to the International Network for the Demographic Evaluation of Populations and their Health (INDEPTH).

A series of international meetings in the 1990s developed the concept of a network of health research centres in low- and middle-income countries (LMICs) running DSSs1. These led to the inauguration of INDEPTH at the 9-12 November 1998 meeting in Dar es Salaam, Tanzania. Initially, it linked a few existing DSSs, with the Niakhar DSS in Senegal being the oldest one in Africa (1962). INDEPTH is envisaged as a medium-term effort to obtain CRVS information while government systems are developed, since this is a problem with a very complex and difficult solution (not a short term time-window). Since then there has been a steady growth in the number of sites in INDEPTH sites (Figure 1.2) (10).

Figure 1.2: Countries and HDSSs members of the INDEPTH Network.

Since most INDEPTH sites work in the field of public health and evaluation of health interventions, the letter "H" (for Health) was added to the acronym DSS. The rational to setup a HDSS nowadays went also beyond the necessity to compensate the lack of CRVS and new HDSSs has been implemented to strengthen the population based research on specific area of interest to provide evidence-base for cost evaluation, policy making and targeting of intervention programs, nevertheless improving the accuracy, efficiency and effectiveness of health and health interventions(11). More recently the terms of reference for these sites has further expanded with the concept of

[1]Meetings were hosted in University of the Witwatersrand in Johannesburg, South Africa, the London School of Hygiene & Tropical Medicine in the UK, Heidelberg University in Germany; Rockefeller Foundation, Bellagio, Italy, and then in Navrongo, Ghana,. Dar es Salaam, Tanzania.

Comprehensive Health and Epidemiological Surveillance System (CHESS) (12). CHESS plan to be the container of demographic, epidemiological, mortality, morbidity, clinical, laboratory, household, environmental, health systems, and other contextual data, all linked by individual using unique electronic identifiers. At the same time they should provide timely morbidity and mortality data of high quality. In practice this requires a HDSS+ (an extended HDSS) that provides integration across population and health facility data.

Recent years have also seen increasing emphasis from funders of HDSS sites on efficient and timely sharing of data, or at least of data summaries, with potential users. Linked to this there is a growing need for comparison between sites. This has led to the INDEPTH Data Management Programme (IDMP, formerly known as iSHARE) (13,14). INDEPTH administers the INDEPTH Data Repository with the goal of sharing HDSS data globally.

HDSS operations

HDSSs depend strongly on continual community-based vigilance for vital event registration and migration in and out from the area of surveillance, with high coverage from a well-defined population base to gather accurate results about rates and trends. As a consequence, setting up and running a HDSS poses an operational challenge, and a solid and adequate platform for data collection and management is a fundamental requirement.

Setting up an HDSS entails first defining the target study area. These usually correspond to an administrative unit, with a total populations between 50,000 and 100,000 people (15). A census is then carried out to capture basic demographic information on all individuals and the locations/households where they reside.

The initial census attaches unique identifiers to all the individuals and locations/households (referred to as enrolled entities) that are included, in a way that makes it feasible to expand it in the future in case of new entities entering the study area. Since the INDEPTH Network was established, the technology and methods to acquire and use geographical data have progressed substantially, and geo-localization of physical entities is a common feature. INDEPTH has made some attempts to provide standard definitions for identifiers as much this can be done by supplying a resource kit for HDSS design (5,10).

Once the HDSS is set up, there is a need to follow-up the population through regular update visits to all the physical entities in the defined area. Multiple visits (also called observations) are carried out each year to each physical location where individuals reside to update the defined core parameters, which including births, and deaths, pregnancies and pregnancy outcomes. Changes of residence, including movements within the area, immigration from outside and departures from the monitored area, are also recorded. The central database, initially populated only with the baseline census data, is thus updated regularly with demographic events recorded as they happen. The date of visits to each household should also be recorded as this is required for computation of denominators for various demographic rates.

The visit updates constitute the majority of the continuing activity of running an HDSS, and careful planning of the number of field staff needed for acceptable data quality is required, taking into account the number of update rounds each per year needed to avoid missing events (especially pregnancy outcomes and neonatal deaths)(16).

Development of data systems within INDEPTH

The maintenance of adequate data quality for HDSSs is challenging, and the institutional development of INDEPTH was accompanied by developments in data systems, as the scale of the challenges became apparent, and as technologies became available to address them. The Matlab software system, called the Sample Registration System (SRS) (17) was too site specific to be adopted in other locations (no core data was defined and data collected were aligned with the needs of the specific objective of calculating cause-specific mortality profiles in the area). This system illustrated the challenge for software development of designing a transferable software data system for such applications.

Maintaining an up to date denominator population by tracking all these events is a very onerous duty for most HDSSs, and different methods are employed. Typically a relational database management system (RDBMS) with some schema to capture the longitudinal characteristic of the HDSS data and to manage the potential high number of data points accumulated during long time periods is used. The RDBMS must be able to record and track relationships, social groups with their members, residences of individuals in various locations, “status” of an individual in time, and all of the events required to delineate the population dynamics.

A conceptual data model that addressed some of these challenges was agreed at a meeting in London in 1997 and commonly referred to as the INDEPTH Reference Data Model (18). It uses the concepts of events and episodes taken from the 1996 Demographic Evaluation of Health Programs (19) as the basis of field procedures and corresponding software implementations for recording longitudinal data. Events correspond to the entry or exit of an individual from a location or state and the term episodes is used to refer to the pair formed by a start event and an end event in the same individual and location (or state). The episode thus defines how the individuals enter (birth, in-migration episode) or exit the study area (death. out-migration episode) and how individuals are related between themselves (e.g marriage relationship episode) and in the "society" (membership episode) (20) (Figure 1.3).

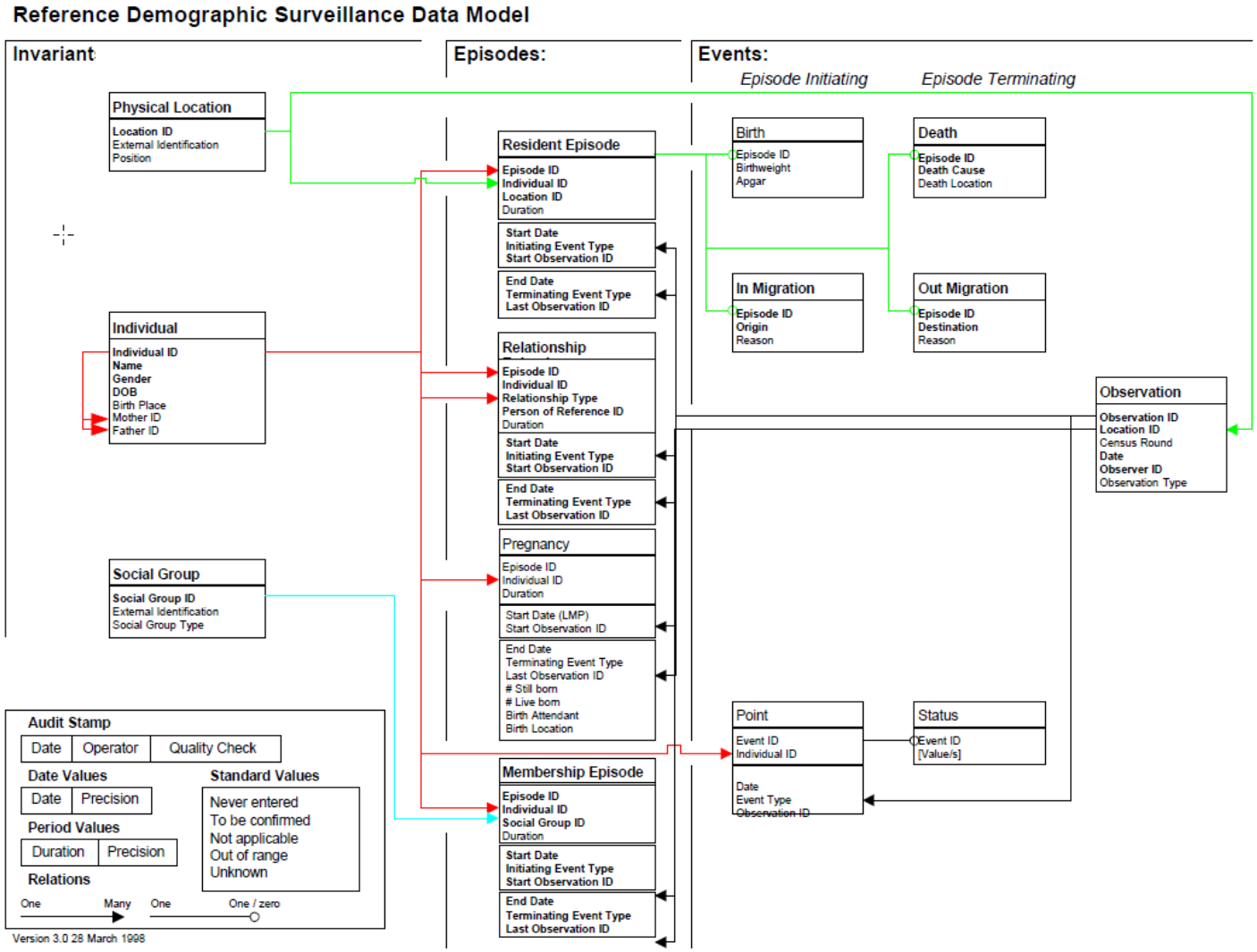


Figure 1.3: Reference Demographic Surveillance Data Model. (source: Ref 8)

The database is augmented with application logic to support appropriate field and data entry processes, along with business logic to enforce data validity constraints.

Navrongo in Ghana, one of the longest standing INDEPTH sites which was set up in 1992(21), pioneered the adoption of HRS(22), which was a DOS-based data system written in an early version of the RDBMS FoxPro. The first version of HRS did not have a concept of residency (the fact of an individual staying in a location) or membership (the role of an individual in a household and his relationship with the head of the household). Residency was inferred from census, births, deaths, and migrations. These limitations became evident rather quickly, and the second version of HRS (HRS 2), written in Microsoft Foxpro v2.5(22) used the INDEPTH Reference Data Model, expanding what could be modeled (e.g. non-resident individuals) by including the concepts of residencies and memberships, and making validation/consistency logic easier.

A number of other INDEPTH members adopted HRS2, which remained the standard software for tracking events and episodes for the following two decades. Several major challenges remained. One was in achieving high quality and timely availability of data. Linking vital episodes to individuals is only possible if these are identifiable. It is challenging to correctly associate events if individual records are not available to the field enumerator at the time of a visit to a household, and correctly linked to the visited location and household. Until recently, HDSS systems relied on paper-based data collection with subsequent data entry into an electronic database. This often lead to long delays between the time of collection and the availability of data in a form that is accessible to HDSS supervisory staff, and was vulnerable to transcription errors, especially since most HDSS did not implement double data entry. Many sites used stand-alone personal computers for data processing, introducing challenges in synchronization of data entered on different machines. All this made timely identification and correction of inconsistencies and other errors extremely challenging.

Hardware and software able to address these challenges were developed and evolved. Client-server based RDBMS were an important technological advance which was implemented in some sites, to improve the efficiency of manual data processing and to reduce error rates. With the availability of low-cost mobile communication and computing devices (e.g. smart phones and tablet computers), there are now a number of

electronic data collection (EDC) technologies that allow direct entry of data at the point of collection, and aggregation of these data in a central location with little delay. EDC found its way into HDSS routines in some member sites of INDEPTH, but these technologies could not easily be interfaced with HRS2.

In addition to the need to interface with state-of-the-art EDC technologies many sites now face other issues linked to the continuing use of obsolescent data management systems. Not only has updating of HRS and other data management applications been limited, but many of these were built on technologies that are now heavily outdated, and in some cases no longer supported by the manufacturers of proprietary RDBMS(23) for instance, Foxpro is no longer supported by Microsoft.

Many sites have legacy datasets that are essentially undocumented and not well integrated with the current core HDSS dataset (24). The ancillary data required as part of CHESS, are also likely be captured and stored using systems that use different technologies from that of the core HDSS, and which themselves differ between HDSS sites, each of which has its own specific foci of activity and objectives, and which have made different choices in how to address the limitations of their original RDBMS. Specialized database programmers and data managers are needed to manage export of data from these diverse systems into sharing platforms like IDMP. These require common terminology, variable names, and core data, which in turn implies clear understanding of the meta-data (information describing the data) and of the required changes in data infrastructure (16).

There is thus a critical need to migrate longstanding HDSS operations and legacy databases to systems that use up-to-date technologies but require less specialist skills at site level. While significant effort and technical skills are needed to carry out such migrations without loss of information or disruption of operations, there is presumably a clear gain in efficiency once sites use EDC linked directly to web-based RDBMS.

The requirements of a new data management system

HDSSs sites and other longitudinal population and health related projects produce large amount of records needed to analyze, define, and study the chain of events and determinants that are linked to individuals and their populations (25). The older an HDSS is, the more temporal data has to be stored and analyzed. This large amount of records needs a standard way to be collected, stored and maintained. If these records are not properly managed, in the long run this will lead to poor or corrupted data, that is

more difficult to analyze or to share with the consequence of HDSS's studies connected to the data losing validity (26).

A standard temporal data model to manage these temporal events at the adequate level of detail needed (27–30) and a standard relational database management system (31–33) are needed, as augmented from many efforts done in the last decades.

Normalization is a key issue on big databases. It is defined as the process to reduce or totally eliminate redundant information on a database: very few data variables should be in more than one table (34). Multiple recording of the same information leads to inconsistency, is more complicated to maintain and should be avoided (26). One event or property once recorded on a unique table should be referenced on other tables through a link (foreign key) to it and should not be re-recorded.

Recognizing that a standard and transferrable data model and a standard database schema are key requirements for correctly managing an HDSS, especially in the long run, then the next requirement is centralized data storage and management (35,36) if the validity of the data is to be maintained (32,37–40).

Because HDSSs, as explained before, work with temporal data, and from the data collected depend how a possible intervention campaign should occur for example, or how a study designed on top of the data should be done, the availability of the data and real time checks on it are really important to guarantee the success and the validity of a study or campaign.

Near-time data collection has been proved in many scientific studies to make an important difference to achievement of the goals, making hypothesis testing more robust and the results more valid (41–45). Data securely transferred (46) to the server almost at the same time as data collection, should then be available through an open interface and timely reporting to data managers whose role now is to provide their input for quality assurance as soon as possible.

An integrated data management system based on a set of data management best practices was thus needed to substantially improve quality, integrity and timely availability of data in longitudinal epidemiological research, and that such a system at the same time has the potential to reduce the high running costs which often threaten the sustainability of long-running HDSSs. Such a system must be based on a standard compliant data model and database schema, that provide centralized data storage and

management through a client-server database management system (e.g. relational DBMS) and a Web-based data management application. This allows near time data centralization with collected digital data transferred securely through the network and near time quality control through open interfaces and automatized, extensible reporting engine (allowing easy export of data for analysis).

The OpenHDS Data System

OpenHDS is an HDSS data system that provides data entry, quality control, and reporting to support demographic and health surveillance designed according to these principles (47,48) . OpenHDS was originally developed by University of Calabar, Nigeria; University of Southern Maine, US; and Ifakara Health Institute, Tanzania; and first deployed in Akpabuyo HDSS, Cross River. The team from Swiss Tropical and Public health Institute (Swiss TPH) have led the development of OpenHDS since late 2013, in collaboration with the existing groups. It consists of two components: web and mobile. OpenHDS mobile is integrated with the Open Data Kit (ODK) system. ODK is an open-source suite of tools that helps organizations to author, field, and manage mobile data collection solutions, and by now established as a quasi-standard in the field (Figure 1.4). (49)

Following the standards of the INDEPTH reference data model (50), OpenHDS , uses web-services that check the integrity of the data transferred from the field to the central relational database (Figure 1.5), and provides reports on the data transfer to the data managers. Due to its reliance on open standards and open source technology stack, the system architecture lends itself to the extension with plugins that can give access to reporting in several formats (including reports which can be layered onto satellite images), and the easy integration with additional data sources.

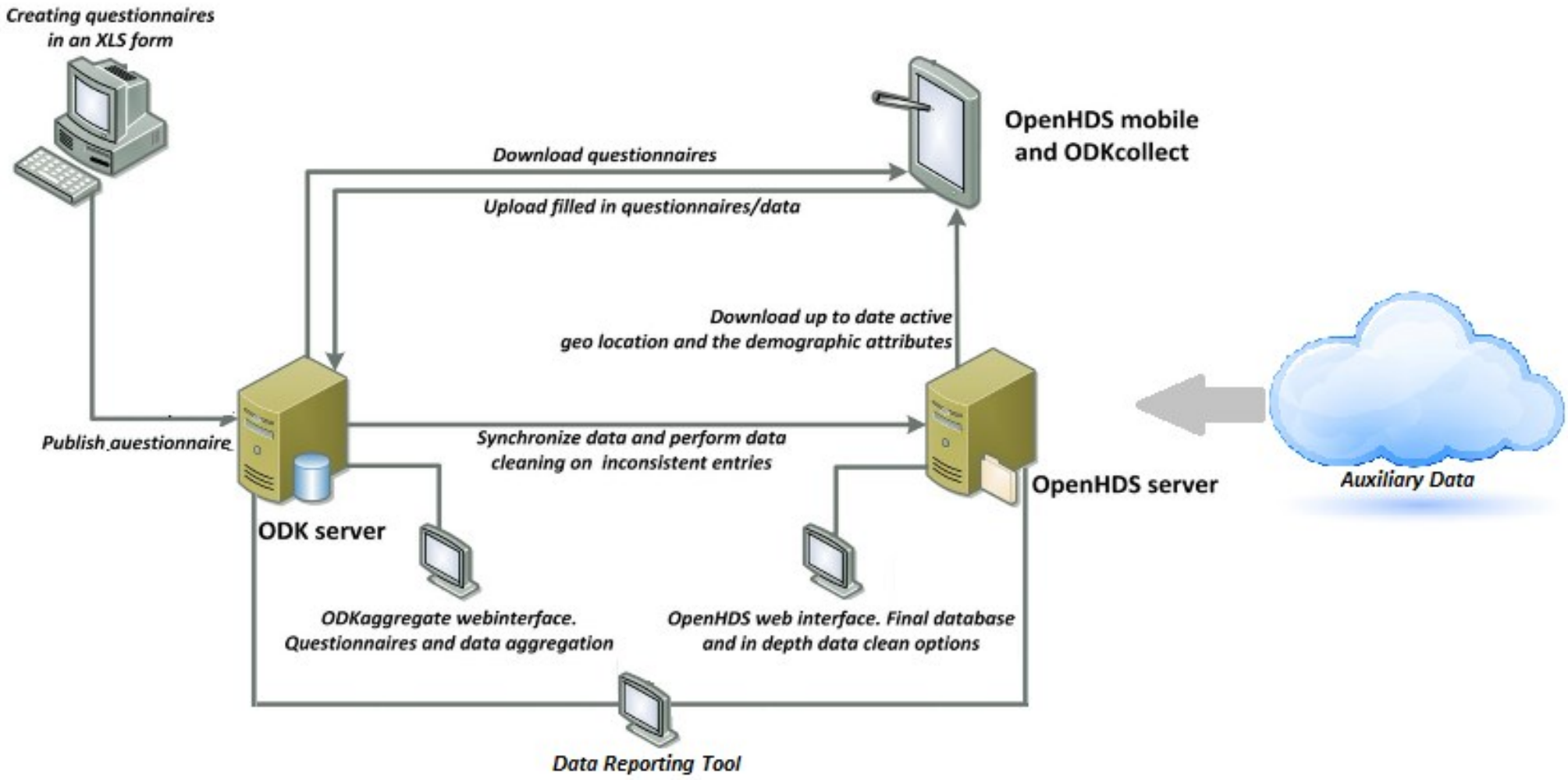


Figure 1.4:. OpenHDS and ODK platforms structure and interaction.

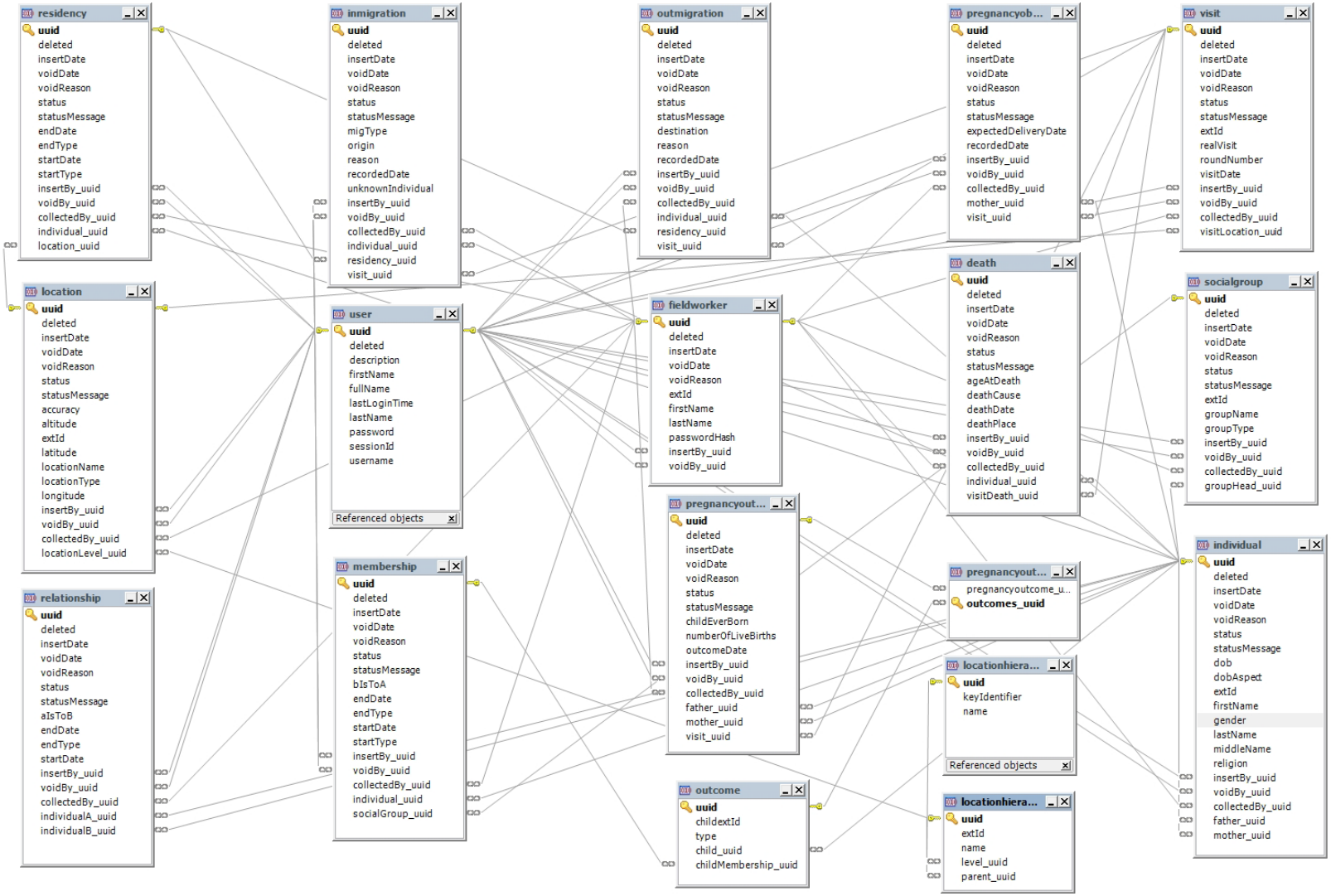


Figure 1.5: OpenHDS database schema.

We want to verify that this offers a number of potential advantages and provide examples of evidence of this: it would reduce the workload of the data management team, no IDs need to be typed in (removing one of the biggest causes of errors on data collection in HDSS systems); and it can provide guidance for the project logistics. The web interface allows viewing of collected data and correction of errors.

There are a number of obvious potential improvements of this novel data system over the alternatives described above (Table 1.1), and there is some anecdotal evidence that these benefits are real. However, up to now there is no proper documentation of measurable advantages. We report a number of studies to gather such evidence, along with proof of concepts that the implementation of OpenHDS is feasible in the context of typical HDSS centres.

	HRS1	**HRS2**	**OpenHDS**
Database	FoxPro (support ended 2015)	FoxPro (support ended 2015)	MySQL, PostGreSQL, MS SQL etc…
RDBMS	lacks transactional processing	lacks transactional processing	Yes
Data Collection	Paper	Paper	Electronic
Data accessibility/Data management	Local Network through local Application	Local Network through local Application	Through internet browser, via secure SSL protected URL.
Data Clerk	Needed	Needed	No
Reference data model adopted	No residency and membership	Yes	Yes

Enabling factors

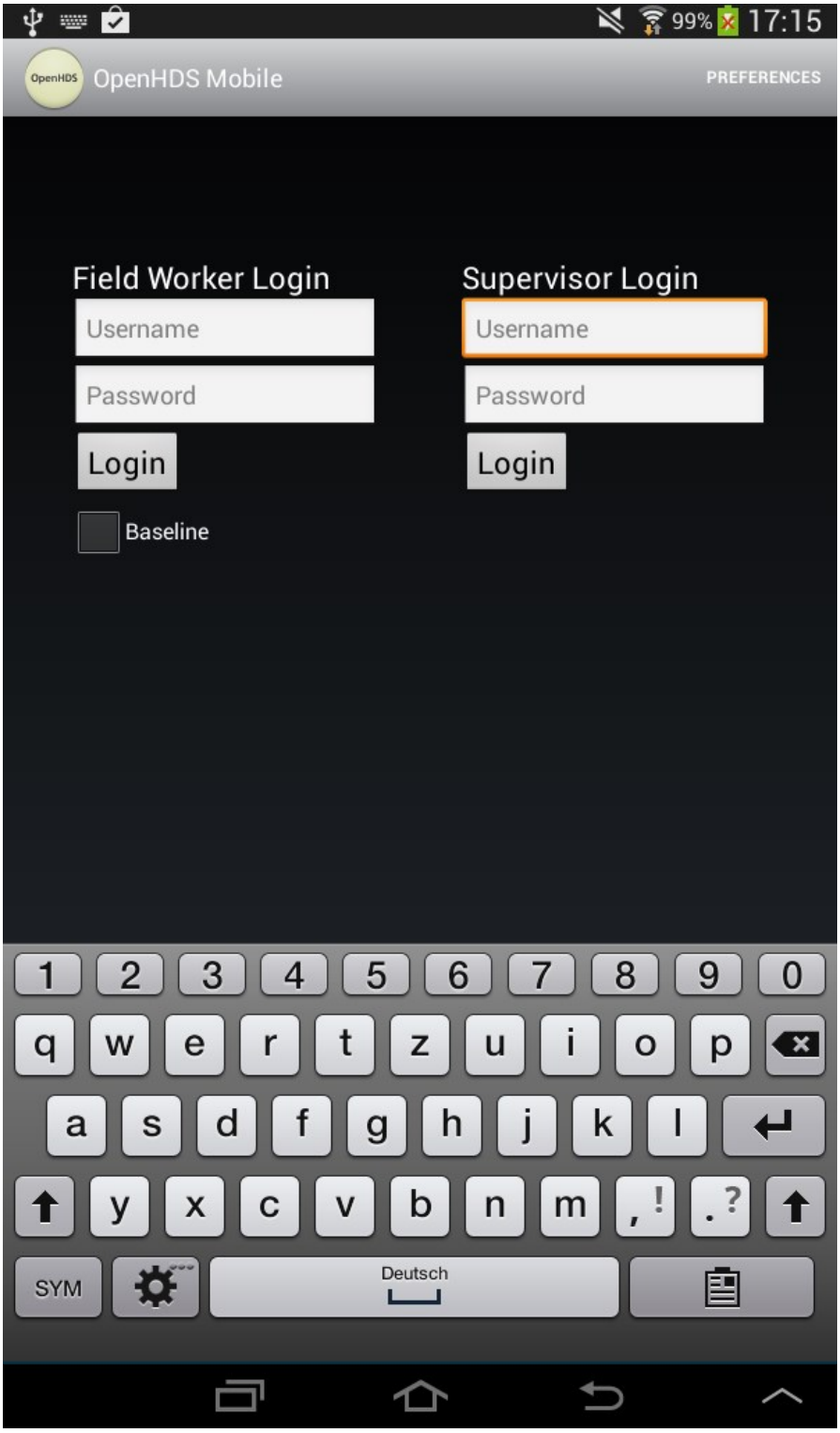
	HRS1	**HRS2**	**OpenHDS**
Electronic Data capturing (Constraints and Skip logic)	No	No	Yes
Real time data availability	No	No	Yes
Central database	Only accessible via intranet	Only accessible via intranet	Yes
Real time reporting	No	No	Yes
Database availability on the device	Paper Household registration book	Paper Household registration book	SqlLite database

Table 1.1: Advantages and disadvantages using different technologies

Field data collection with OpenHDS

Each HDSS has a defined location hierarchy in the area under surveillance. The lowest level of this location hierarchy is the one leading the ID generation for the HDSS entities and is important for the identification of the location where the individuals live.

At village level the fieldworker collects location information where individuals were living. This task is performed through OpenHDS mobile integrated with the ODK collect application. (Figure 1.6). The fieldworker selects the location if it already exists or he has to create the location by pressing the ‘create location’ button. Once the information about the location is recorded the visit form needs to be filled.



.**Figure 1.6:** OpenHDS mobile application snapshot of Login screen.

The visit is the basis of the demographic statistics for the various rounds. It records that the household was visited in a specific round, on which date, and except for the census round (where the visit date is the only useful information) it records whether there is any update on the household or if the house was empty and need to be re-visited. After the visit form is completed then all the relevant events for the individual's resident in the location visited are recorded.

All the data collected are, under field supervisor control, sent to a central database server.

Use cases: evidence from the field

The OpenHDS system can be implemented in a novel HDSS area, but even an existing HDSS can be migrated to the new paperless data system to manage demographic surveillance. We provide example of evidence for it.

We set up the OpenHDS system in Rusinga island (Figure 1.7), Nyanza (Western Kenya), in 2014, during the Solarmal Project (51) in collaboration with the ICIPE research center in Mbita, and the University of Wageningen in the Netherlands. The main aim of the Rusinga HDSS was to monitor the effectiveness of the vector control intervention deployed as part of the Solarmal project with the intent to eliminate malaria from the island through mass trapping of mosquitoes using odour-baited traps. The OpenHDS demographic database provided a sampling frame for the study, and allows data collection for the periodic surveys of malaria incidence and parasitology through the tablet devices. Moreover, the data provides guidance for the planning and logistics of the intervention roll-out, giving a visual help to the project manager for the daily field team planning.

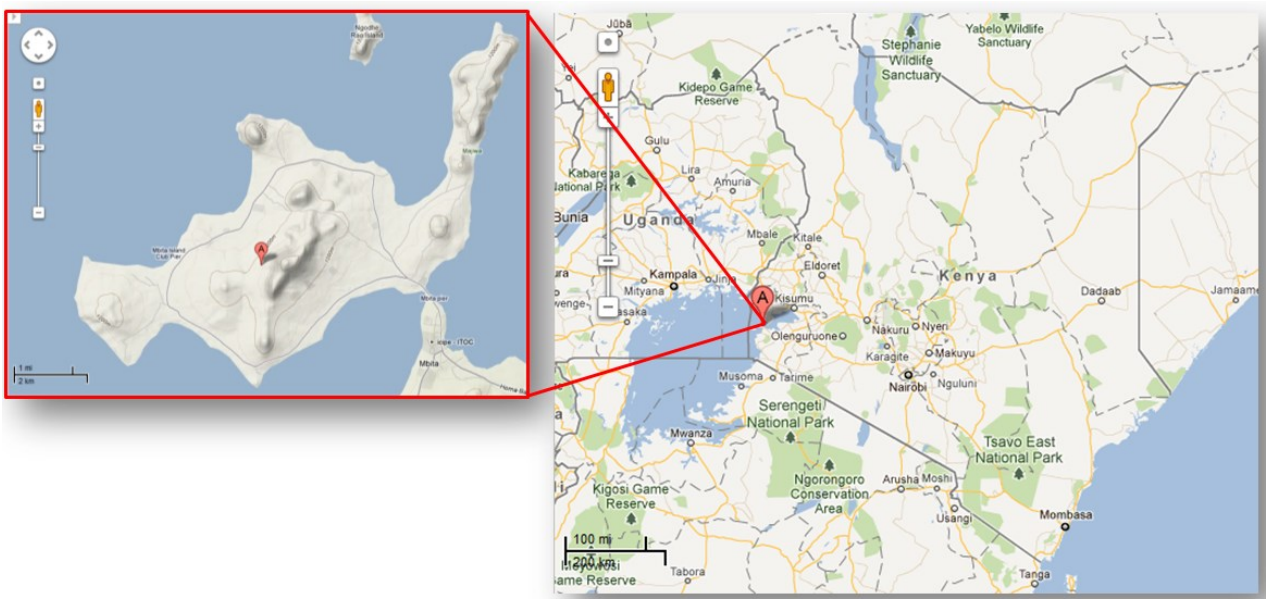


Figure 1.7: Zoom on Rusinga Island in Lake Victoria, Kenya

The HDSS team in Rusinga (47) consists of 10 Fieldworkers, 1 Coordinator, 1 Data manager and a software expert provides offsite advice. The system has been running since 2012, and covers 24.972 individuals in three-yearly update rounds.

The Majete Malaria Project Health and Demographic Surveillance System, in Malawi is another example of site where an HDSS was set up from scratch to support a project with the aim of studying the reduction of malaria using an integrated control approach by rolling out insecticide treated nets and improved case management supplemented with house improvement and larval source management (52). Ifakara Health Institute (IHI) in Tanzania was the first centre to migrate its HDSS sites from the previous Household Registration System (HRS/HRS2) to OpenHDS. Legacy data sets from three long-running HDSSs (Ifakara rural, est. 1996, Ifakara urban, 2007, Rufiji, 1998) were migrated to the new database (53,54) (Figure 1.8). Update rounds started in 2013 (Ifakara) and 2014 (Rufiji).

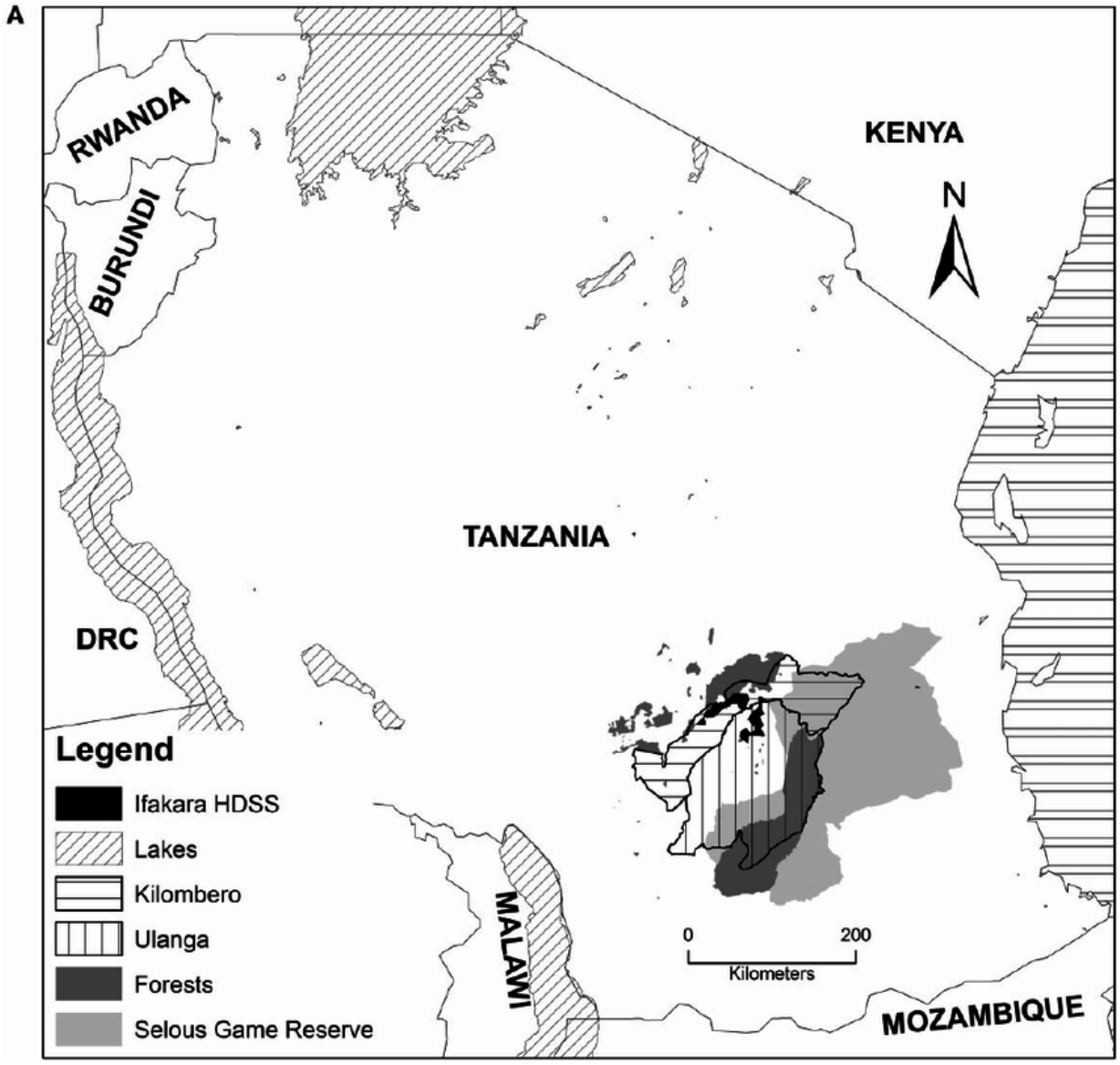


Figure 1.8: Location of Ifakara HDSS in Kilombero and Ulanga districts in Tanzania.

In order to ingest legacy data collected in the Rufiji and Ifakara HDSSs into the new platform, data had to be extracted from the existing HRS (Household Registration System) and HRS2 (second generation HRS) data-systems, and transformed to match the OpenHDS data base (22,55–57). This required the conversion from the FoxPro to MySQL format; the reshaping and renaming of database tables to match the OpenHDS database schema; and the cleaning of data to adhere to the more stringent requirements for internal consistency of the OpenHDS database vs HRS and HRS2.

For the mapping of the data onto the OpenHDS and ingestion into the OpenHDS database, a web-service interface similar to the one used to aggregate data collected on tablets during routing field operations was developed. This allowed mapping of data to the new schema (i.e. rename database table fields, or normalize data where this was appropriate), and flagging invalid records while creating meaningful descriptions of the data issues. This last step is a prerequisite for data cleaning, a process that was carried out in close collaboration with the data managers and field supervisors to resolve as many of the inconsistencies of the legacy data as possible Criteria for consistency of the core population data included not only referential integrity, but also temporal integrity and other checks as implemented by the iShare2 framework, developed by the INDEPTH Data Management Project (14).

A series of training and field testing workshops were held both Ifakara and Rufiji, and attended by members of the IHI data central team; data managers; IHI IT staff; field supervisors and enumerators. These workshops also provided an opportunity to refine certain software features and data-management tools based on the feedback from attendants.

Supervision, continued advice, and further refinements of the data collection and management processed happened over the complete course of the technical assistance by means of email, instant messaging, and analysis of database and system logs by the Swiss TPH team.

After IHI another INDEPTH site the Nanoro HDSS run by the Clinical Research Unit of Nanoro (CRUN) - Institut de Recherche en Sciences de la Sante (IRSS), Nanoro in Burkina Faso (58) decided to migrate their HRS2 system to the OpenHDS system. This second site demonstrated the easy transferability and adaptability of the OpenHDS system, able to adapt to the West Africa francophone setting after it was proved its functionality in the East African one.

Conclusion

OpenHDS is a system that manages data in a standard reference format, transferrable to different settings. It is developed to work on a any relational database management system (Mysql, PostgreSQL, MS SQL Server etc.) , designed to keep track of all temporal sequence of events that characterize a demographic surveillance system. OpenHDS enforces rigorous checks on demographic events, adding the flexibility to introduce entire questionnaires, variables that a longitudinal study could require. OpenHDS can replace conventional demographic surveillance data systems, that don't address properly modern data management best practices, this new technology is a real-time paperless opportunity to take advantage of ICT advances and innovate research systems today in use in low-income countries.

In the idea of INDEPTH OpenHDS is the starting point for the CHESS, the new generation of population based surveillance conceptualised by INDEPTH, able to provide timely morbidity and mortality data of high quality. CHESS is a HDSS+ that provide integration across population and health facility data.

Competing interests

The authors declare that they have no competing interests.

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Feasibility of running an HDSS using computer tablets and OpenHDS software

2. Innovative Tools and OpenHDS for Health and Demographic Surveillance on Rusinga Island, Kenya

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Abstract

Background: Health in low and middle income countries is on one hand characterized by a high burden associated with preventable communicable diseases and on the other hand considered to be under-documented due to improper basic health and demographic record-keeping. Health and Demographic Surveillance Systems have provided researchers, policy makers and governments with data about local population dynamics and health related information. In order for an HDSS to deliver high quality data, effective organization of data collection and management are vital. HDSSs impose a challenging logistical process typically characterized by door to door visits, poor navigational guidance, conducting interviews recorded on paper, error prone data entry, an extensive staff and marginal data quality management possibilities.

Methods: A large trial investigating the effect of odour-baited mosquito traps on malaria vector populations and malaria transmission on Rusinga Island, western Kenya, has deployed an HDSS. By means of computer tablets in combination with Open Data Kit and OpenHDS data collection and management software experiences with time efficiency, cost effectiveness and high data quality are illustrated. Step by step, a complete organization of the data management infrastructure is described, ranging from routine work in the field to the organization of the centralized data server.

Results and discussion: Adopting innovative technological advancements has enabled the collection of demographic and malaria data quickly and effectively, with minimal margin for errors. Real-time data quality controls integrated within the system can lead to financial savings and a time efficient work flow. Conclusion: This novel method of HDSS implementation demonstrates the feasibility of integrating electronic tools in large-scale health interventions.

Key words: Health and Demographic Surveillance System; Mobile data collection; Data management platform; Malaria; Kenya

Background

Health and demographic surveillance systems [HDSS] are used to provide a framework for prospective collection of demographic and public health data within a community. Such systems, originally called population laboratories, have been in operation since the late 20th century, and constitute the basis of population-based research in areas where national or local authorities lack a proper registration system to monitor the most important demographic events [1].

In order for population and health researchers to acquire longitudinal data on communities, systematically constructed systems have undergone several developments [2]; where originally the focus remained on surveying demographic data (demographic surveillance systems, DSS), principally due to efforts of the INDEPTH network (International Network of field sites with continuous Demographic Evaluation of Populations and Their Health in developing countries), health indicators became a routine part of science-driven surveillance systems, retitling the concept as HDSS (health and demographic surveillance system) [3]. Despite these developments, public health systems in developing countries often lack adequate infrastructure to monitor demographic and health information; rural areas in particular experience challenges with the collection of reliable health-related data. The World Health Organization [WHO] states that vast rural areas in Sub-Saharan Africa are a reservoir for a variety of predominantly preventable communicable diseases such as HIV/AIDS, tuberculosis and malaria (WHO; World Health Statistics 2014) .The absence of well-operating national or local demographic and health surveillance systems hampers evidence-based research into these diseases. Over the past decades there are numerous examples of scientific institutions deploying community-based HDSSs in order to provide policy makers and governments with recommendations on health planning and intervention methods. A classic example is the Garki project in Nigeria where, during the 1970s, field experiments were conducted to understand the effects of Indoor Residual Spraying [IRS] and Mass Drug Administration (MDA) on malaria and entomological outcomes [4]. Another, more recent, malaria control study which used HDSS to capture prospective data was the Asembo Bay Cohort Project, which ultimately showed a large protective effect of Long Lasting Insecticidial Nets [LLIN] against malaria infection.

Nowadays, community-based HDSSs are established at an increasing number of sites to investigate a range of different health indicators and diseases. The main goal of the INDEPTH network is to harmonize the data of HDSSs from different sites in

developing countries to achieve a valid comparison of information and accordingly get more insight into health related trends [5].

There are currently 43 INDEPTH associated centres that run one or more HDSSs for scientific purposes [6].

At all these HDSS sites, the field and data management operations pose logistical challenges.

Interviews in most sites are essentially paper based which makes conducting questionnaires time consuming and error prone. Visiting households and individuals can be time consuming, as keeping track of where fieldworkers navigate and which community members have been visited can only be done manually. Likewise, transferring data from paper into a digital form is a lengthy process with a lot of room for error. Not only the content of data can be entered incorrectly, but assigning new data to the right entity or ID is an error-prone process with small typos leading to unrecognizable and ultimately squandered data [7-10]. Finally, accumulating and managing data relies heavily on obsolete database software with limited data quality assurance structures.

The past decade has borne witness to major developments in mobile computer technology as well as software applications. Advanced computer tablets and improved data collection and management software have become accessible and affordable to the wider public. In high and middle income countries there are numerous examples of ways to utilize the available technologies to improve health [11, 12]. Although there have been several pilot studies which experimented with a telephone-based technology to collect health and demographic data, in the lower income countries these technologies remain mainly underused because of logistical and organizational constraints [13, 14].

In some low- income countries, mobile computer technology and advanced data collection and management software has been tested. In Akpabuyo Nigeria, the use of computer tablets with practical collection software and a comprehensive data management system has been tested [15].

The study showed that it is possible to save a great deal of time compared to the paper-based and analogue data collection and management. Not only time could be saved, costs could also be decreased considerably and data quality increased. Another study in Malawi investigated how the use of computer technology and software could best be organized to create a feasible system of health data collection and management [16]. A

governmental initiative in Kenya in 2006 marked a first step towards a digitalized health management [17].

In 2012 an HDSS was initiated on Rusinga Island, western Kenya, to facilitate a large malaria control trial, the SolarMal project [18].This paper describes the computer-based HDSS developed for this project. It is shown that community-based health research served by HDSSs can be of higher quality, more cost-effective and more time efficient than currently deployed surveillance systems.

Methods

Study location and population

Rusinga Island with approximately 25,000 inhabitants, is located in Lake Victoria, western Kenya (0°21′ S and 0°26 south, 34°13′ and 34°07’ east). The island is administratively part of Homa Bay county in western Kenya (Figure 2.1) and is connected to the mainland with a causeway. The land surface area of Rusinga Island is approximately 44 km2 with an elevation between 1100 m and 1300 m above sea level. Average daily temperatures lie between 16 and 34 degrees Celsius with temperatures higher during the dry seasons which occur between June-October and late December-February. The SolarMal project, including HDSS activities, operates through the International Centre of Insect Physiology and Ecology [icipe] at the village of Mbita Point just across the causeway, on the mainland. The population of Rusinga Island belongs to the Luo ethnic community and, besides the national language of Swahili, DhoLuo is primarily spoken. Fishing and farming are the principal occupations. There are several health facilities in the area; one public health centre, three government-run dispensaries and three private clinics. A district hospital is found at Mbita Point.

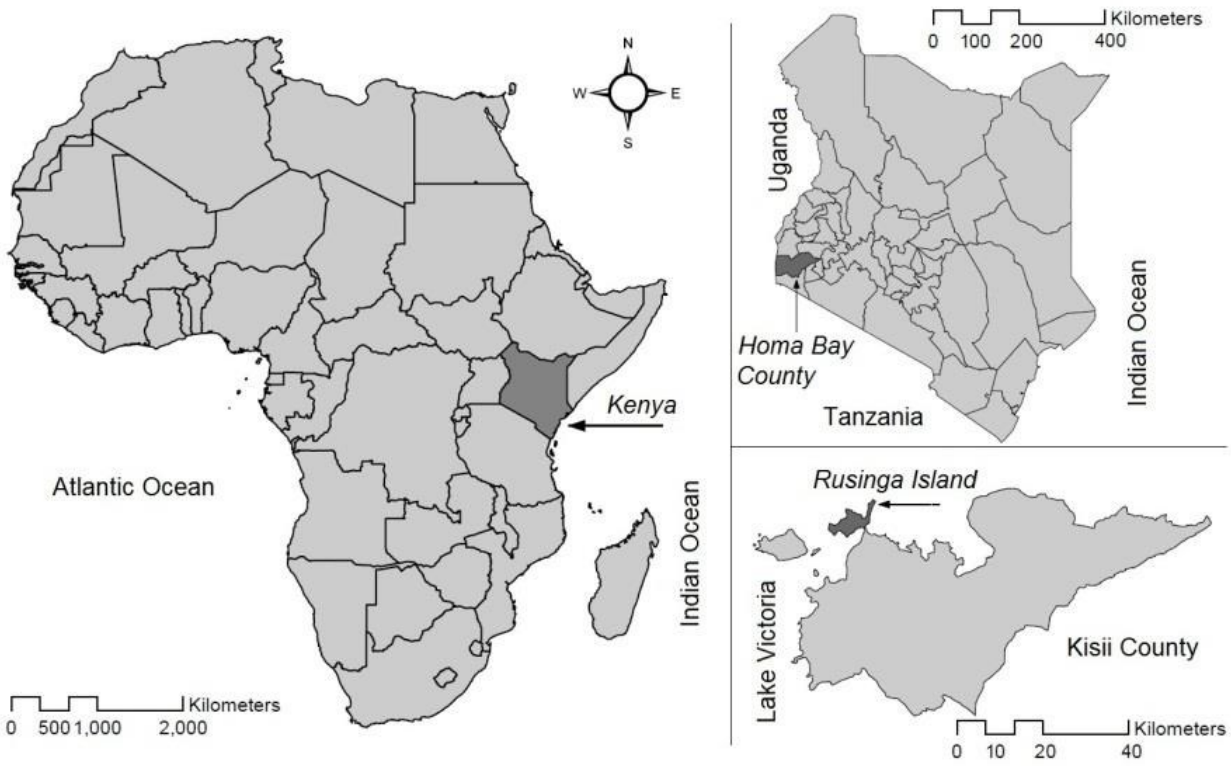

Figure 2.1 Study site: Africa with Kenya highlighted dark grey; in the right upper corner Kenya with Homa Bay County highlighted; Homa Bay County with Rusinga Island tinted in dark grey**.**

Malaria transmission occurs throughout the year, with peaks in transmission at the end of the rainy seasons where parasite prevalence is around 30% (WHO Country Profile 2013: Kenya, Malaria).

Furthermore, schistosomiasis, filariasis, HIV, and tuberculosis are endemic on Rusinga (Central Bureau of Statistics MoPaND. Kenya Demographic and Health Survey 2003)

Data collection system

The HDSS team consists of 10 fieldworkers [FWs], one fieldworker manager [FWM], a database manager and a system developer. Fieldworkers who spoke DhoLuo fluently and had a prior basic knowledge of computing were trained to use mobile tablet computer devices (Samsung Galaxy Tab 2, 10.1). A pilot study was conducted to test the usability of the computer tablets, as well as digital questionnaires, prior to the initial HDSS census. The HDSS uses the Open Health and Demographic Surveillance [OpenHDS] data system [15], a software platform that is based on a centralized database. This database is linked to a web application for data management, linked to a tablet computer-based mobile component which allows digitalization of data at the point of capture, and wireless synchronization to the central data store based on the Open Data Kit [ODK] platform [15, 19] (Figure 2.2). ODK is a free, open-source application intended to facilitate mobile data collection services. ODK consists of two software components for data collection, transfer and storage, and various tools exist for the authoring of the electronic questionnaires used in the data collection process. ODK-Collect is used to render electronic questionnaire forms on mobile devices running the Android operation system, which includes forms to report core vital events as well as customized forms. ODK-Aggregate is a web application that supports data transfer and storage at a local server or a “cloud” server.

In addition to ODK-Collect, the OpenHDS mobile data collection application is installed on the tablets.

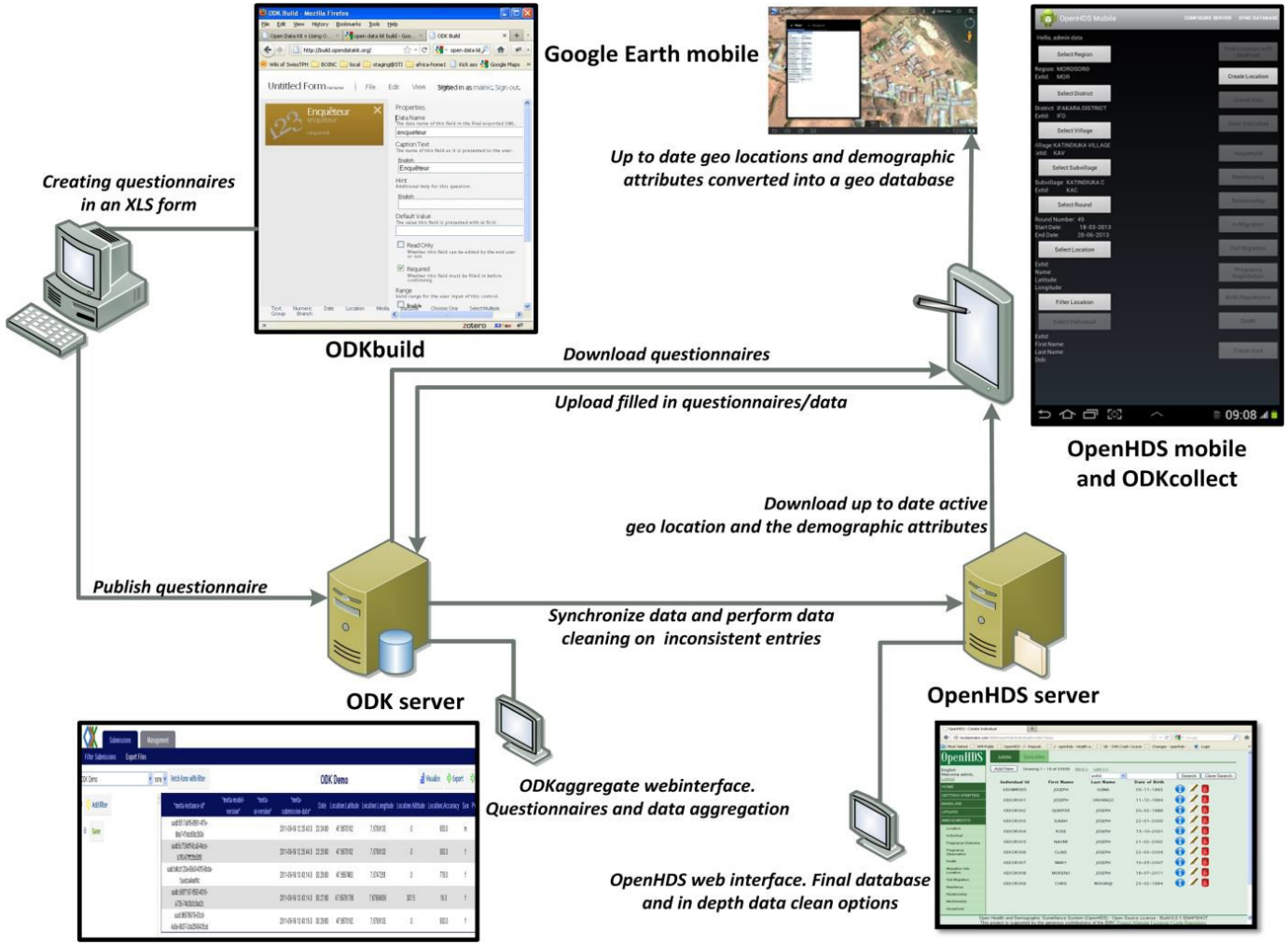

Figure 2.2: Data pathways using the ODK and OpenHDS platform: Electronic questionnaires are created uploaded to the computer tablets by the ODK server. Wireless synchronization of digitalized data collected at the point of capture is transferred to the central data store based on the ODK server. Cleaned data is transferred to the OpenHDS server that in turn synchronizes the up to date database to the computer tablets.

This application contains a database which is pre-populated with data on the administrative location hierarchy in the study area (district, villages, neighbourhoods), and any information previously collected on individuals, houses and households in the area. This allows selection of the individual or house using the software during a visit to a household, and makes it possible to simply amend or add new information associated with the individual or house that has been selected. The differentiation made between houses and households follows the local culture, where the term dhala is used for a group that is socially and financially dependent or formed of related family members sharing the same facilities and recognizing one member as head of the household. A house is always defined as a single residential structure. The XLS-Form application is used for authoring questionnaire forms for ODK in the X-Form format. This allows integration of all possible structures of questions into the questionnaire: open answers, multiple choice answers, as well as posing constraints and requirements to answer outcomes. Questionnaires are published to ODK-Aggregate, and then downloaded to the tablets using ODK-Collect. This includes both questionnaires for capturing core vital events (births, deaths, in- and out-migrations) and study-specific questionnaires (parasitology, malaria incidence etc.). Electronic forms which are completed in the field using OpenHDS mobile are stored in ODKCollect and synchronized over a Wi-Fi connection at the field station to the central database through ODK-Aggregate server (Figure 2.2). After subsequent automated customized data checks, cleaned data is then submitted to the definite OpenHDS database. At the end of each update round, clean data is synchronized to the tablets to ensure that the most up to date information is taken back to the field for consecutive follow up surveys.

Data collection rounds

The SolarMal project was initiated in January 2012 and will run through December 2015. The population census survey took place from June to September 2012, enumerating households, houses and individuals on the island. During the census survey, fieldworkers were assisted by individuals of the local community that are enrolled in a malaria programme, the Rusinga Malaria Project. The fieldworkers of the HDSS were familiarized with the population and geography of the island. In subsequent rounds of data collection, regular communication with the Rusinga Malaria Programme members and village elders enabled fieldworkers to find newly created households. All houses were mapped using the Global Positioning System function on the tablet, recording latitude and longitude with an accuracy of five to 15 meters. Households are

given a unique code consisting of two letters, relating to the name of the village where it is located, followed by a two digit number. Houses within a multi-house household have one extra letter, and all individuals are assigned a unique code comprising of five letters and two digits. Individuals were asked to provide their full name, sex, date of birth, main occupation and their relationship to the head of household. Subsequent analyses of individual data were performed using unique individual ID codes in order to ensure the anonymity of personal data.

To ensure that FWs are adding data to the correct corresponding house and individual in the field in subsequent follow up surveys, each house was provided with a door sticker showing its unique ID (Figure 2.3).

Figure 2.3: Project sticker with barcode on the doorpost of a house: Barcode scanning, integrated into the mobile data collection, allows quick identification of locations and study population to add or amend health and demographic information.

The unique ID is also expressed as a barcode which is scanned with the tablet on arrival at the house and recorded in the data base. Once scanned, the barcode is validated against existing barcodes in the mobile application of OpenHDS and the application allows questionnaires to be filled in and stored. Each household is visited three times a year to collect and update demographic and malaria-related data. Members of the HDSS team visit all residential structures in nine geographic areas on the island simultaneously taking approximately three months to cover their area. At all households observed pregnancies, new births, deaths and migrations which have occurred since the previous

visits are recorded and updated. Digital questionnaires concerning demographic information are consistent with the HDSS questionnaire format of the INDEPTH network (Table 2.1). Moreover, the standardized questionnaire formats are widely used in East Africa and Kenya and therefore apply well to our research site.

Question	***Answer possibility***
Individual ID	*ABCDE100*
Fieldworker ID	TO01
Illness over past 2 weeks	**Yes**; No
If illness reported: what symptoms?	1) Diarrhoea, **2) Fever**, 3) Vomiting, 4) Rash, 5) Bowel ache, **6) Head ache**, 7) Cough/sore throat,**8) Joint pain**, 9) Dizziness, 10) Other (manually specify)
Fever over the last 2 days?	Yes; **No**
Current fever?	**Yes**, No
Under malaria treatment now?	Yes; **No**
If illness or fever reported: take temperature measurement	37.6
If temperature 37.4 °C or above: RDT test	1) Negative, **2) *P. falciparum***, 3) Other *Plasmodium*, 4) Mixed malaria infection, 5) respondent refused to take test
Do you suffer respiratory symptoms?	**Yes**, No
If respiratory symptoms are experienced: Did you seek medical attention?	**Yes**, No
If medical attention: what medical attention was sought?	1) Doctor, 2) Nurse, 3) Community health worker, **4) Traditional healer**, 5) Other (manually specify)
Do you use any drug for the fever?	**Yes**, No
If using drugs against fever: which drugs?	1) Anti malarials, 2) Antibiotics, **3) Pain killers**, 4) Other (manually specify)

Table 2.1: An individual health questionnaire administered to everyone enrolled in the study. In the right column an example of an individual's answer in bold.

Upon arrival at a household the barcode is scanned and a digital log, which includes the interview date and time, is automatically created. After recording deaths and births, migrations into or out of the household are documented. There is a differentiation between migrations within the island and from elsewhere. Individuals moving within the island maintain their individual ID which becomes associated with the new household. These individuals found in the system by filtering on their previous village and their name, subsequently selecting and migrating him or her. Moving out of Rusinga puts the individual in an inactive state in the database; people moving into

Rusinga are provided with a new unique ID code if not previously enumerated, and all personal information is collected, as in the census survey.

These individuals are found in the system by filtering on their previous village and their name and subsequently associating the individual ID with the new household ID through the completion of a migration form. If it is known that the individual in question does not plan to be a resident of the island no questionnaire is filled out. If it is known that an absent person is definitely coming back, no out migration is documented. To distinguish between temporary and permanent migration we use six months as a threshold. General information about the house construction, composition of household members and the presence and use of bed nets (as a malaria preventive tool) is collected for every house which is newly added to the database and for existing houses once per year.

Use of geographical information on basis of the geographical coordinates of houses and demographic as well as malaria-related data gathered during the census of July 2012, the study design for the sequence of the rollout of the SolarMal intervention was developed and has been described elsewhere (Silkey et al., Personal Communications). Briefly, the island is divided into 81 clusters each containing 50 or 51 households, with nine clusters making up one metacluster. Metaclusters form the geographical basis for the HDSS follow up surveys. The fieldworkers are each assigned one of the metaclusters in which to visit every house and individual once during an interval of three months. One fieldworker is deployed to an area conditional on relative progress in the surveillance. For navigational purposes, the demographic database is converted into a geographic database (KML file), allowing us to plot houses to be visited in the Google Earth mobile (Version 7.1.3. 1255) application integrated in the tablet (constructed with ESRI 2011. ArcGIS Desktop: Release 09. Redlands, CA: Environmental Systems Research Institute).

Using the GPS function, FWs can track themselves on the map navigating in real time from one house to another (Figure 2.4). Furthermore, the geographic database also includes all server data enabling the FWs to select any house on the Google Earth map, consequently displaying the personal information of people living there.

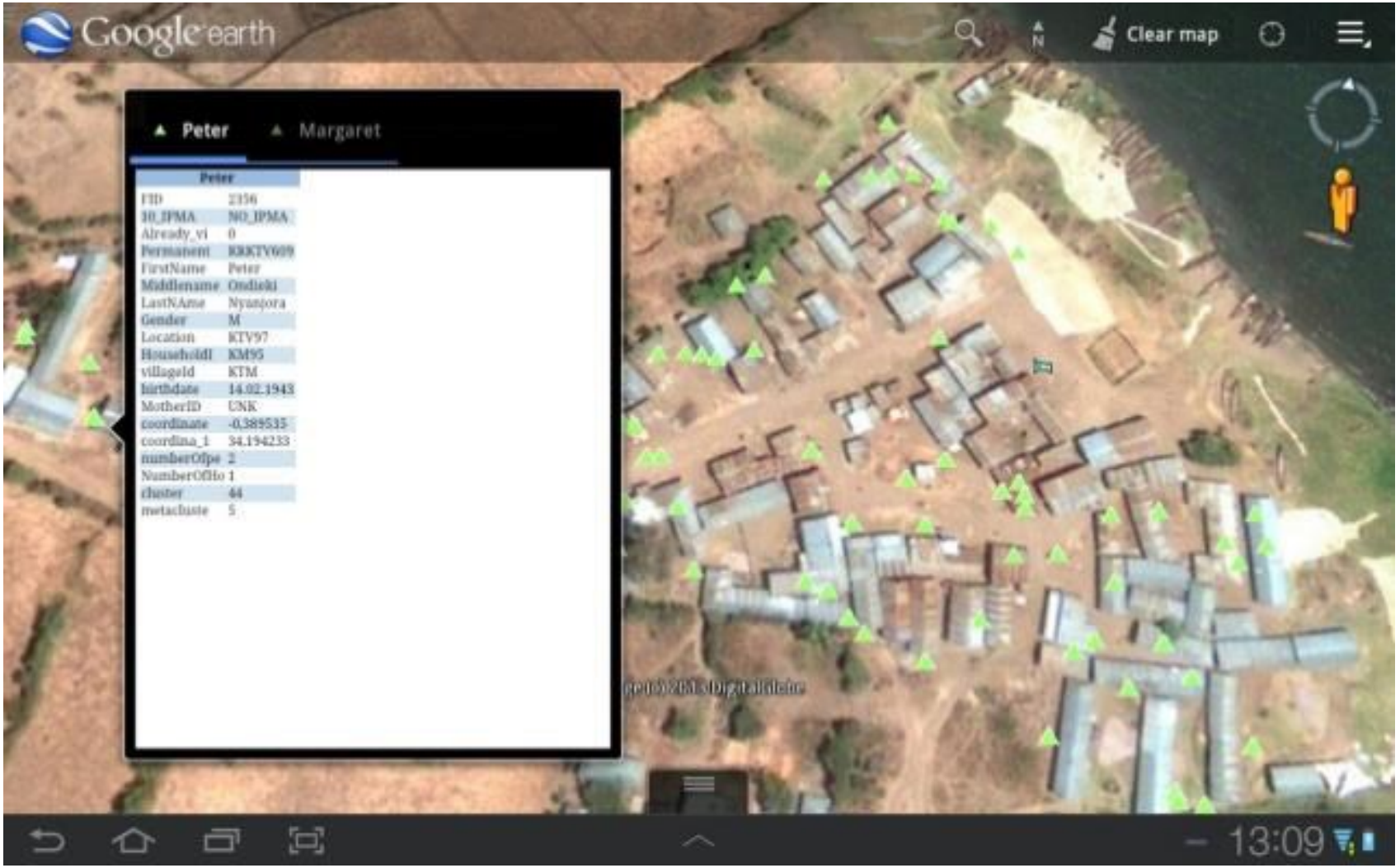

Figure 2.4: Navigating assigned houses: Converting the up to date population database into a geodatabase displayed with Google Maps Mobile assists fieldworkers with tracking every house.

Data quality and management

Data quality is initially controlled by designing questionnaires which permit answers to fall within an acceptable range. For example, using input constraints a date can only be entered as a date format, only women can deliver a child, a body temperature must lie within 35 to 42 degrees Celsius. After questionnaires have been entered in the field, the data is transferred to the ODK-Aggregate server.

Unique IDs for individuals, houses and households are automatically generated per FW to ensure that no duplicate values are entered in the system. Questionnaires which were not fully completed are not accepted for upload to the server. Data is then transferred from ODK-Aggregate to the OpenHDS server using the Mirth Connect data integration platform [20]. All events entered during field visits are checked for inconsistencies during this step. Faulty records are filtered for further checking, and an error report is sent to the data manager by email. Births or deaths registered with an event date long in the past, multiple new-borns or separate deaths with the same date of event will be double checked with the FW or with the head of household. In addition, doubtful migrations are double checked, for instance if a child of three years old was found to be migrated because of marriage or work. Once in the OpenHDS server, the data manager has access to information about all individuals who have ever been active in the database, as well as their event history. A range of options to detect residual inconsistencies and perform data cleaning are available. An error often found in HDSSs is that individuals or households were duplicated during the census round under a slightly different name with different unique IDs at geographical border areas of FWs. An option to merge individuals and their past events provides a practical solution to this problem. In addition to this real time data quality control a web-based monitoring system was introduced that allows the data manager and FWM to extract a weekly snapshot of certain fieldwork related matters in the database [21]. The web interface displays information on where FWs have been in the past week, as well as which household visits are yet to take place. Subsequently, the geographical database converted to KML files are uploaded to tablets at the beginning of every follow up round. The tool automatically removes individuals and houses which have already been visited during a given round of surveillance from the visit plan, publishing a file with remaining houses to be visited that can be uploaded to the computer tablets.

Furthermore, the tool can be used to produce graphs of how many individual and houses were visited and how many forms were filled in during the previous week, allowing the performance of fieldworkers to be tracked. The tool gives the opportunity to see where

FWs have been, how long they have taken to conduct the work delivered, as well as which forms have been filled in and how often. This information gives the FWM a quick insight into every FW's performance, so that inconsistencies can be addressed promptly and systematically. Additionally, on a weekly basis the tool generates 20 houses on basis of the houses already visited, to be revisited by the FWM. During re-visits, the usual procedure of demographic questionnaires is conducted and discrepancies between the results obtained by the FWM and FW are discussed with the FW in question.

Finally, all data of the HDSS, as well as entomological, parasitological, geographical and sociological data are fed into a MySQL relational database ready to be analysed. All data are linked through the unique individual, house or household IDs, making extraction of spatial and temporal data a mere case of entering the desired query in to MySQL. Nightly backups of the databases are automatically copied to a network-attached storage system The local server is a highly secured drive located at the field station icipe.

Ethical clearance

Ethical approval was obtained from the Kenyan Medical Research Institute (KEMRI); non-SSC Protocol No. 350. All participants are provided with information regarding the project outline, the ongoing HDSS procedures, the implementation of the intervention, and the collection and use of blood samples. Adults, mature minors and caregivers of children provided written informed consent in the local language agreeing to participation in the SolarMal project.

Results and Discussion

Resource allocation

We describe a data collection and management platform which advances the electronic systems employed in HDSSs in developing countries a step further mainly by integrating mobile-device based data collection with a centralized real-time data system. This integration is one of the important improved aspects within the described HDSS, resulting in organizational and scientific advantages.

HDSS sites often rely on paper-based conducting of questionnaires before the data is entered in to a digital database [7, 9, 10, 22, 23]. The Android operating system is used on powerful tablet computers, allowing us to develop or deploy the desired software. In

combination with the freely available mobile data collection software, ODK-Collect and OpenHDS mobile, collecting data on paper is set to become obsolete. This not only saves time because data can be entered by merely navigating through the digitalized form, and the process of double-entry of paper questionnaires in to a digital format is no longer necessary. Fewer field workers and staff are required to perform the same job as before.

Besides the cost-effectiveness on the basis of reduced staffing, the use of stationery is reduced to a minimum amount. Fieldworkers are provided with computer tablets, tablet protection covers and a paper notebook for occasional notes. Stationary in the office is reduced to a flip board to manage discussions, and some paper notebooks and pencils. All data collection and management is fully digital. Thus where traditional paper based HDSSs would approximately use one A4 for updates on household information and one A4 for individual health information, a digitalized data collection with 25,000 people and 8,000 houses would save over 30,000 A4 papers per survey. In the last five years there are sites where HDSSs have migrated from paper-based to some sort of digitalized entering system [8, 24-27]. However, none of these sites have linked data collection software in the field directly to a real-time database. At the moment of writing, there is at least one other collection system using computer technology to integrate collection, management and database utilities; the LINKS system is in some ways similar to the system described in this paper [28]. LINKS also uses the ODK platform to collect data and is deployed at several sites in Africa. It is an easy implementable, cost reducing and efficient platform; however, the concept of a near real time database and its advantages seems not to be exploited. Furthermore, there are examples of health data collection systems where PDAs and telephones are used, which is considerably more efficient than the paper based surveillances. However, they show major limitations in terms of user-friendliness and scalability [29, 30]. This is mostly caused by the obsolescence and limited compatibility of software and hardware used.

Time and organizational efficiency

Making use of the latest openly available technology, data collection in the field enables researchers and field workers to be time efficient, resulting in cost reductions and organizational efficacy. At most INDEPTH affiliated HDSS sites the Household Registration System [HRS] is used for managing demographic and health-related data, either by digitalizing filled in paper forms or direct digital entry in the field [8, 10, 22, 25, 26]. There are also examples of HDSS sites where a different data management

system is developed relying on paper or non-paper based data collection [7, 9, 24]. The data collection system described in this paper has several advantages compared to the HRS in terms of organizational efficiency [31]: Firstly, traditional cleaning of data accumulating to an entity like an individual or household is largely removed. As the OpenHDS mobile application is a copy of the aggregated longitudinal database, in the application interface, adding data is only possible after selecting an existing entity. The constant uploading of collected data to the OpenHDS server and the synchronization of the database to the tablets makes reliable continuity of the data achievable.

Secondly, the entire process of creating an electronic questionnaire, up to viewing the collected data in a server, is a manageable, time efficient task for any scientist once basic training has been provided.

The XLS-Form authoring tool allows also non-computer scientists to create a questionnaire with the option to apply the preferred constraints. Concepts in questionnaires such as skip logic, input constraints, structured data model and an entry concept from the start, which the HRSs lack [31], have in our project let to only few forms of mistakes and errors that were relatively easy to detect. In a sample of our data we detected some incorrectly entered dates of birth and names, however in the following visit this personal data is always checked and corrected appropriately. The number of corrected mistakes in demographic data after one data collection round was never more than one percent. Simply uploading the XLS- form within ODK-Collect on the computer tablet allows one to conduct the questionnaires in OpenHDS mobile. All questionnaires related to the core demographic data collection are standardized and configured to OpenHDS mobile.

Thirdly, translating the real time database into a geographical database is a convenient way to assist FWs in real-time navigating their area of data collection. Demographic or disease-related data can be linked to a house location with its coordinate using the free Google Earth software. Tapping a house location on the device shows all the available household information. This combination of real time GPS navigation and fixed visiting points in space enables the FW to invest a minimal amount of effort in locating households at the study site. In this way fieldworkers of the HDSS manage to visit an average of approximately 15 houses and 40 people per day. The visiting of houses without a digital navigation platform can leave room for suboptimal walking routes.

Finally, after data collection has finished and data content has been cleaned, records can immediately be used to guide other parts of the project that rely on data collection structure of OpenHDS. Also, where the analysis of data in current HDSSs can only

commence after it is manually entered and cleaned, this system allows one to have a dataset ready for analysis shortly after collection. Data cleaning is performed on a daily basis and, with roughly 500 data entries per day the data manager usually finishes routine cleaning in less than two hours. Manually entering great amounts of questionnaires and post-hoc cleaning of entered data can take many more hours even if every single questionnaire is digitally entered and cleaned in one minute.

One aspect of this particular HDSS is the facilitation of healthy team cohesion. The SolarMal project is a multidisciplinary project with multiple researchers collecting data on sociological, entomological and parasitological outcomes integrated with a HDSS. The complete project data and storage is linked to the OpenHDS infrastructure, there are twice-monthly meetings with all project staff to discuss data related issues and all research areas make use of the data gathered through the HDSS in planning and carrying out data collection activities and subsequently analysing the data.

Data quality assurance

Organizational efficiency and data quality assurance go hand in hand, commencing from the OpenHDS platform where all data is centrally stored. Having the ODK-Aggregate and the OpenHDS server opens up the possibility for the data manager to check and clean the contents of data in a consistent way on a daily basis. This near-real-time quality assurance is conducted on the level of the ODK-Aggregate by means of a customized list of queries looking for inconsistencies that are easily detectable, like double visited individuals. The more in-depth data cleaning is then possible at the level of the OpenHDS. The platform offers a range of tools to check, research and amend all aspects of the demography in a population. Another large advantage of this system is the automatic generation of unique IDs. Automating the assignment of IDs avoids duplication of individuals or multiple individuals with the same ID. All data collected in the project are related to one of these three levels of unique IDs, in this way it is safeguarded that data collected is attributed to the right person or house. Furthermore, by means of the KML file, the FW knows which house is visited. Selecting the house ID in the OpenHDS mobile application directly gives access to editing and attaching new data to the individuals living there. Demographic and other questionnaires can easily be filled in and attached to the right unique ID, thus reducing confusing data accumulation drastically. In addition, all houses are provided with a door sticker with a unique bar code and the house and household ID. Scanning the barcode confirms the physical presence of the FW at the house, so that the data entered truly correspond to

the house that is visited and it is not possible for a FW to enter data remotely. Lastly, a web-based monitoring of the database to monitor the performance of FWs is under development. This monitoring allows the FWs and data manager to follow the performance of every FW. Monitoring of fieldworkers to increase data quality is not a new concept [14, 15]. However, a near-real-time database that automatically displays FW performance is a convenience never described. Tracking the route walked by FWs, and observing the number of individuals and questionnaires filled in are currently the most prominent and helpful tools to detect fieldworker inconsistencies. More importantly, simple analysis of this data can shed light on interviewer bias, which can directly be discussed with the FW in question.

Challenges and future research

Despite the advancement of and improved accessibility of information technology, the development and implementation of the described infrastructure in low and middle income countries will meet obstacles and limitations. Primarily, the requirement of electricity and a computer server near the field work site are vital. Likewise, this operation only becomes truly feasible with a trained data manager who has advanced I.T. skills. During this pioneering phase, having access to or collaborating with a software developer is also necessary. So, although on one hand cost and time savings are made in the long term, setting up the initial facilities requires a significant financial investment and demands a well-designed strategic plan for the context of the HDSS. Another complementary investment is the training of staff involved in the HDSS in how to handle the hardware and the software. Digitalization of the HDSS process from an existing paper-based system can lead to a drastic reduction of personnel, which facilitates the operational procedures of the HDSS.

Furthermore, there are many HDSS currently using paper based systems that desire to migrate to a fully digitalized HDSS. This transition can introduce a whole set of unforeseen difficulties that rely on complex logistical issues which necessitate more data and software professionals [32].

One of the biggest issues experienced throughout the past HDSSs, is dealing with migration of the population under study. Where the OpenHDS system allows this problem to be handled much more promptly than paper-based or obsolete household registration systems, it is still a challenge to make sure that internal migrations between households are correctly processed. Individuals can always be immigrated again, but the

reintroduction relies on the name given by the person in question. We experienced that sometimes other names are given or the original name was incorrectly provided.

Conclusion

In regions lacking adequate organization to monitor demographic and health information little is known about population dynamics and the epidemiology of disease. It is these areas where health is often heavily compromised and where collection of specific health-related data can greatly improve our understanding of health issues. The HDSS within the SolarMal project provides an example of a user friendly infrastructure for field data collection in evidence-based research in low and middle income countries by making use of the currently available technologies. Whereas most HDSSs still work with paper based or obsolete digital systems, this paper describes a totally digitalized platform that allows fieldworkers and field managers to quickly and systematically keep clean data, make fewer mistakes with data collection and make use of a structured data model and entry concept from the start.

Stakeholders such as government health officers, local administrators and scientists have easy access to real time data storage on a secure central database which enables them to conduct near-real-time quality assurance. Besides, remote progress monitoring allows scientists to quickly detect inconsistencies. Most importantly, this system could radically increase cost-effectiveness by saving time and money on stationery, data clerks, organizational costs and manual logistics.

Competing interests

The authors declare that they have no financial, political or other kind of competing interests.

Authors' contribution

AdP is the software developer that helped with improving and advising on the data management platform as well as providing expert comments on the manuscript. KO is the local database manager applying the OpenHDS and ODK platform in the field. IK is the fieldworker manager, organising the field activities and linking this to the data management platform. AH, CM, WM and WT are part of the overall program management and have directly worked a lot on embedding and integrating the data management platform into the SolarMal project. NM has supervised the complete implementation of the platform and provided expert comments on the manuscript. All authors read and approved the final manuscript.

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3. Profile: The Rusinga Health and Demographic Surveillance System, Western Kenya

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Abstract

The health and demographic surveillance system on Rusinga Island, Western Kenya, was initiated in 2012 to facilitate a malaria intervention trial: The SolarMal project.

The project aims to eliminate malaria from Rusinga Island using the nationwide adopted strategy for malaria control (insecticide-treated bed nets and case management) augmented with mass trapping of anopheline mosquitoes.

The main purpose of the health and demographic surveillance is to measure the effectiveness of the trial on clinical malaria incidence, and to monitor demographic, environmental and malaria-related data variables. By the end of 2014, the 44 km² island had a population of approximately 25,000 individuals living in 8746 residential structures. Three times per year all individuals are followed up and surveyed for clinical malaria. Following each round of surveillance a randomly selected cross section of the population is subject to a rapid diagnostic test to measure malaria. Additionally, extensive monitoring of malaria vectors is performed. Data collection and management is conducted using the OpenHDS platform, with tablet computers and applications with advanced software connected to a centralized database. Besides the general demographic information, other health related data is collected that can be used to facilitate a range of other studies within and outside the current project. Access to the core dataset can be obtained through the INDEPTH Network or the corresponding author.

Why was the HDSS set up?

A malaria intervention study based on removal trapping of anopheline mosquitoes in addition to the Roll Back Malaria [RBM] control strategy [1] was initiated on Rusinga Island, Western Kenya in 2012.

Mosquito traps baited with a synthetic lure that mimics human odour are placed at the household level to reduce mosquito population density and, as a consequence, lower the intensity of malaria transmission [2]. Traps are powered by solar energy, which is also used to provide electric light and mobile phone charging points for the household members. The combination of solar energy with malaria control led to the project being named SolarMal. A health and demographic surveillance system [HDSS] was established to facilitate continued monitoring of demographic, and particularly malaria-related, variables. In addition, the complex roll-out logistics of the SolarMal intervention required accurate and up-to-date information about the population and their housing. Although the main objective of the HDSS is to measure the effectiveness of the vector control intervention on health and population outcomes, the collected demographic and malaria specific data may be used for validation of epidemiological models as well as entomological and parasitological research. The most prominent objectives facilitated by the HDSS are:

(i) Longitudinal monitoring of demographic dynamics to provide a robust framework for research.

(ii) Studying the epidemiology of malaria,

(iii) Analysing the effect of the SolarMal intervention on malaria prevalence, transmission and mosquito abundance.

(iv) Measuring the interaction between the intervention and existing approaches to malaria control, and environmental and socio-economic variables.

The SolarMal HDSS collects demographic information, malaria related variables and other information on factors that are likely to influence malaria epidemiology and malaria mosquito ecology. The HDSS provides different disciplines within the project with an up-to-date population database. The entomological and parasitological experimental designs, as well as the logistics for rolling out the intervention, rely on the continued updating of the study population (WT, personal communication.).

An important component of SolarMal is the inclusion of sociological studies and the population database enables social scientists to conduct targeted sociological research. Since 2012 an extensive baseline survey and 8 subsequent follow up rounds have been

conducted. The roll out of the intervention traps started in June 2013 and was completed in May 2015, at that point covering all households on the island.

Where is the HDSS area?

Homa Bay County is located in Western Kenya at Lake Victoria, within the former province of Nyanza, exposed to the south of the Winam Gulf. Rusinga Island is situated between latitudes 0°21′ and 0°26 South, and longitudes 34°13′ and 34°07’ East (Figure 3.1). A causeway connects the island with the mainland. Rusinga Island stretches over 44 sq. km with an elevation between 1100 m and 1300 m above sea level. Mean daily temperatures vary from 16 to 34 degrees Celsius with higher temperatures in the dry seasons that occur between June-October and late December-February.

Figure 3.1: The upper Figure shows Africa with Kenya highlighted dark grey in the middle, Kenya with Homa Bay County highlighted; lower Figure depicts Homa Bay County with Rusinga Island in dark grey.

Seasonality in precipitation is traditionally experienced as one long rainy season ranging from March into May (average of 198 mm per month in the period 2012-2014) and a short rainy season from October to early December (average of 132 mm per month). The local administration comprises of two chiefs, each governing one part of the island; Rusinga East and Rusinga West. The local authority divided the island into eight subzones containing a total of 36 villages and about 10 beach communities (Figure 3.2). For the purpose of the SolarMal trial and to measure the impact of the intervention most effectively, the island was divided into nine metaclusters each consisting of nine clusters. Each cluster comprises of 50 or 51 households. The HDSS operates from the International Centre of Insect Physiology and Ecology [icipe] at the village of Mbita Point at the mainland side of the causeway.

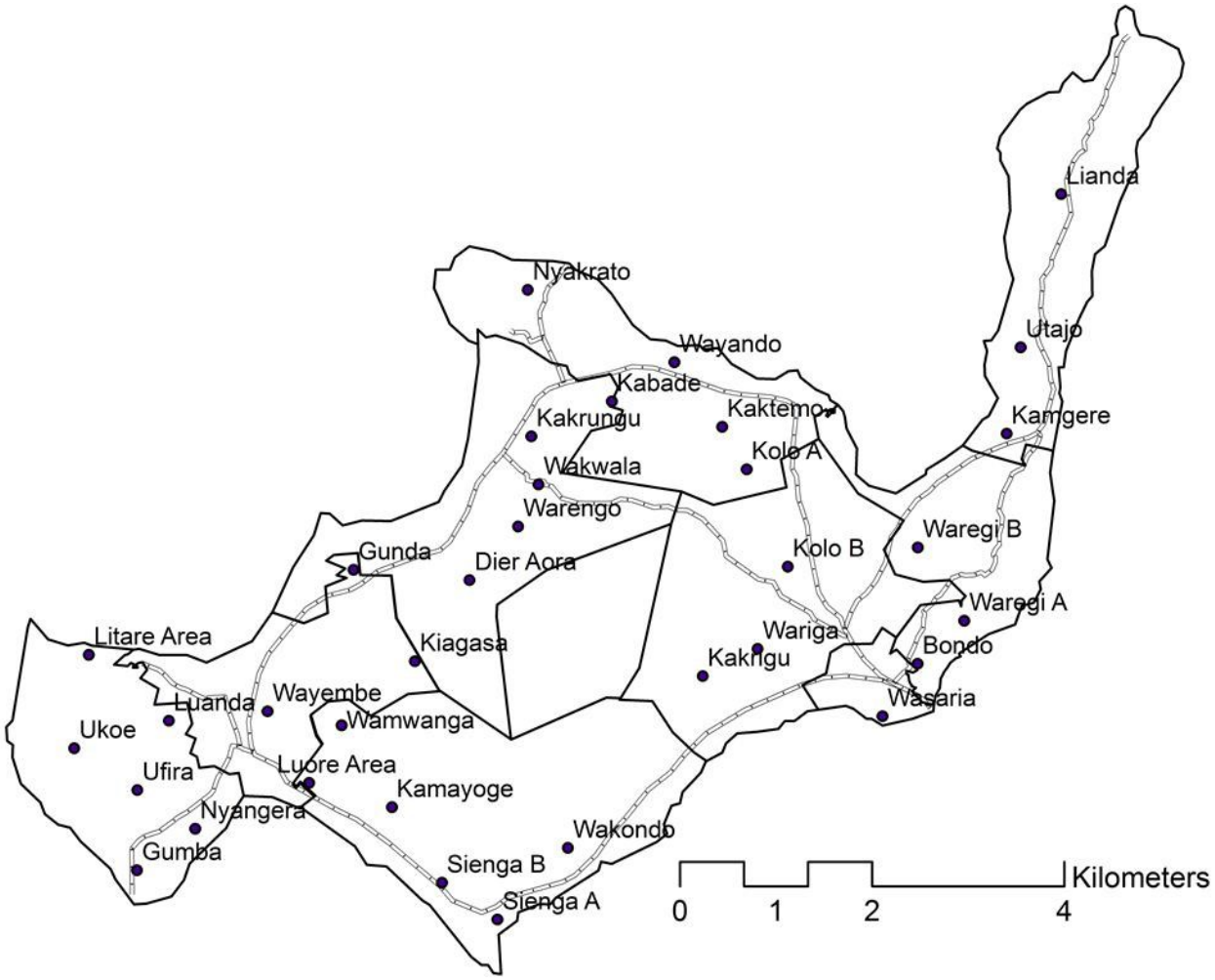

Figure 3.2: Rusinga Island with an uninhabited hill in the middle. Boundaries of metaclusters (thick black lines); villages (indicated with dots); roads (dashed lines).

Who is covered by the HDSS and how often have they been followed up?

The population of Rusinga Island belongs to the Luo ethnic group and DhoLuo is the main spoken language. The national languages (English and Swahili) are also used. Fishing and farming are the principal occupations, with people typically harvesting millet, sorghum and maize and fishing tilapia and Nile perch. Christianity is the predominant religion (84%) in this area; the Muslim community (12%) forms a minority.

Most houses on the island are made of mud or cement walls with iron sheet roofs. Connection to the electrical grid is rare and there is little to no supply of piped potable water. There are several health facilities on the island; one governmental health centre, one government clinic, two private clinics and one drug dispensary. Non-governmental organisations have established a further two clinics. A district hospital is found at Mbita point village.

All members of the population are visited three times a year. By August 2015, each location had been visited eight times, including the baseline enumeration. With the baseline conducted in 2012, and the latest update round completed in mid-2015, currently eight rounds of surveillance have been carried out in the course of the first two complete years of health and demographic surveillance. During this period, a total of 33,283 people were registered in the database, with residences divided over 8746 houses, and belonging to 5457 households. The actual number of people living on Rusinga island mid-2015 was 24,643.

The leading causes of death in this area are HIV/AIDS related, with an HIV prevalence of

26% (Ministry of Health Kenya: HIV estimates, 2014). Malaria is hyper-endemic and existent in this region throughout the year, with peaks in transmission at the end and just after the rainy seasons, where Plasmodium parasite prevalence of around 30% is reported (WHO Country Profile 2014:

Kenya, Malaria). The population is characterised by a seasonal influx of labourers searching for jobs in the fishing industry. Temporary in and out migrations are distinguished from permanent migration within the Rusinga HDSS. Households are recorded following the Luo description of a dhala: any set of houses that share a head of household and/or are economically dependent.

The age distribution of Rusinga has a typical East-African profile. Baseline studies (2012) and 2 years of data collection (2013 and 2014) demonstrate that approximately

40% of the population is under the age of 25 and almost 90% of the population is under the age of 45 (Figure 3.3). All consenting individuals living on the island are subject to the HDSS to monitor demographic and malaria-related variables.

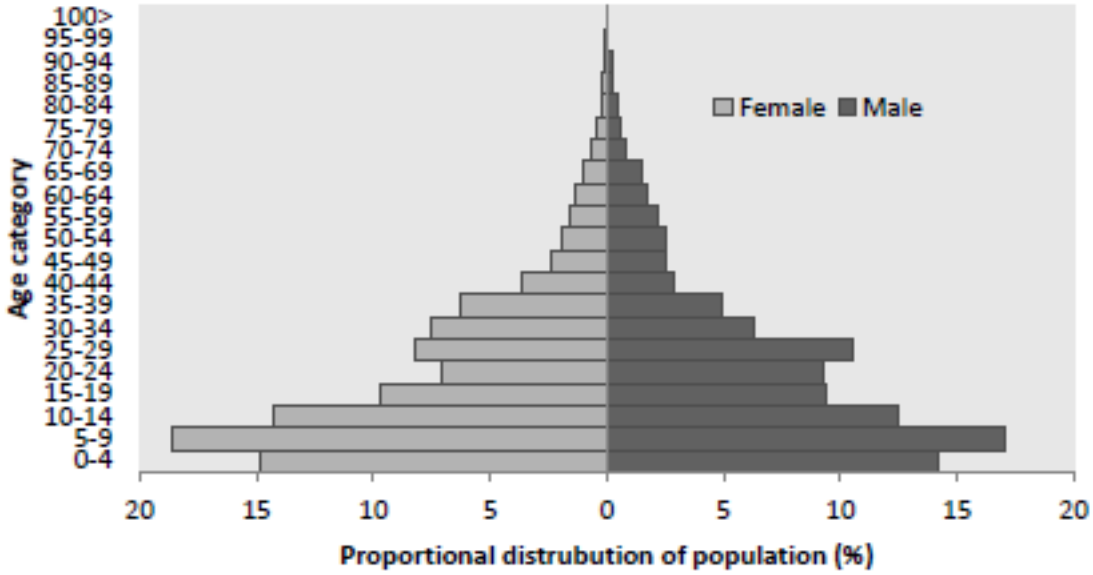

Figure 3.3: Population pyramid of Rusinga Island with the percent of people illustrated per age category.

The HDSS, local population and the intervention programme are strongly connected by means of a community advisory board [CAB] which, together with project staff, regularly evaluates the progress of the project and matters encountered during fieldwork.

What has been measured and how have the HDSS databases been constructed?

The baseline enumeration was carried out from June to September 2012, recording all households, houses and individuals on the island. All households were provided with an odour-baited malaria mosquito trap to attract and kill mosquitoes using a stepped-wedge cluster randomized trial design.

The hypothesis is that mass trapping of malaria vectors leads to reduced malaria transmission, incidence and prevalence. All structures with residents were mapped using the Global Positioning System [GPS] function on a tablet computer Households, houses and individuals are assigned unique identification codes. All inhabitants were requested to provide their full name, sex, date of birth, main occupation and their relation to parents and the head of household. During the census round, fieldworkers [FWs] were assisted in locating all houses and individuals by a local community based

organisation, the Rusinga Malaria Project [RMP], which has been involved in malaria control practices on the island for over a decade. From January 2013, collection and updating of demographic and malaria and health related data started. The HDSS operates by house-to-house interviews, visiting on average 120 houses per day equally distributed across the nine metaclusters. Interviews take approximately 30 min. depending on the size of the household. Each HDSS round is completed in approximately three months. During household visits, observed pregnancies, new births, deaths and migrations which have occurred since the previous visit are recorded and updated (Table 3.1). Clinical malaria is recorded during HDSS rounds based on fever recalls and a conditional RDT, and at the end of each round the team performs blood collections on a random sample of the population. Digital questionnaires on demography are consistent with the HDSS questionnaire format of the principal HDSS association globally; INDEPTH network [3, 4]. These standardised questionnaire formats are widely used in East Africa, including Kenya, and therefore apply well to our study site. The HDSS uses tablet computers and the OpenHDS system, which allows for rapid centralization of the data without a need for processing paper forms. This reduces data management overhead and allows for rigorous and timely quality control. A detailed description of this system can be found elsewhere [5]. The HDSS team consists of 10 FWs, a fieldworker manager [FWM] and a data manager. The local team has access to a senior software manager. A server running the OpenHDS software is hosted at the icipe field station in Mbita.

Visit form: scanning bar code on house to confirm follow up visit and set date of interview	**Pregnancy observation:** mother ID, # of months pregnant, attended health facility during pregnancy, received tt-injection1, other medicines, estimated date of birth, woman's first pregnancy
Household (*): new household ID, number of houses in the household, name and ID of household head ID and name	**Pregnancy outcome:** delivery outcome, name of child, date of birth of child, sex, creation of new individual ID, house ID, household ID, link to parents ID
House (*): new house ID, longitude and latitude, household head ID and name, photo of the house, number of individuals	**Migration-Out:** individual ID, house ID, household ID, date of migration, within Rusinga, to which village/zone, out of Rusinga, reason for migration
Individual (*) : new individual ID, names, date of birth, sex, level of education, occupation, relation to the household head	**Migration-In:** previously registered by SolarMal, village/zone, new individual ID, names, date of birth, sex, highest level of education, primary occupation, relationship to the household, house ID, household ID, date of migration, reason

	of migration, moved from
Household characteristics (**): ownership of dwelling, # of rooms, # of bedrooms, location of kitchen, source of electricity, source of light, agricultural land ownership, wall construction, floor construction, roof construction, whether eaves are screened, whether IRS has been applied during the past year, bed nets reported, bed nets observed, # of bed nets, when were bed nets obtained, condition of bed nets, other mosquito control methods used by household members	**Individual health:** individual ID, any illness during the past 2 weeks, current fever reported, under malaria treatment at the time of the visit, temperature (if indicated illness), RDT2 result (tested if > 37.3 ° C), any respiratory symptoms, medical attention, what medical attention, drugs against fever, which drugs
Death registration: individual ID, name, date of death, outcome of verbal autopsy, verbal autopsy performed by, cause of death, place of death	

Table 3.1: Content of questionnaires administered during the census and each follow up survey. (*) data is collected only when a new subject is enumerated. (**) indicates that the questionnaire is administered for all new residential structures, as well as every second year for all registered residential structures**.**

[1] tt-injection is a tetanus vaccine, which can be injected during pregnancy to prevent neonatal tetanus

[2] RDT is a rapid diagnostic test performed to promptly detect evidence of malaria parasites in the blood.

OpenHDS, a software platform that is based on a centralised database, a web application for data management [6], is linked to a tablet computer-based mobile component which allows digitisation of data at the point of capture, and wireless synchronization to the central data store based on the Open Data Kit [ODK] platform [7, 8]. Samsung Galaxy Tab 2 tablet computers were used from the start for data collection, and upgraded after years to the successor Galaxy Tab 3. Data entry errors are minimised through basic range checks and the integration of different questionnaires through systemwide IDs in a guided workflow. The ODK and OpenHDS platforms allow the FWM and data manager to use a range of data cleaning options, many of which are guided by reports generated automatically on a nightly basis. This process enables scientists to use the clean data for analysis with minimal delay. Furthermore, to monitor the performance of FWs a web-based tool was developed that monitors progress of the work FWs conduct over time, allowing the project to optimize the quality and effectiveness of data collection. Finally the data of all sub-disciplines of SolarMal are connected to each other by one of the three levels of unique codes and kept in a MySQL relational database.

Calculation of demographic rates and further quality assurance is conducted using the iShare2
software (http://www.indepth-ishare.org).

Key findings

The demographic data collected during the census survey in 2012 up until May 2015 is the basis for Table 3.2. Reported demographic figures are calculated for the complete years of 2013 and 2014. To place the reported rates in context, the same measurements calculated by other HDSSs operating close to Rusinga in the years 2007 and 2010 are also reported in Table 3.2. Kaneko et al. [9] published demographic information on the basis of the Mbita HDSS covering Rusinga and neighbouring areas in 2011. An HDSS at Kisian and surrounding areas operated by the KEMRI/CDC some 150 km North-East of Rusinga reported rates for 2007 [10]. In calculating person-time at risk we defined residents as those who stayed in the HDSS area 60 days (two months) or longer. Registered individuals who stayed less than 60 days during a year were removed for the calculation of total person-years. Table 5.2 shows the key demographic indicators of the Rusinga HDSS for the years 2013 and 2014. The total population that was registered in the database by the end of 2013 was 29 206 and the total contributed person-years in 2013 was 24 350. The total number of individuals enumerated by the end of 2014 was 33 283. By December 2014 the HDSS registered a total of 8746 residential structures divided over 5457 households. The sex ratio is skewed towards females with 91 men for every 100 women. The average population density was 553 (2013) and 577 (2014) person years per square kilometre calculated on basis of 44 km² of landmass. However, as shown in Figure 3.4, the population is not evenly distributed and there are densely populated fishing beaches and a large village in the southeast; the hill in the centre of the island is uninhabited. The total fertility rate [TFR] is calculated as the average number of children that would be born per woman if all women lived to the end of their childbearing years (15-49 years) yielding a TFR 2.1 for both years.

Indicator	Unit	Rusinga 2013	Rusinga 2014	Mbita 2010	KEMRI 2007
Total population visited	Total number of individuals enumerated	29.206	33.283	-	-
Total houses visited	Total number of houses enumerated	8141	8746	-	-
Total households visited	Total number of households enumerated	4948	5457	-	-
Male : Female ratio	Proportions of sexes	91	91	91.2	90.1
Population density	Average number of people per km2	553	577	-	-
Total fertility rate	Average number of live children per woman	2.1	2.1	3.7	5.3
Crude birth rate	Births per 1000 person years	18.7	18.5	29.7	36.8
Crude death rate	Deaths per 1000 person years	6.3	5.8	9.1	15.9
Life expectancy at birth (Male)	Expected years to live at birth	66.9	68	57.5	46.5
Life expectancy at birth (Female)	Expected years to live at birth	68.8	68.6	61	46.5
Infant mortality ratio (<1 year)	Infant deaths per 1000 live births	17	11	14.1	76
Child mortality rate (1-4 years)	Child deaths per 1000 person years	7.4	6.8	-	16.5
Child mortality ratio (1-4 years)	Deaths between age 1 and 5 per 1000 children	29	27	-	58.8
Under-five mortality rate	Under-five deaths per 1000 person years	9.7	7.5	-	29.5
Under-five mortality ratio	Under-five deaths per 1000 live births	45	37	91.5	167
Crude in-migration rate (external)	In-migrations per 1000 person years	(*)	127.9	64.1	115
Crude out-migration rate (external)	Out-migrations per 1000 person years	164.6	148.9	86.2	111
Malaria prevalence	Percentage of population with a positive RDT	27.1	28.1	-	-

Table 3.2: Key demographic indicators over the years 2013 and 2014 on Rusinga Island; compared with indicators reported during the Mbita HDSS in 2010 and the KEMRI HDSS in 2007.(*)No in-migration rates reported for 2013. Catch-up enumerations in the first months of 2013 enumerated households which were missed in the baseline survey, and could therefore not reliably be distinguished from in-migration events.

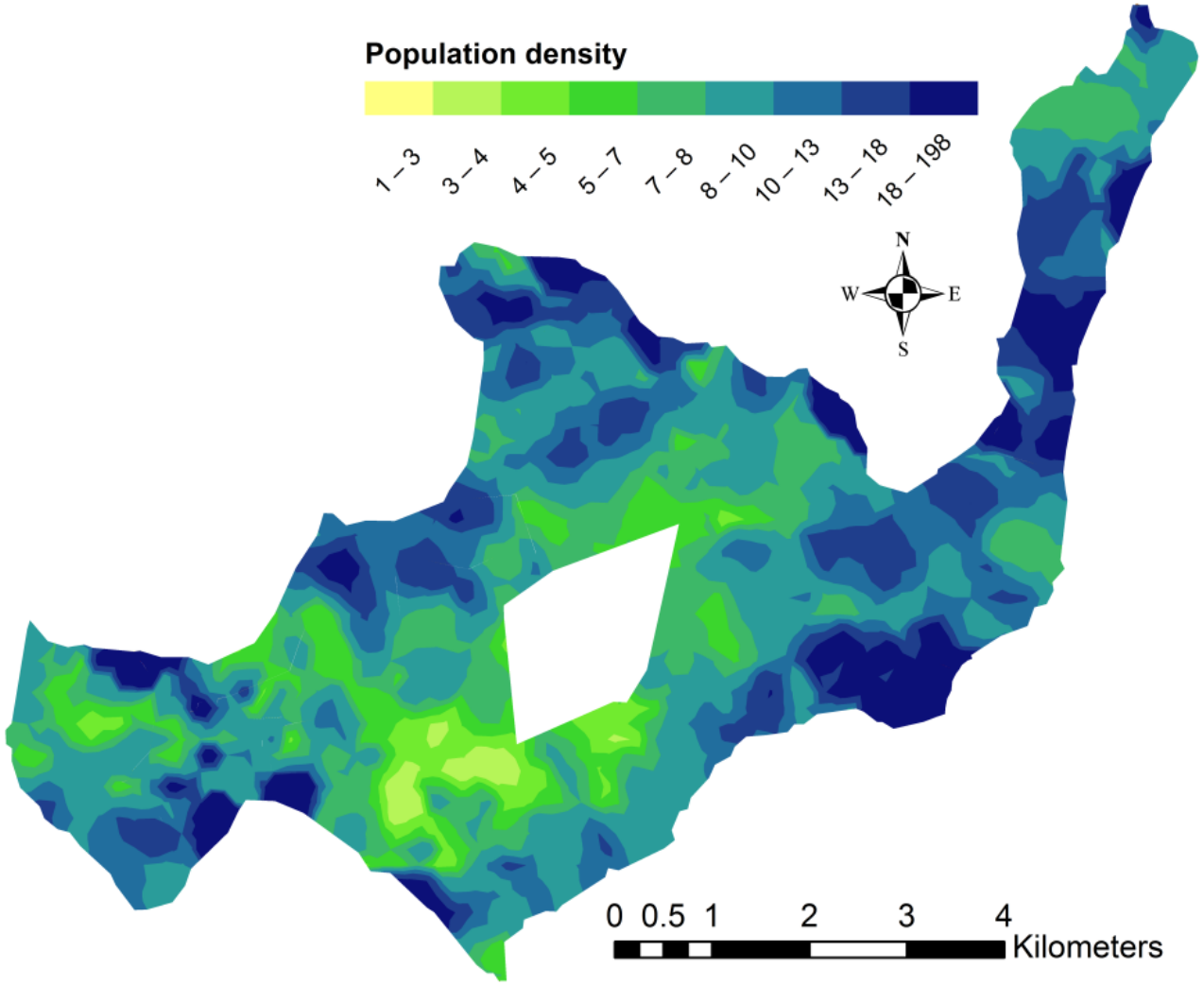

Figure 3.4: Distribution of population density on Rusinga Island for the year 2013.

The crude birth rate [CBR] and death rate [CDR] are presented as the number of live births or deaths per 1000 residents. We found a CBR of 18.7 (2013) and 18.5 (2014), and CDRs of 6.3 and 5.8 were determined for 2013 and 2014. Compared with the HDSS of KEMRI/CDC at Kisian, both the Mbita and the Rusinga HDSS report a lower CDR. The life expectancy [LE] at birth for females and males is calculated as the total number of person-years lived in all age intervals of the static population divided by the number of alive individuals at the start of every 5year age interval. For males in 2014 the LE at birth was 68 years, for females the LE at birth was 68.6 years.

The infant mortality ratio was 17 in 2013 and 11 in 2014 (number of infant deaths, <1 year, per 1000 live births). This relatively large difference may be explained by the protective effect of the malaria vector intervention. The child mortality ratios in consecutive years were remained 27 (number of deaths between 1-4 years per 1000 children) and the under-five mortality ratios are presented as the number of deaths in that age category per 1000 live births was 45 and 37.

Calculation of all mortality rates as well as the CDR yield lower rates and ratios than the KEMRI/CDC HDSS. Our findings are comparable with the results of the Mbita HDSS [9]. Unlike the Mbita and the Rusinga HDSSs, the KEMRI/CDC HDSS worked together with at least two health clinics in recording deaths, which most likely resulted in a more sensitive death registration system. In addition, it is common in Luo culture, to return to the place of birth at the time of death. As there are many working immigrants residing on Rusinga Island, this could explain the lower number of recorded deaths taking place on the island.

The in-migration and out-migration rates are also calculated using person-years. The analysis of the migration rates for the year 2014 show a crude in-migration rate of 12.9 per 1000 person years and a crude out-migration rate of 148.9 [10].

Table 3.3 summarises characteristics of 6640 inhabited houses of which information about the house was collected. These results are comparable to other HDSSs in Western Kenya, such as Asembo and Gem [10] and around Mbita [9, 11]. On Rusinga a typical house is made from mud walls, a roof of iron sheeting with a cement floor. Most houses have bed nets, but are not protected against mosquitoes flying into the house through the open eaves [12]. Only a fraction of the population has access to the electrical grid and the main sources of indoor light were kerosene lamps at the time when the SolarMal intervention was rolled out.

Finally, the average the island-wide malaria prevalence and the average number of malaria mosquitoes caught per trapping night for the rainy seasons in 2013 and 2014 are reported in Table 3.2. The malaria prevalence is established on basis of a cross sectional survey of 10 percent randomly selected people tested with a RDT. Malaria mosquito abundance is established on basis of three surveys of mosquito monitoring at 80 randomly selected households. Ignoring intervention arms, malaria prevalence did not differ much island wide between both years with 27.1% and 28.1% prevalence, respectively. However, we found a significant difference in malaria mosquito abundance with an average of 0.30 mosquitoes per trapping night in 2013 versus 0.21 in 2014.

Indicator	No.	%
I) Ownership of house		
Owner	4955	74.6 %
Rent	1327	20 %
Other	358	5.4 %
II) Number of rooms		
1	1725	26 %
2	2090	31.5 %
3	2142	32.3 %
4	417	6.3 %
5	152	2.3 %
>5	114	2 %
III) Location of kitchen		
Outside the house	2217	33.4 %
Main living area indoors	1413	21.3%
Separate kitchen building	1271	19.1 %
Separate room in the house	209	3.1%
In another house	1065	16 %
Daytime outside; night inside	465	7 %
IV) Source of electricity		
None	6137	92.4%
Connected to power grid	162	2.4 %
Generator	58	0.9 %
Battery	65	1%
Solar power	218	3.3 %
V) Source of light		
Kerosene powered	6356	93 %
Candle light	16	0.2 %
Electric light	392	5.7 %
None/other	64	0.9 %
VI) Level of education of head household		
Pre school	76	1.1 %
Primary	4078	61.4 %
Secondary	1814	27.3 %
Higher	459	6.9 %
Non-standard	174	2.6 %
Unknown	39	0.06 %
VII) Land for farming		
Yes	1480	22.3 %
No	5160	77.7 %

Indicator	No.	%
VIII) Wall structure		
Wood and mud	4327	65.2 %
Bricks and/or blocks	1161	17.5 %
Mud and cement	489	7.4 %
Iron and sheet	565	8.5 %
Other	98	1.4 %
IX) Floor structure		
Carpet	3694	55.6 %
Cement	2480	37.3 %
Earth, dung or sand	442	6.7 %
Other	24	0.4 %
X) Roof structure		
Iron sheets	6559	98.8 %
Thatch	52	0.8 %
Asbestos	25	0.4 %
Other	4	0.1 %
XI) Screened eaves		
Yes	441	6.6 %
No	6199	93.4 %
XII) IRS sprayed within 12 months prior to visit		
Yes	2709	40.8 %
No	3604	54.3 %
Unknown	327	4.9 %
XIII) Bed nets reported		
Yes	6215	93.6 %
No	425	6.4 %
XIV) Bed nets observed		
Yes	4830	72.7 %
No	1810	27.3 %
XVI) Condition of nets		
Undamaged or new	3929	59.2 %
At least one breach	2301	34.7 %
Unknown	410	6.2 %
XVII) Other mosquito control		
Burning a mosquito coil	125	1.8 %
None	6257	94.3 %
Other	261	3.9 %
Total	6640	100%

Table 3.3: Summary of house information collected over the year 2013**.**

Future analysis plan

The HDSS data are a valuable resource when studying the parasitological, entomological and sociological [13] aspects of the malaria interventions. For example, the spatial and temporal distribution of malaria, and its vectors, in combination with environmental data, will be used to measure the effect of the introduction of odour-baited traps in combination with pre-existing widespread use of LLINs and case management. Other topics being studied are the emergence of malaria hot spots, models of the interaction between vector presences, and the spatial analysis of malaria. Data from the HDSS and the trial are used to parameterise mathematical models of malaria. However, this HDSS provides a platform not only to study and analyse malaria related outcomes within the SolarMal project, but also for other public health related research on Rusinga Island. From 2016 we establish prolonged monitoring of the intervention, and we strive to introduce eave screening to enhance the possible effect of odour-baited traps on malaria transmission. Furthermore, we will introduce verbal autopsy and various other standardised types of health related data. Knowledge, resources and objectives will be combined to equip the Rusinga HDSS with a broader scope of health-related subjects after the SolarMal project comes to an end.

What are the main strengths and weaknesses of the Rusinga HDSS?

A major strength of this HDSS is the innovative process for data collection in the field (OpenHDS and ODK) using tablet computers which simplifies the management of system-wide unique identifiers for individuals and houses and their linking to health- or intervention-related data. Point-of-capture digitization and the client-server architecture of the data management system saves time and money in terms of entering, accumulating, managing and processing data compared to its predecessor Household Registration System 2 [14]. Data quality is of great importance in a HDSS, and due to a digital data collection organization rather than a paper based system, the error rate of the collected data in the Rusinga HDSS is well below 1% according the quality metrics of iShare2. A weakness of the pioneering system in this phase is that support of a skilled software developer and data manager is required. Other applications with web interfaces that make this HDSS distinct are the real-time monitoring of demographic and health related events, keeping track of the performance of FWs and the use of geographical information systems to assist in precise navigation, and spatial research and analysis. Data can thus immediately be processed and used to facilitate all scientific disciplines in the project. Another strength of the Rusinga HDSS is the fact that it closely works

together with the interest groups in the study area. By communicating with community health workers, and delegates from different segments on the island, a sustaining cooperation and interaction has been created. In the future it would be possible to expand the system to capture information on other health outcomes.

A priority and an important improvement for the near future is the integration of verbal autopsies as part of the demographic surveillance.

Data sharing and collaboration

After the main publications of the effect of the SolarMal intervention are published, all basic data and descriptive maps are available through the INDEPTH network or the SolarMal project management.

Individual and household level data relating to demography or malaria for the purpose of new analysis are open to scientists in collaboration with Wageningen University. Please contact tobiassolarmal@gmail.com for any enquiries and queries regarding datasets of the Rusinga HDSS.

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Conflict of interests

None declared

KEY MESSAGES

- The Rusinga HDSS covers an island in Lake Victoria, Kenya. Living conditions and health indicators on Rusinga suggest to be better compared to HDSSs nearby.

- The Rusinga HDSS facilitates in-depth studies into the transmission of malaria. A trans-disciplinary intervention trial aiming for the elimination of malaria transmission is the core driver behind this surveillance.
- The HDSS uses the OpenHDS system which provides a cost-effective way to collect, store and manage data, as well as to safeguard quality assurance.
- The HDSS provide a robust foundation to conduct not only malaria research; future collaboration with local and international institutes will enable researchers to combine resources and interests.

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Evidence for improved quality/timeliness of data and cost savings

4. Assessing the population coverage of an Health Demographic Surveillance System using satellite imagery and crowd-sourcing

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Abstract

Remotely sensed data can serve as an independent source of information about the location of residential structures in areas under demographic and health surveillance. We report on results obtained combining satellite imagery, imported from Bing, with location data routinely collected using the built-in GPS sensors of tablet computers, to assess completeness of population coverage in a Health and Demographic Surveillance System in Malawi.

The Majete Malaria Project Health and Demographic Surveillance System, in Malawi, started in 2014 to support a project with the aim of studying the reduction of malaria using an integrated control approach by rolling out insecticide treated nets and improved case management supplemented with house improvement and larval source management. In order to support the monitoring of the trial a Health and Demographic Surveillance System was established in the area that surrounds the Majete Wildlife Reserve (1600 km2), using the OpenHDS data system.

We compared house locations obtained using GPS recordings on mobile devices during the demographic surveillance census round with those acquired from satellite imagery. Volunteers were recruited through the crowdcrafting.org platform to identify building structures on the images, which enabled the compilation of a database with coordinates of potential residences. For every building identified on these satellite images by the volunteers (11,046 buildings identified of which 3424 (ca. 30%) were part of the censused area), we calculated the distance to the nearest house enumerated on the ground by fieldworkers during the census round of the HDSS. A random sample of buildings (85 structures) identified on satellite images without a nearby location enrolled in the census were visited by a fieldworker to determine how many were missed during the baseline census survey, if any was missed. The findings from this ground-truthing effort suggest that a high population coverage was achieved in the census survey, however the crowd-sourcing did not locate many of the inhabited structures (52.3% of the 6543 recorded during the census round).We conclude that using auxiliary data can play a useful role in quality assurance in population based health surveillance, but improved algorithms would be needed if crowd-sourced house locations are to be used as the basis of population databases.

Introduction

Detailed, high resolution and up-to-date maps on human settlements are not available for many rural areas in low and middle income countries, but such information on human population distribution would be invaluable for measuring precisely the impacts of population growth, for monitoring changes and for planning interventions (1), in particular in the health sector. The absence of such information makes the planning and implementation of field studies of public health a challenge in these places.

One approach to resolving these challenges is to establish Health and Demographic Surveillance Systems (HDSS). An HDSS is a system that collects longitudinal data on core demographic events (births, deaths, migration, and relationships) and certain health indicators at regular intervals (normally between 3-4 times per year) from a target population in an area where government-based data for these events and indicators are unreliable due to total absence of a Civil Registration System (CVRS) in the area or improperly recorded data (2). HDSS are an importance source of demographic information in areas where routine vital registration is absent or incomplete and serve as sampling frames for intervention trials, providing a comprehensive list of households to be selected when monitoring trial outcomes. Without an HDSS, the absence of high resolution population maps makes establishing the level of population coverage inherently difficult.

The Majete Malaria Project (3) in Malawi (MMP) is an operational research project in southern Malawi that aims to increase community participation in malaria control through education and community engagement, and to study the impact of structural house improvements and larval source management on malaria transmission when implemented in addition to standard malaria control interventions (3).

Ensuring completeness and accuracy of the population database is essential for accurate characterization of core demographic as well as key health indicators in an HDSS, but ground censuses are labor-intensive, time-consuming, and are not necessarily complete. Unlike ground-truthed maps of house locations, high-resolution satellite images are generally available (4), and easy to access through an application programming interface (API). There are many popular or less popular available online as Google Maps, Bing Maps, OpenStreetMaps, and MapQuest... All provide similar services with some more specialized on a specific feature (traffic, driving directions, education etc…). Bing map was used rather than Google Maps because of a suspected incompatibility

between the OpenLayer library and Google Maps at the time of the development of the web application.

We present an approach for estimating the population coverage of an HDSS using geolocations of buildings, crowd-sourced from satellite imagery, to assess the completeness of the population data. This exploits features of the OpenHDS data system, which is increasingly used as a standard in HDSS sites, combined with volunteered geographic information (VGI) (5), and show the results of applying this to the area of the MMP.

A crowd-sourcing approach was used to collect geo-locations of houses in the study area of the MMP from satellite images. This was used to establish a database of building geolocations for comparison with that established from the census of the population by field teams, allowing us to identify buildings which were possibly missed in the HDSS census. The population coverage of the census for the HDSS was estimated on the basis of visits by a supervisor to a sample of locations identified as buildings on the satellite images but absent from the census database at the end of the census-round (ground-truthing).

Methods

Population

The HDSS is run in the Chikhwawa District, an area in the lower Shire River Valley region of southern Malawi. The district, mainly rural, has a population of over 530,000 people distributed in an area of about 4,800 km2 (6). Since starting in 2014, MMP has initially concentrated efforts in three regions, referred to for convenience as focal areas A, B and C, respectively. Focal areas were delineated to cover the same villages as those targeted by one of MMP's implementing partners, The Hunger Project (7), and spaced roughly evenly around Majete Wildlife Reserve (MWR) to capture a maximum amount of the ecological variation present in the area. Villages neighboring these three focal areas, but which were not covered by The Hunger Project, were not eligible to be enrolled in the HDSS.

Data System

The HDSS data were managed using the OpenHDS System (6,8,9). OpenHDS is an HDSS data system developed on a standard relational database management system (Mysql, Postgress, MS SQL Server etc.), designed and developed to enable simpler and

more robust data collection and data management routines than possible with paper-based data collection traditionally used in population-based surveillance. Data collection in the field uses an application running on tablet computers.

The OpenHDS System (8,10) was set up at the startup of the HDSS in Majete, requiring installation of server components of the system on local server. The OpenHDS system is interfaced with the Open Data Kit (ODK) an open source suite of tools to author, manage and run data collection with mobile devices (11). Samsung Galaxy Tab-3 Android tablets running the version 4.1.2 of Android (Jelly Bean) (12) were configured with the OpenHDS mobile (13) and the ODK Collect (14) applications, to communicate with the ODK Aggregate (11) and OpenHDS web (15) component through the wi-fi network at the field station.

During the census, demographic surveillance visit to each location in the study site, location coordinates were captured through the tablets' in-built GPS to build a database of inhabited buildings. This approach allowed the aggregation of data points in a central database in near-time, i.e. within days after a house was visited.

Field data collection

12 fieldworkers recruited from the target communities for their knowledge of the area and to ensure good relations with the communities were trained on the use of the OpenHDS mobile system.

Each HDSS has a defined location hierarchy in the area under surveillance. The lowest level of this location hierarchy is the one leading the ID generation for the HDSS entities and is important in our study for the identification of houses that became part of the ground-truthing (see section "Ground truthing"). A complete list of the villages (lowest location hierarchy level) was obtained from African Parks-Majete, the management authority of MWR and implementing partner in MMP. In the area targeted for the HDSS surrounding MWR, there are 62 villages (Figure 4.1).

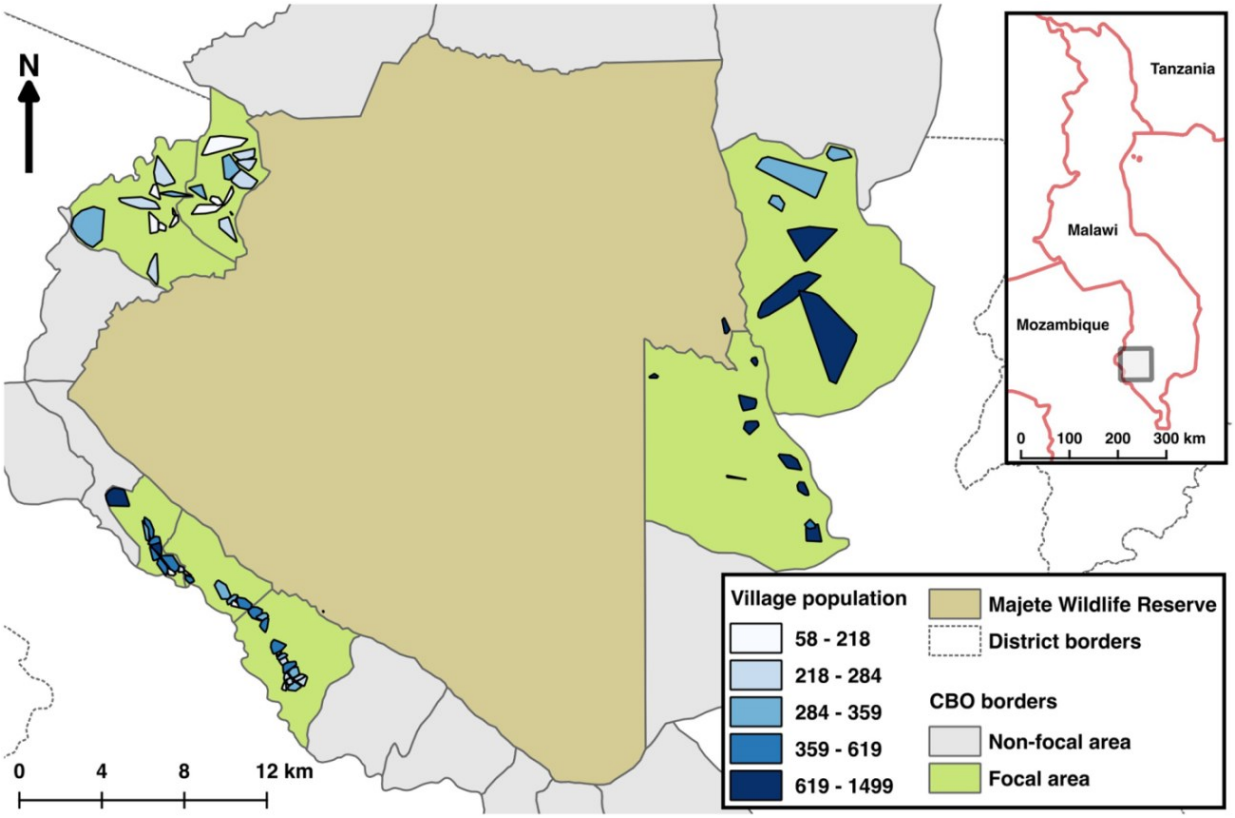

Figure 4.1. **Map showing Majete Wildlife Reserve, surrounded by 19 groups of villages known as community-based organizations (CBO).** The 62 villages enumerated in the current study are located in three focal areas. Village populations are as indicated in the legend (Reprinted with slight modification from Kabaghe et al 2017 under a CC BY license, with permission from PLOS, original copyright 2017).

At village level during the census round, the fieldworker collected location information where individuals were living. This task was performed through OpenHDS mobile integrated with the ODK collect application. After the login into the OpenHDS mobile application, the fieldworker had to select the village where the house was located, going through selecting the hierarchies available in the OpenHDS mobile (Figure 4.2). Once he selected the village, he had to create the location by pressing the create location button. An ODK Xform was automatically opened on the tablet, pre-filled with data previously selected in the OpenHDS app, plus a unique ID identifying the fieldworker, a unique ID associated to the location automatically generated through the OpenHDS mobile application according with the INDEPTH standardized identifiers (4,15), and the date of the visit to the location. At this point, the coordinates of the location were recorded by the fieldworker using the GPS sensor of the tablet. If the sensor reported accuracy of 5 meters or less, the coordinates were recorded automatically. In cases where such accuracy could not be reached due to weak GPS signal, the fieldworker was

allowed to manually accept a positioning with lesser accuracy. The information of the locations was then transferred to the system central database.

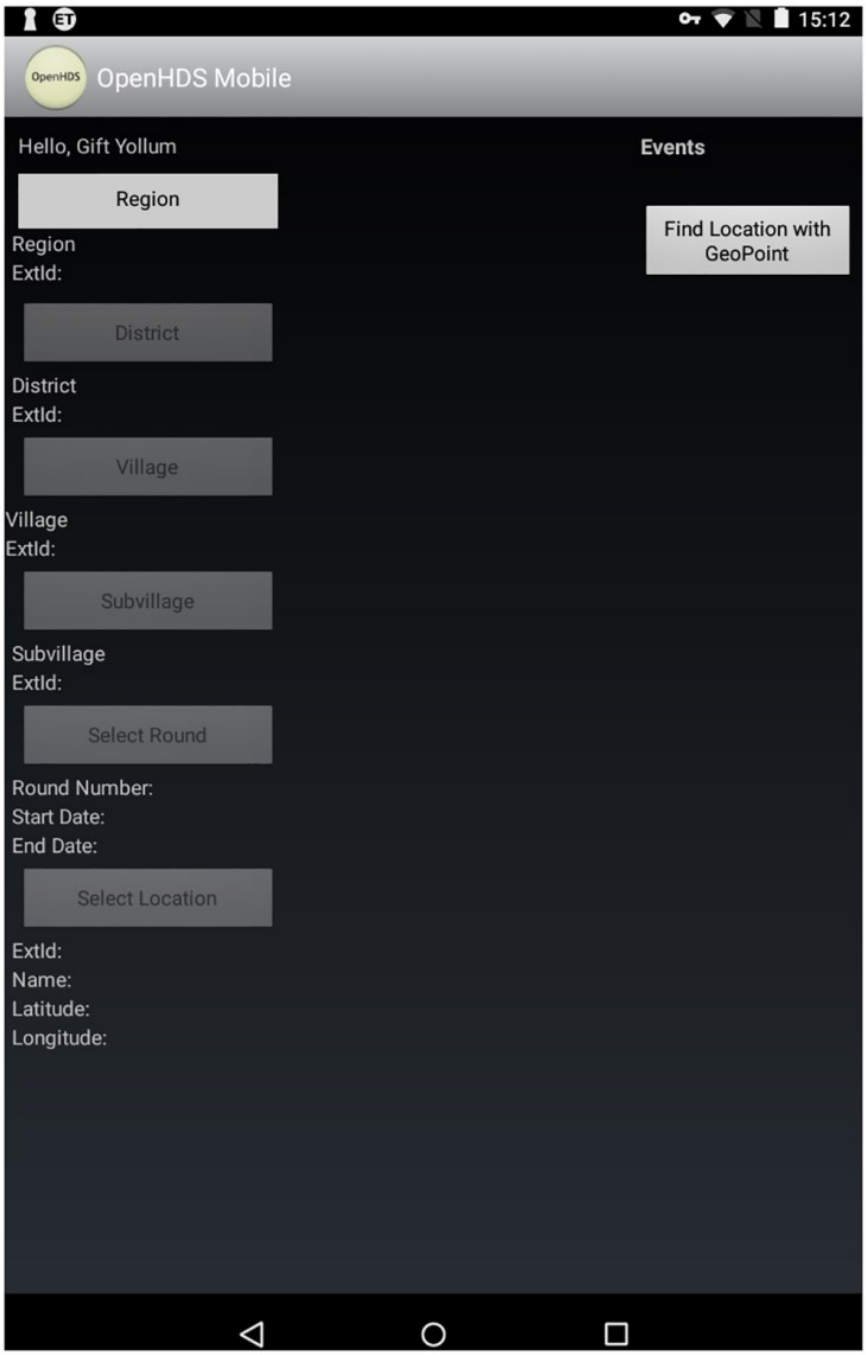

Figure 4.2. OpenHDS mobile application snapshot of location hierarchy selection.

Volunteered locations

A software application called Rural Geolocator was developed using the PyBossa framework (17) and the Openlayers library (18) to present satellite images from Bing (19–21), of the study areas in a web-browser (22). PyBossa (inspired by the Bossa platform(23)), is an open-source platform for applications using human interaction or recognition through the help of volunteers (crowd-sourcing) to obtain information that

a machine alone cannot easily deduce. Rural Geolocator was hosted on the easily accessible crowd-sourcing platform named crowdcrafting.org (24–26) (Figure 4.3). Volunteers were recruited via this platform by advertising the project on crowdcrafting.org, and on social media. The volunteers were provided with a simple and well defined task each time, which consisted of visually inspecting a small section of the study area (300-350m x 500-600m) and marking all potentially inhabitable structures using mouse clicks. If no houses were spotted in the determined area, the volunteer would submit the task without marking anything. Tasks were replicated at least three times, i.e. each section was processed by a minimum of three different volunteers. Volunteers were distinguished either by their user id (for registered volunteers), or on the basis of the IP address of their computer (for anonymous volunteers). Replicate results submitted for each task were consolidated using the following clustering approach: contributed geolocations were processed sequentially and added to a set of points, but only if the set did not yet contain a location less than 10m away. In case such a location was already in the set, it was replaced with a location mid-way between the contained and currently processed point. The number of replicates contributing to each of the geolocations in the resulting dataset was recorded.

Figure 4.3. Rural Geolocator: A web-application for identifying houses on satellite images by visual inspection (illustrative purposes only)**.**

The tasks processed by the volunteers were grouped into three batches corresponding to the three focal areas described above (A, B, and C). The batch sizes for focal areas A, B and C were and 682, 2953, and 1031 tasks, respectively. The area covered by each batch was defined prior to the completion of the HDSS census, and therefore the spatial extent of each batch was greater than the village borders eventually identified by the HDSS census.

Ground truthing

At the end of the census, crowd-sourced geolocations were compared with the GPS-based coordinates collected by the study team to identify locations which were potentially missed in the census. In a first step, data points from the census were processed by grouping the points according to the village in which they were collected using the location id assigned by the fieldworker. A convex hull was placed around the points in each village (27). Next, the crowd-crafted geolocations were processed sequentially. Points that were located outside a village defined by the convex hull described above were discarded, assuming that these locations were unlikely to be valid locations for the HDSS villages. Points inside a village were classified as either “near” if a geolocation from the census was closer than 40m, or flagged as “distant” if this this was not the case (Figure 4.4). The rationale for this was that research assistants would visit any house they could see while walking through a village, and we considered it most likely for “distant” locations, if any, to have been missed by the field team’s visual assessments. A random sample of 85 of these locations were mapped and provided to a supervisor for “ground-truthing” to determine the nature of these potential discrepancies, and to estimate the coverage of the population during the census. Fieldworkers, guided by the generated maps and by the coordinates collected for each location, visited the randomized candidate locations and recorded what they observed there. The goal was to verify if these “missing” houses in the census round were meant to be part of the HDSS or for any reason were correctly excluded.

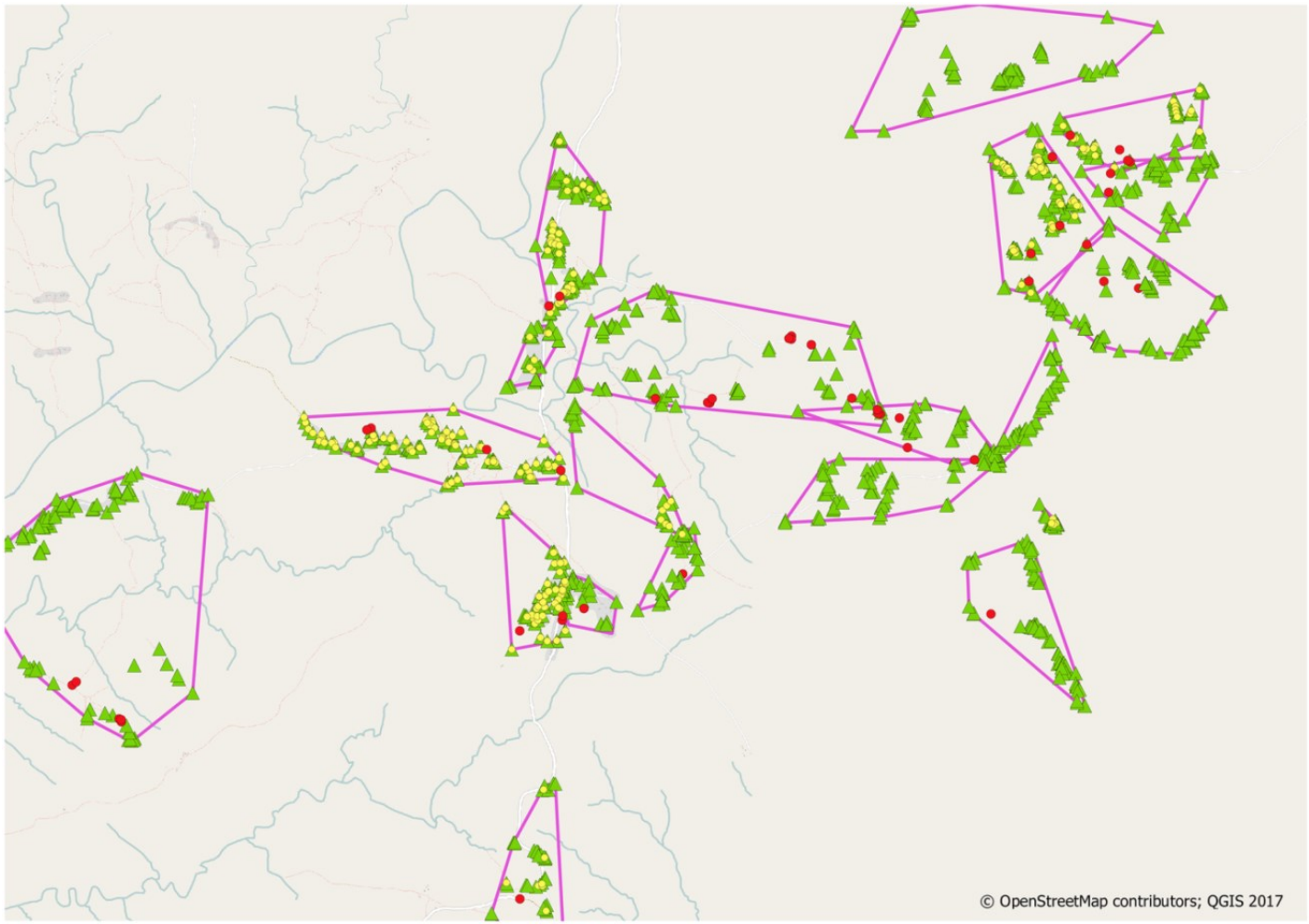

Figure 4.4. Overlay of crowd-sourced and ground-collected locations. Red pins denote candidate locations for a visit during ground-truthing, i.e. volunteer-provided locations without a GPS-collected match. Green pins are the location recorded as enumerated houses by research assistants during household interviews. Yellow pins are geolocations far from the census one but closer than 40m.

Only locations that were identified in all three replicates were eligible for a ground-truthing visit, as the limited time available for visits was focused on the most promising candidate locations.

We also tested if there were houses which were enrolled during the HDSS census but absent from the set of locations identified on satellite images. We used an approach analogous as described above, i.e. we classified HDSS locations as "distant" if they did not have a nearby location among the set of locations identified on the satellite imagery, again using a threshold of 40m.

Ethical consideration

Ethical clearance for the HDSS was obtained from the University of Malawi, College of Medicine Research Ethics Committee (COMREC) in Malawi (P.05/14/1579). Permissions were obtained from the Ministry of Health and the district health authorities in Chikwawa District. Prior to the start of the study, a series of meetings were held in participating communities to explain the nature and purpose of the study. We obtained individual written informed consent from all participants.

Results

The census round in the MMP projects started on 20 August 2014 and ended on 14 November 2014, data were collected in one additional village in February 2015. During this census round 6,543 locations and 24,129 individuals were registered in the OpenHDS System.

A group of volunteers from more than 30 different countries contributed to the crowd-sourced geolocation effort (Figure 4.5). 299 registered volunteers (i.e. with a user account on crowdcrafting.org) processed a total of 10,445 task replicates, and unregistered volunteers processed 3,091 task replicates connecting from computers with 174 distinct IP addresses. The processing of the all 4,306 tasks representing the study area was completed within four months.

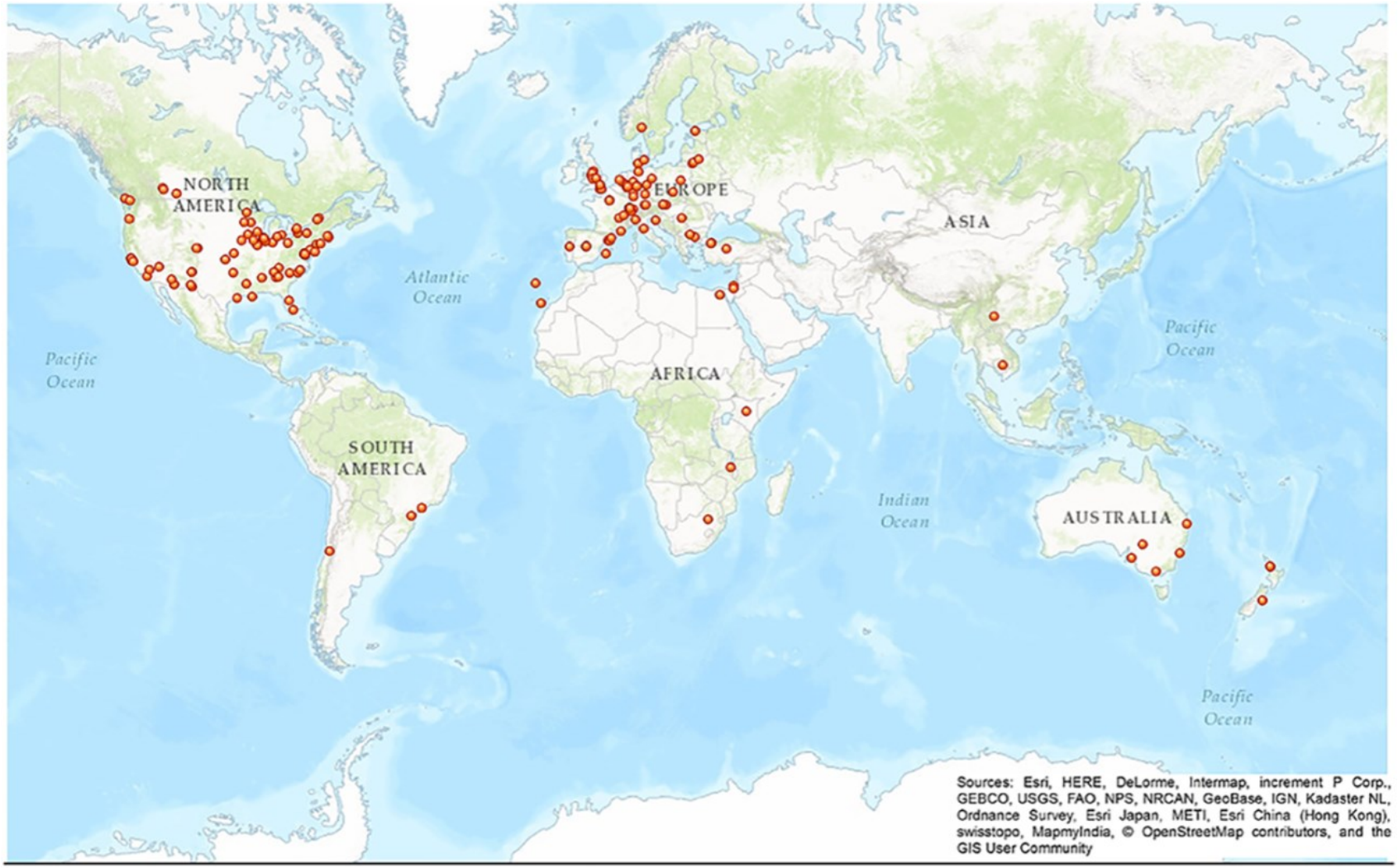

Figure 4.5. Geographic distribution of volunteers who contributed to the geo-location of buildings.

Volunteers contributed a median of 7 task replicates each, but the distribution of task replicates was highly overdispersed, with the top 20 contributors having processed roughly 50% of the tasks (Figure 4.6).

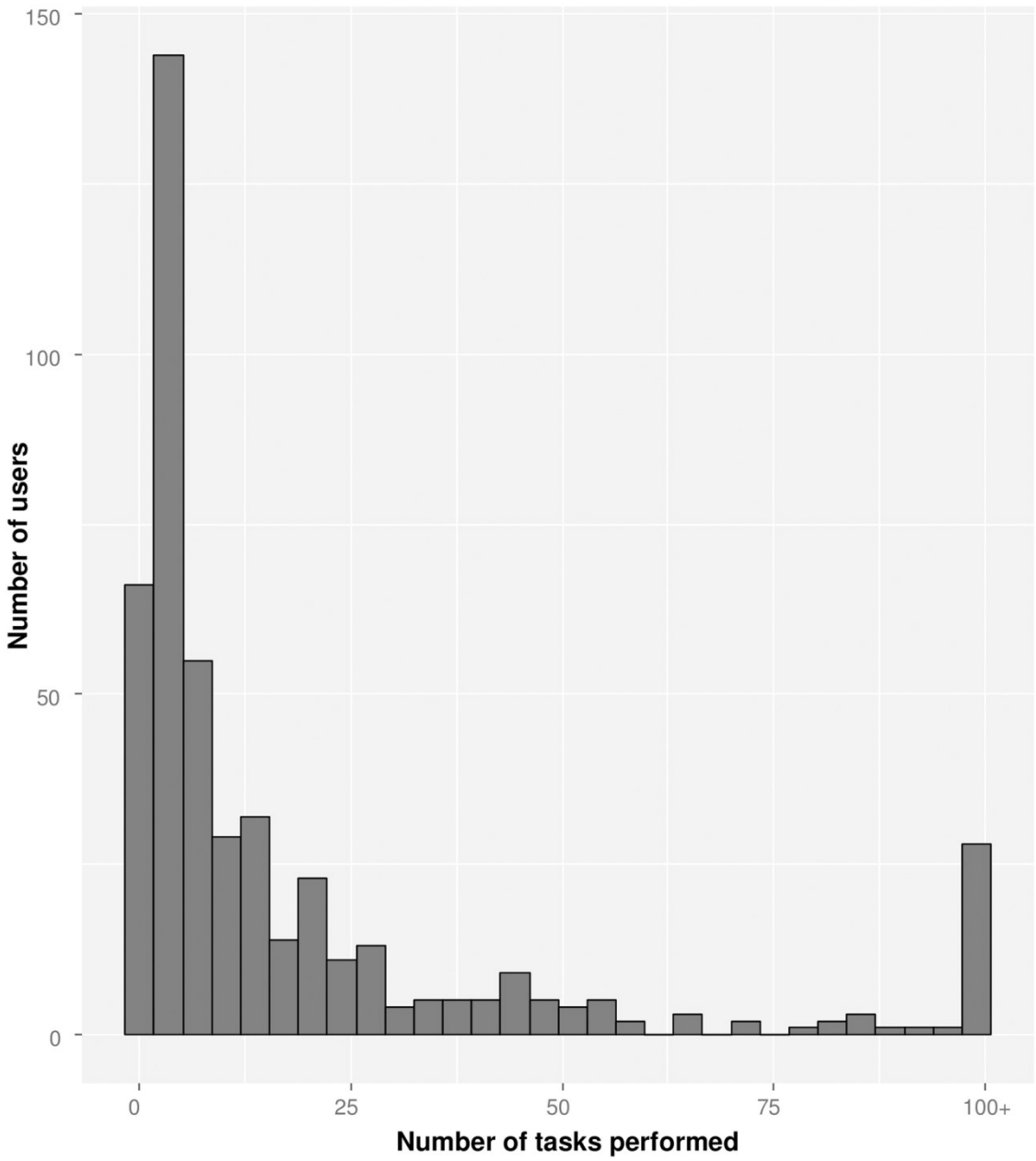

Figure 4.6. Distribution of numbers of tasks contributed by volunteers. The bin labeled "100+", contains volunteers who completed 100 or more tasks.

The data processed and the results of the crowdsourcing are available to be downloaded from the Crowdcrafting.org website (28).

A total of 62,946 geolocations were submitted via mouse-clicks by the volunteers. When applying the replicate-consolidation algorithm to cluster points, a total of 26,247 suspected houses were identified. Of those, 11,046 (42.1%, 95% confidence interval

0.4149 to 0.4268) were confirmed by being identified in all three replicates, and 3,424 of these were within the censused areas (Figure 4.1). 445 (13.0%, 95% confidence interval 0.1189 to 0.1412) of the volunteer-provided locations within the censused areas were "distant" from the GPS location of the nearest of the 6,543 inhabited houses identified in the HDSS census. Table 4.1 provides these results disaggregated by focal area. Conversely, 1,490 of the GPS locations of inhabited houses identified in the census were "distant" from the nearest confirmed crowd-sourced location, and 279 censused houses were "distant" from the nearest crowd-sourced location on any of the replicates (Table 4.2).

	Focal Area A	**Focal Area B**	**Focal Area C**
Mouse clicks (across all replicates)	6749	30235	25962
Locations identified (through clustering of mouse clicks)	2769	12780	10698
Houses (identified in all three replicates)	1143	5444	4459
Houses eligible for ground-truthing (as above, but also within a village)	576	1003	1845
Houses identified as "distant"	62	205	178

Table 4.1: Locations found on Satellite imagery

	Focal Area A	**Focal Area B**	**Focal Area C**
Houses enrolled in the HDSS census	1,157	2,275	3,111
Houses enrolled in HDSS census which were "distant" compared to the satellite-located houses identified in all three replicates	320	670	500
Houses enrolled in HDSS census which were "distant" compared to the satellite-located locations identified in at least one replicate	122	101	56

Table 4.2: Locations found in the HDSS census

In all 85 cases where all three crowd-sourcing replicates identified a house that was absent from the GPS database, ground-truthing indicated that the location had been correctly excluded from census (Table 4.3). Most of these potential locations vacant or abandoned houses (37 cases, 43.5%) or non-residential buildings such as churches and schools (30 cases, 35.3%).

Classification	Number of occurrences	Comments
Empty House	37	Uninhabited or abandoned house
Non-residential building	30	Schools, churches, health facilities, shops
Not eligible during census	6	Constructed or vacant during census
No building	6	Tree, anthill, open space
Other reason	4	Indistinguishable from census house
Refused consent	2	Inhabitants refused consent for participation in the census

Table 4.3: Classification of ground-truthed locations: 85 locations were visited after census because the satellite image-sourced locations showed a potentially missed house.

For a small number of locations, classification on the ground was not possible. None of these locations were inhabited houses that had been missed during census when empty houses were not taken into account in the system. This indicates that a high percentage of the population coverage was reached using the OpenHDS system in the census round of the HDSS.

A total of 1,490 of the locations visited during the census were found to be distant from all houses identified by volunteers in all three replicates of a task (Table 4.2). This number was reduced to 279 when considering all locations identified by clustering clicks (irrespective of their presence in other replicates).

Discussion

The collection of volunteer-provided geolocations for a sizable study area required about the same elapsed time as the ground survey. The crowd-sourcing provided a convincing check of the coverage of the ground census, demonstrating that the HDSS achieved a high coverage of the population of the study area.

However, as implemented, the crowd-sourcing missed many of the inhabited locations.

The cost of crowd-sourcing was negligible because the PyBossa software is a publicly available resource.

The number of houses identified in all three replicates processed by the volunteers, deemed “eligible for ground-truthing” in Table 1 was much lower than the houses enrolled in the HDSS census in the same area. This was both because close-standing

buildings cannot always be distinguished on the satellite imagery, and because the algorithm chosen for consolidating replicates groups nearby buildings into single locations.

For the application described here this is of no consequence, except that it introduces an asymmetry between the HDSS and volunteer-provided locations which makes it difficult to compare some results in absolute numbers. For example, the 455 points identified as distant probably represent a higher number of buildings. We think that it would be scientifically interesting to follow up with a more detailed analysis using a supervised learning algorithm (29,30) to explore the potential for locating houses in some of the areas from the volunteer provided data, and then test how it works on the other area(s).

The large number of houses enrolled in the HDSS but not identified in all three replicates of a task was not expected and merits some discussion of possible reasons. One factor that may explain the classification of HDSS-enrolled houses as distant is that for a number of those databases records the reported GPS-accuracy was substantial (up to 50m). A more detailed analysis showed that many of the HDSS houses had close-by analogues in at least one of the task replicates. This raises a number of questions related to the optimal way of presenting tasks to volunteers.

The first concerns the number of replicates. Is three replicates per task are sufficient, or would a higher number of replicates provide a more solid foundation for distinguishing reliably located buildings from spurious mouse clicks? There were 164 tasks in which one replicate was submitted with no clicks, but more than 10 clicks in both other replicates, suggesting that a quorum smaller than the replicate number might increase the quality of volunteered data.

The second is related to task size. It may be useful to make the task size (i.e. the area to be inspected as part of a task) smaller. Due to a glitch of the PyBossa software at the time of the data collection, we lack information on how long it took a volunteer to process each task replicate. This issue has since been fixed, and we recommend that future applications focus on this metric for optimizing the size of the task.

Most of the volunteer work was done by a small number of individuals, whereas most volunteers stopped contributing after a small number of tasks. It is possible that simpler tasks (i.e. smaller area to analyze) would lead to a volunteer contributing more task

replicates. Further, it might be possible to identify incentives for those who only contributed a few results to do more, rather than spending effort on recruiting more volunteers (31).

To our knowledge this is the first time that VGI has been employed in an effort to establish the population coverage in an HDSS, and the approach is an important addition to the tools available to HDSS program managers, allowing them to ensure that the entire population was covered during the census or successive rounds. The approach is easily transferable to other areas, and could be used to estimate coverage in any surveillance system which requires geo-locations of houses.

Beyond using the approach described here for quality control in population-based surveillance, we see further applications in the planning of observational or intervention field studies. Potentially, crowd-sourcing of such images could provide improved sampling frames for household surveys, even in areas where there is no population database. This could even be used for generating samples stratified according to other characteristics identifiable on satellite images (e.g. vehicles, or gardens etc.). Similarly, crowd-sourcing could be used to count or localize the numbers of such features within a research area for comparison between different areas. All of these extra studies could be also decided after the data collection and not predetermined a priori.

In general crowdsourcing projects have an outreach component (citizen, civic or amateur science), and the benefit is probably more than the data because people learn about the research (32,33).

VGI (5,34,35) and crowd sourced data (geodata) (36–39) have changed the collection of digital spatial data. This volunteer approach is giving us a new way to improve the data collection, and new ways of comparison.

In last 3-4 years computer image recognition has improved significantly (40), but still this kind of technology is limited to the pharmaceutical or military industry, or in general to research with funding behind and that needs fast response, and analysis of the data, so in general algorithmic image analysis of such remote-sensed images is still challenging (41–43).

Developing and tuning an image analysis application is technically challenging, while crowd sourcing data is relatively straightforward and can be implemented quickly. On the other hand, the problem of identifying houses on satellite images is recurrent and will not go away because even existing population databases need frequent updating, so it is probably worth investing in automating it. VGI, combined with the ground-truthing methodology presented here, may contribute to the process of training image recognition algorithms.

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5. Migrating an established DSS site to OpenHDS: evidence for improved quality/timeliness and cost

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Working paper

Introduction

Health and Demographic surveillance systems (HDSS) can provide valuable information in geographic zones where vital registration systems are not present or not running at an acceptable level, and play an essential role supporting health intervention studies in such areas. Setting up and running an HDSS is operationally challenging, and requires a reliable and efficient platform for data collection and management. The advent of affordable information technology including hardware and software has opened new opportunities to eliminate some of the problems posed by paper-based HDSS which were the standard instruments for collecting data in household surveys. Mobile technology that in the past was considered a luxury, is nowadays common everywhere in the world including low and middle-income countries (LMIC) (1,2). Most non-governmental organizations (NGOs) or research institutes provide their staff with new generation mobile devices (smartphones).

Using mobile devices for data collection (EDC) brings with it some advantages. The data is entered only once and the data clerk role is not needed anymore. Validation can be done directly at data collection time using constraints, and enumerators can rely on advanced features for guidance, like the conditional display of questions available with electronic forms ("skip logic"). EDC is faster than paper data collection (PDC), partially because of skip logic that makes it possible to avoid questions on the basis of previous answers. The more complex and long the survey, the more time is generally saved (3). Data can be sent in near real time to a central database for analysis and review. A substantial part of the review protocols can be automated, where reports of data issues can be made available to data managers and management via email or dashboards. In addition, this allows for the near real time possibility to review and amend data collection instruments and processes.

EDC and adoption of data management best practices using OpenHDS software (Figure 5.1) have the potential to resolve many of the major shortcomings of running a paper data collection HDSS. Together with the possibility of cleaning data inside OpenHDS (4–7)

this can give a huge advantage in term of promptness to fix errors and the possibility of accruing high quality data. Integration of OpenHDS with external tools to calculate demographic rates (e.g. INDEPTH IShare2 tool) (8,9) further expands the options available to analysts and data managers for obtaining statistics and demographic rates and reviewing the data from any single application.

This chapter reports an evaluation of the hypothesis that the system is superior to previous approaches with regard of quality and timeliness of data and running costs of the system.

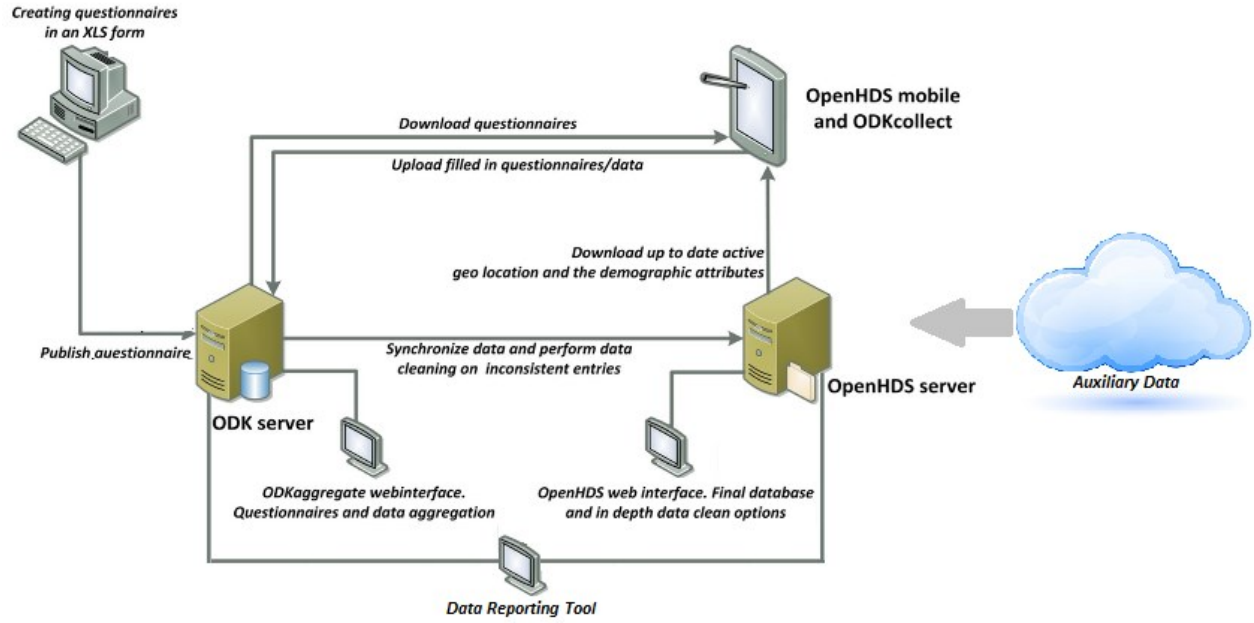

Figure 5.1: OpenHDS System Architecture

Specifically, four of the six data quality dimensions proposed by DAMA UK (10) (completeness, uniqueness, timeliness, consistency) were compared, as well as the costs for setting up and running a PDC vs a paper-free data system. The PDC system was compared with the Household Registration System 2 (HRS2)(11), which has been in widespread use over many years in HDSSs.

Methods

The study was performed in the Nanoro HDSS site (12), situated in Central West region of Burkina Faso (85km from Ouagadougou) and including 24 villages with 63’000 inhabitants, 11’500 households at 5’500 distinct locations (Figure 5.2). This site migrated to the OpenHDS system from the previously used HRS2 in June 2015.

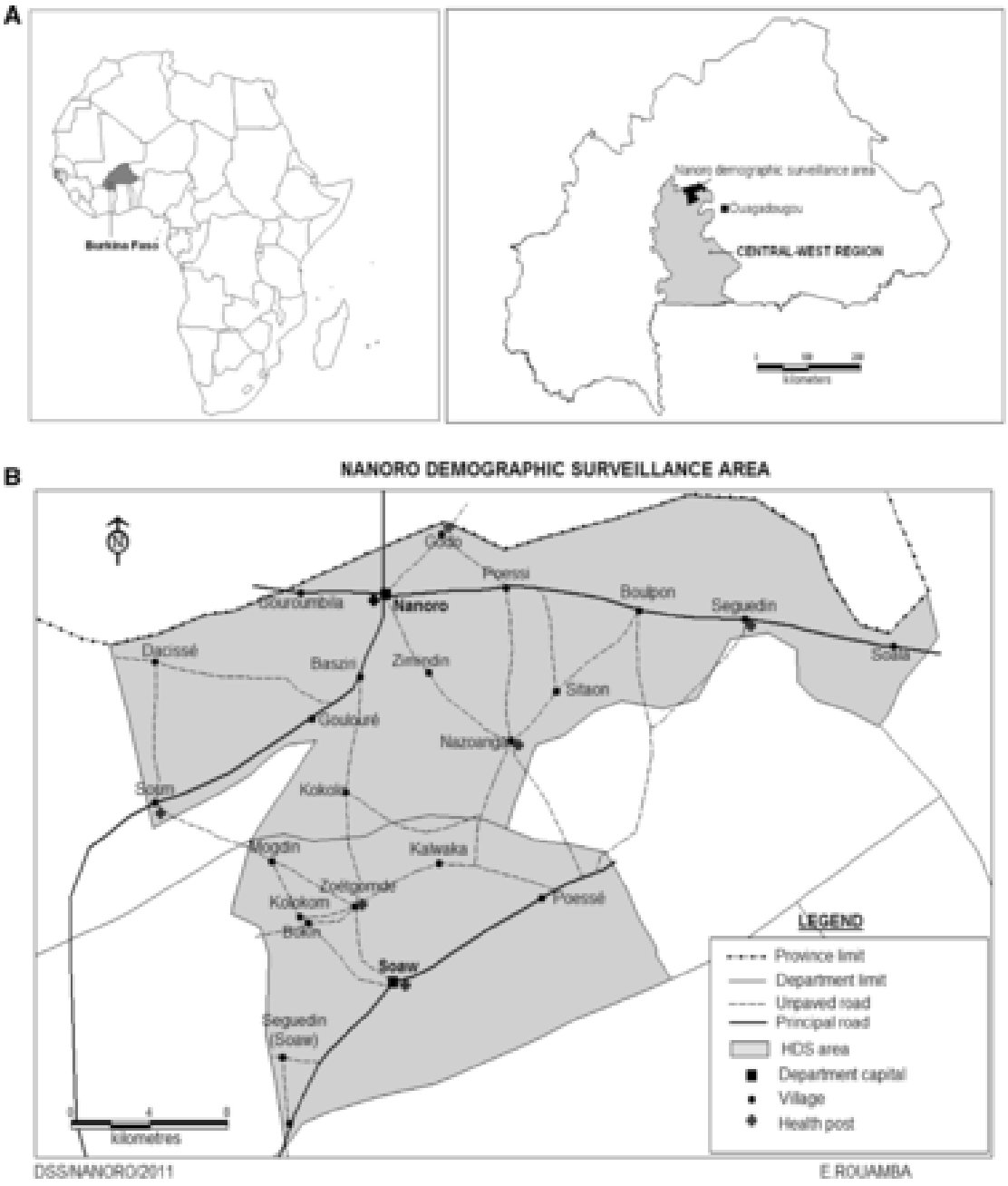

Figure 5.2: Site maps. (A) Location of Burkina Faso in Africa and the Nanoro site area in Burkina Central West region. (B) Nanoro Demographic Surveillance Area

The HDSS started in 2009 and had followed up the target population for 14 update rounds prior to the study. The starting point for this study was then a migrated pre-round 15 databases in OpenHDS and HRS2 (the basis to migrate the data to openHDS was to clean the HRS2 one). The study to compare quality and effectiveness of the electronic data collection was conducted by collecting one round the data for a subset of 8 villages in parallel with both OpenHDS and with the traditional paper-based approach.

Data Quality

The villages were randomized to select 8 of the 24 villages as first step (all villages are in rural areas and we hypothesized there were no relevant appreciable differences of possible collected data between villages). During the round, fieldworkers were sent in pairs to the same location to record the vital events with the two data collection instruments. Fieldworkers had the same skills and had the same training on data collection for HDSS. To avoid bias introduced by the person the two fieldworkers were alternating during data collection to work 50% with the tablet and 50% with the paper.

The Quality measures taken into account in the study were:

-Timeliness: Distribution of time difference between visit to a household, and availability in the central database (i.e. availability for use by and analyst or supervisor) To evaluate this, the differences between date of the visit to the household on round 15 and the data entry of the record on the systems were compared.

-Completeness: the proportion of stored data against the potential of "100% complete": this was challenging to assess in practice. An extra complication was due to the fact that some Social Groups were added in the HRS2 system after the start of the data collection (they were registered on round 14 but there was no time to enter them on both openHDS and HRS2 system baseline for this study). The number (by type) and identity of events collected by the two methods in the village were compared, computed by difference between the baseline database and that obtained post-entry and cleaning of round 15. These outcomes are presented in the form of sets, where we assume the union of HRS2- and openHDS-collected data after removal of duplicates (see below) represents 100% completeness.

-Uniqueness: Number of entities in real world/Number of records describing different entities. Duplicate entities (individuals, locations, socialgroups) and events were identified based on their attributes, to establish the number of duplicates introduced in round 15. In case of the enrolled entities the uniqueness was based on unique associated ID (INDEPTH standard identifiers). Events were assessed according to ID of the entity associated, the date of the event (e.g. for Inmigration the individual ID, the location ID, and the date of migration were checked).

-Consistency: The absence of difference, when comparing two or more representations of the same thing against a definition: We use some of the quality metrics defined by the iShare2 project to assess consistency. In particular, we use the iShare2 ETL (8,13) for auditing data quality to calculate the following metrics for both databases: illegal start events (the first event must be Enumeration, Birth or Inmigration), illegal end

events (the last event must be End of observation, Death or Outmigration), illegal transitions (Figure 5.3).

The data entry for HRS2 was performed by 4 data clerks full time working on data entry, while for openHDS we had a data manager who performed the data cleaning when records were rejected from openHDS and reset a flag on the database for the record to be reprocessed- This operation was less than full-time work for the data manager but was performed on a "when needed" basis. The openHDS system sent automated emails with records that failed the validation process and the data manager he started the cleaning process only when he received those records.

Event Codes	ENU	BTH	IMG	EXT	ENT	DTH	OMG	OBE	None
ENU									
BTH									
IMG									
EXT									
ENT									
DTH									
OMG									
OBE									

Legend: Event codes:
ENU: Enumeration; **BTH**: Birth; **IMG**: Inmigration; **EXT**: Exit event;
ENT: Entry Event; **DTH**: Death; **OMG**: Outmigration; **OBE**: Observation End

	Legal Transition
	Illegal Transition
	Legal in case of multiple movements

Table 5.1 Table showing transition checks (source iShare2 Project)

Costing

One expectation frequently stated by site leaders is that switching to EDC leads to substantial cost savings compared to PDC. There are some documented cases in the literature about cost saving (14,15). Some anecdotal evidence from sites that switched to electronic data capture indicates some of the advantages of the new system that could lead to significant reductions in cost of the program.

"The elimination of big amounts of paper, the reduction of physical persons previously involved in the study (data clerks), the fact that we don't need any more archiving physical space to keep the data collected, the cut on expenses to transport the data just this induce to think that costs are reduced using EDC vs. PDC." (16)

However, there is currently no solid data to substantiate the claim that an integrated data management system like OpenHDS indeed reduces the total cost of ownership of an HDSS data system. We investigated on how the system costs compare to a traditionally run system by doing a detailed costing analysis, in collaboration with the Burkina partner in Nanoro as a second issue to investigate during the visit planned on site (17) of major cost drivers (personnel costs, cost of stationery, etc…).

The approach on data cost we chose to perform this analysis is the bottom up costing methodology, also known as micro-costing (18,19). To conduct the micro-costing, the inputs were precisely identified and measured the inputs required for running the HDSS, and then converted everything into value terms to estimate the cost.

This allowed not only identification of differences in cost of the two programs (EDC-PDC) at the aggregate level but also pointed to specific activities and resource categories where cost savings are realized.

Once this approach was selected the next steps were to:

Identify the activities involved in running the HDSS

Identify the types of inputs such as personnel, equipment, materials and supplies needed to undertake a specific activity

Identify the discrete unit by which each input is counted

Assign a monetary value to each input unit

Estimate the quantities of each of the units required to complete the specific activity

Multiply the unit costs by the quantities required to obtain input cost estimates

Add the input cost estimates together to get a total activity cost estimate

The cost of paper data collection was obtained by reviewing historical program data from Nanoro HDSS site from 2014 (the year before the switch to electronic data

collection was implemented). The cost of establishing the openHDS system for data collection, cost of change in policy, as well as operational costs post-implementation were assessed from 2015 accounting records at the same site.

The costs we compared between EDC and PDC are thus financial costs that represent current expenditures on goods and services and economic costs that define costs in terms of the alternative uses that have been forgone by using a resource in a particular way.

Cost classification

Costs of running a HDSS may be classified by input type (Capital or recurrent costs); and or fixed or variable costs.

Resources that are utilized within a year and are purchased regularly should be categorized as recurrent, while resources that last longer than a year should be considered capital goods. Table 5.2 provides a summary of recurrent and capital costs.

Capital costs	Recurrent costs
➢ Building space: fieldworker office, data unit office, administrative offices, IT office, storage facilities ➢ IT equipment (Server, Tablets, Laptops, printers) ➢ Vehicles: bicycles, motorcycles, four-wheel-drive vehicles, trucks	➢ Personnel (all types): administrators, fieldworkers, data management, IT staff, geographers, demographers. ➢ Recurrent training costs : trainer/facilitator costs; participant travel and per diem costs; ➢ Building maintenance and utilities: plumbing, roofing , painting, electrical repairs, electricity, water, sewage, and telephone ➢ Vehicles maintenance and operation: fuel, lubricants, spare parts, registration and insurance ➢ Other travel costs including staff per diems for outreach activities ➢ Other recurrent operating costs

Table 5.2: Classification of routine HDSS costs by input type

To calculate the value of capital goods, the replacement value or purchase price of the good was spread over the lifetime of the item. When calculating financial costs of a capital good, it was assumed that an equal proportion of the good was used each year and the replacement cost of the good divided by its useful years of life.

If calculating economic costs, the alternative opportunities for having resources reserved for the capital goods was evaluated. This was done by estimating the interest income not earned during this period. Thus, to estimate the annualised economic cost of capital items we used a discount rate of 0.05.

When resources, such as personnel and building space, were used by more than one service, the shared costs attributable specifically to HDSS services was estimated. To calculate the value of these resources, the proportion that is used for HDSS services was estimated based on clearly stated assumptions. For example, in a situation where a data unit spends a proportion of his time on HDSS data, a similar proportion of the data manager's salary was allocated to HDSS program costs.

Costs of HDSS were divided into start-up, HDSS management, survey management, and service routine costs.

When a HDSS is starting or is being modified (e.g. introduction of EDC) then we talk of start-up costs. Start-up costs relate to activities that are conducted at the beginning of a project or program and rarely repeated such as such as planning, training of staff and development of information and communication materials.

Planning for new programs includes meetings to develop a strategic action plan and timelines. Training of providers on implementation of the new program includes workshops, meetings, training publications, training related travel, including training per-diems. The core training should be distinguished from refresher trainings which occur annually. To estimate resource requirements for training, the program manager should estimate the value of the resources used such as the facilitators' fees.

The other start up activity is development of communication materials. This activity includes the preparation activities for IEC and social mobilization such as material development and printing of materials or production of radio/air spots. Table 5.3 presents the types of resource requirements for start-up activities by whether these are financial or economic costs. If start-up costs are included in the costing analysis, then they should be treated as capital costs and annualized over the expected lifetime of the program.

Start-up activities	**Financial Costs**	**Economic Costs**
Planning	➢ Rental of meeting location ➢ Development of meeting materials	➢ Rental of meeting location ➢ Participants' time

Training	➢ Facilitators/trainers' time ➢ Development of training curricula ➢ Venue rental ➢ Per diem and travel expenses for facilitators and trainees	➢ Facilitators/trainers' time ➢ Training Curricula ➢ Venue rental ➢ Participants' time ➢ Per diem and travel expenses for facilitators and trainees

Table 5.3: Breakdown of start-up costs

HDSS management costs includes costs as planning of rounds and strategy; training of field workers on routine data collection and protocols; production of information and education materials; surveillance, monitoring and evaluation; and programme personnel. There are three main survey management parts: survey implementation, data collection, supervisors' monitoring of data collection activities, staff undertaking data management activities (Table 5.4).

Function	Costs
Survey implementation	➢ Planning and design ➢ Staff time spent on survey implementation
Storage	➢ Warehouse/server room rental ➢ Maintenance and utilities of IT and server space ➢ Data manager team time
Management	➢ Fieldworkers salary cost ➢ Transportation management ➢ Drivers salary cost ➢ Drivers per diem ➢ Fuel and vehicle maintenance

Table 5.4: Cost components for the Survey management

Results

The "Timeliness" validation showed (Figure 5.4) that while with the openHDS system the data started to flow in the database the same date it was collected, that in the first 5 days 73.9% of the data collected was already available for analysis and that the system was "ON" 23 days (there are 23 different insert dates).The maximum delay before a record was cleaned and passed the validation in openHDS was 209 days.

Before the data was entered in the HRS2 system, after it was collected, reached the Nanoro Data center and the data clerks were able to start the data entry the first record had to wait 167 days, and it took 43 days and 4 people working before 76% of the data was in the HRS2 database for analysis. The record that entered the system with most difference between visit and date of entry had to wait 300 days.

A summary of the analysis is available in table 5.5.

	Min.	Median	Mean	Max.
HRS2	167	244	245.2	300
openHDS	0	25	30.01	209

Table 5.5: Summary of time difference between data entry and the original visit date

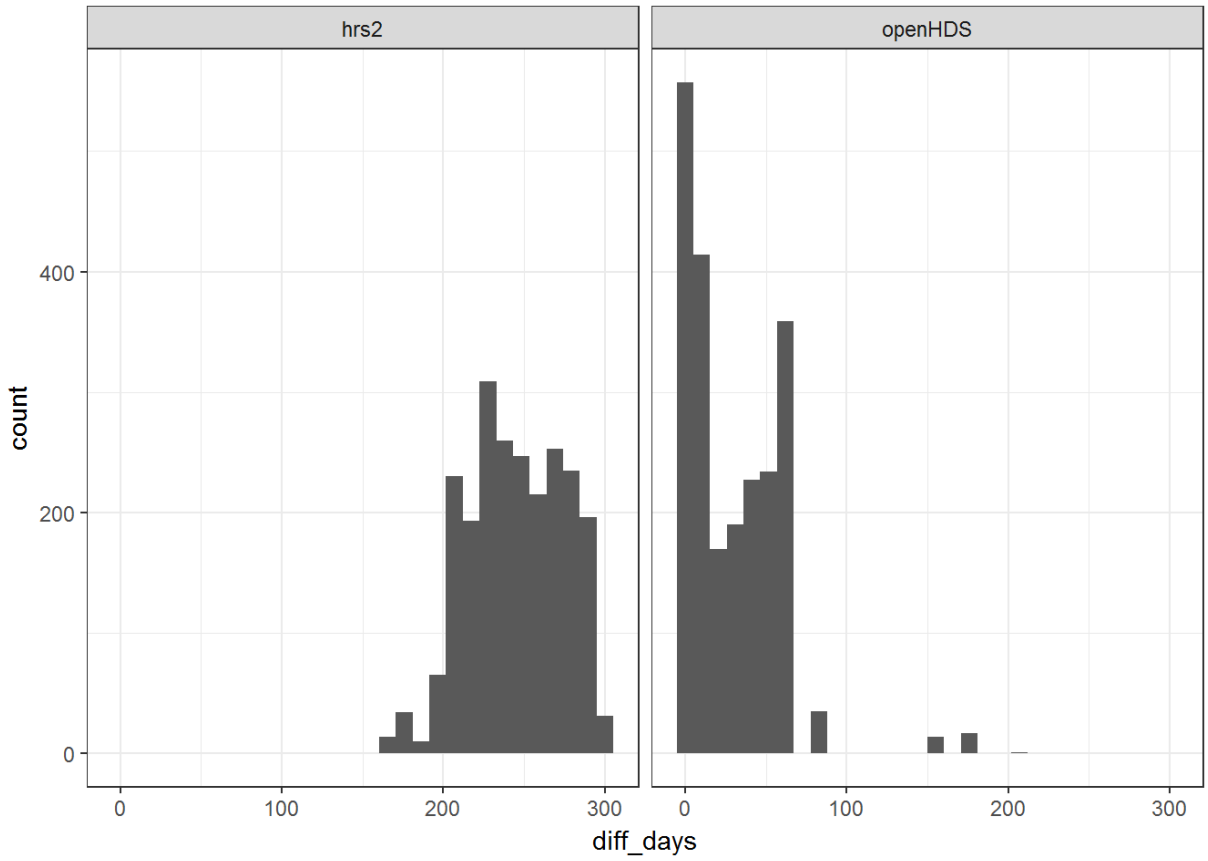

Figure 5.3: Time difference between data collection and data entering into the central database in the two systems (HRS2 left, openHDS right)

Time to availability of a record is on average reduced by 215 days with OpenHDS (compared to 4 data clerks working full time for data entry). Data transfer from mobile devices plus cleaning of inconsistencies took less days with one data manager compared to 1 month of manual entry carried out daily by 4 data clerks, plus the data manager time required for sorting out the inconsistencies with the paper-based system.

Fieldworkers take on average 20 minutes less for a visit than with paper forms. This value was obtained from supervisors comparing household visits done with paper vs. mobile device.

The “Completeness” analysis is rather more complex. The table 5.6 shows in the first two columns the number of records captured in the round 15 in the two systems. The table shows some differences between the two systems, but does not highlight problems. The most important difference was found in the individuals table due to a bug in the HRS2 system during the last weeks of the data entry when a trigger that was meant to enter newborns in the individuals table after they were entered in the pregnancy outcome table did not function. Those individuals were not entered in the individual table.

The Social group difference has to be inferred to the short timing for starting the round 15. We learned a-posteriori that to synchronise the tablets in time, the data manager entered socialgroups from round 14 into the openHDS system and not on HRS2 and these were entered later on in the HRS2 system (this was easily tracked looking at the data entry date compared with the date of recording the new socialgroup on the table socialgroup of HRS2).

Differences in the Outmigration table were mainly evident as additional records in openHDS, because the openHDS system automatically generates an outmigration if there is an internal Inmigration closing the old residency and opening a new one.

In the Inmigration table some of the differences (ca. 280) result from internal migrations that are not captured in HRS2 (e.g. people that moved away and that now after months come back to the same house), and external Inmigrations from round 14 that were not registered in HRS2. (This is linked to the socialgroup issue. A socialgroup was entered in HRS2 but the migrations were not recorded).

There were very few differences in the other tables. Most of these cannot be classified as either real missing information or errors, but rather as results of unclear field procedures (for instance a the difference in location captured may be due to occasional recording of empty locations depending on the fieldworker who’s collecting the data).

Missing pregnancy outcome that was recorded as inmigrations instead of pregnancy were considered as errors in HRS2. This arose when the family migrated and after Inmigration they had a baby (the date of birth is post migration date). This was correctly captured in openHDS that check this kind consistency (dob < Inmigration data).

Similarly, extra relationship records in HRS2 can be rejected by openHDS because of date inconsistency (e.g. if a marriage is recorded in the future or before the start of the HDSS).

For "Uniqueness" analysis we found the results on the last two columns in table 5.6, that confirm that no duplications were introduced in the round from openHDS while there were some brought into the HRS2 system.

Round 15 summary	New records HRS2	New records openHDS	# of duplicates HRS2	# of duplicates openHDS
Individual	1412	1608	0	0
Location	32	34	0	0
Visit	2257	2218	1	0
Socialgroup	161	122	0	0
Deaths	116	117	5	0
Pregnancy outcome	503	511	3	0
Inmigration	1602	2230	2	0
Outmigration	1797	1907	0	0
Relationship	60	51	0	0

Table 5.6: Round 15 Summary results of new record captured and duplications found for HRS2 and openHDS

Demographic rates calculated through the IShare2 software (8) show lower error rate 0.55% vs. 0.75% with the OpenHDS than with HRS2 ($p < .001$) (Figure 5.5).

Nanoro OpenHDS15												
EventCode	**None**	**BTH**	**DTH**	**ENT**	**ENU**	**EXT**	**IMG**	**OBE**	**OBS**	**OMG**		
BTH	.00	.00	524.00	.00	.00	1,274.00	.00	7,607.00		2,188.00		
DTH	2,841.00	.00	.00	.00	.00	.00	.00	.00		.00		
ENT	523.00	.00	486.00	71.00	.00	4,777.00	.00	20,982.00		15,054.00		
ENU	5.00	.00	1,830.00	.00	.00	11,192.00	.00	24,536.00		17,388.00		
EXT	.00	.00	.00	17,350.00	.00	.00	.00	.00		42.00		
IMG	34.00	.00	1.00	.00	.00	16.00	.00	1,129.00		65.00	Invalid	1,216.00
OBE	54,196.00	4.00	.00	23.00	.00	58.00	23.00	.00		1.00	Total	219,251.00
OMG	34,520.00	.00	.00	336.00	.00	72.00	79.00	24.00		.00	Error rate	0.5546%
Nanoro HRS2 15												
EventCode	**None**	**BTH**	**DTH**	**ENT**	**ENU**	**EXT**	**IMG**	**OBE**	**OBS**	**OMG**		
BTH	2.00	.00	474.00	12.00	.00	1,216.00	.00	8,137.00		1,740.00		
DTH	2,467.00	.00	.00	.00	.00	.00	.00	.00		.00		
ENT	390.00	.00	387.00	136.00	.00	4,609.00	.00	25,100.00		12,140.00		
ENU	.00	.00	1,604.00	120.00	.00	10,834.00	.00	26,469.00		15,927.00		
EXT	.00	.00	.00	16,741.00	.00	.00	.00	.00		30.00		
IMG	.00	.00	.00	1.00	.00	2.00	.00	34.00		4.00	Invalid	1,623.00
OBE	59,867.00	2.00	.00	1.00	.00	2.00	.00	.00		2.00	Total	218,630.00
OMG	29,229.00	.00	2.00	632.00	.00	106.00	26.00	132.00		53.00	Error rate	0.7424%
Legend: Event codes:												
ENU: Enumeration; **BTH:** Birth; **IMG:** Inmigration; **EXT:** Exit event;												
ENT: Entry Event; **DTH:** Death; **OMG:** Outmigration; **OBE:** Observation End												

Figure 5.4: Demographic Rates comparison obtained through IShare2

Financial and Economic costs with OpenHDS are respectively 10 and 6.9% lower (Figure 5.6).

Total cost estimated in the sample

	Paper		OpenHDS	
	Total Financial Cost in 2015 (USD)	Total Economic Cost in 2015 (USD)	Total Financial Cost in 2016 (USD)	Total Economic Cost in 2016 (USD)
Start Up activities	600	694	3,513	5,563
Refresher training & workshops	298	1,207	298	1,207
delivery & Analysis	114,899	122,218	101,528	109,812
TOTAL	115,797	124,119	105,340	116,582

Figure 5.5: Cost comparison details

The tabulation of total costs per input (Figure 5.6), demonstrates that the highest part of the cost is attributable to personnel. A breakdown of the costs of the personnel (Figure 5.7) we better indicates what can be saved.

For the first year after transition from HRS2 to openHDS, the management of the HDSS made very conservative decisions on staffing. The only personnel affected were the data clerks (3 full time data clerks removed from the HDSS costs). There was of course elimination of paper but the biggest impact on the cost was the 3 salaries less per year. The results obtained on timeliness and time needed to perform a household visit show that less time was required to visit the same number of households, and this could be translated into fewer interviewers. The reduction of number of interviewers would imply lower cost of “refresher trainings and meetings” and “communication” (e.g. less sim-cards), maybe reduction of supervisors, and could also lead to a reduced need for motorcycles with a consequent reduction of fuel, insurance and reparation expenses. This reduction of personnel would not necessarily mean dismissing staff, since these could be diverted to other projects and spend less time on the HDSS’s activities.

A more accurate analysis could determine the staffing needs more accurately and could lead to a higher level of savings compared to the HRS2 system. This goes beyond the immediate objective of this study, which was to compare the cost of the openHDS with a paper system, taking into account the initial investment needed for the tablet devices.

Input	Financial cost in 2016 (USD)	% of financial costs	Economic cost in 2016 (USD)	% of economic costs
Start-up costs				
Trainings, workshops & meetings	-	0%	5,563	5%
Other start up	-	0%	-	0%
Total start-up costs	**-**	***0%***	***5,563***	***5%***
Recurrent costs		0%		0%
Refresher trainings & meetings	298	0%	1,207	1%
Personnel	83,312	82%	83,312	71%
Communications	4,446	4%	4,446	4%
Maintenance	4,411	4%	4,411	4%
Supplies & other recurrent	9,360	9%	9,360	8%
Total recurrent costs	***101,826***	***100%***	***102,735***	***87%***
Capital costs		0%		0%
Buildings	-	0%	1,185	1%
Equipment	-	0%	5,746	5%
Vehicles	-	0%	2,548	2%
Consultants	-	0%	-	0%
Total capital costs	**-**	**0%**	***9,479***	**8%**
Total Annual Costs	**101,826**	**100%**	**117,777**	**100%**

Figure 5.6: Total cost per input for openHDS

	Position Description	Number of staff in this position	Gross annual salary (USD)	% to HDSS	Total annual salary for HDSS (USD)
1	HDSS interviewers	11	2,371	90.00%	23473.2
2	Field supervisors	7	3,754	90.00%	23651.1
3	Community outreach health workers	22	395	100.00%	8693.8
4	IT helpdesk	2	6,916	20.00%	2766.2
5	Demographer	1	10,867	80.00%	8693.8
6	Geographer	1	7,903	100.00%	7903.4
7	Drivers	7	2,569	15.00%	2697.1
8	Logistician	1	9,879	10.00%	987.9
9	Accounting	2	2,964	15.00%	889.1
10	Data Managers	2	8,891	20.00%	3556.6
11	Data Clerks	3	3,952	100.00%	11855.2

Figure 5.7: breakdown cost of the personnel involved in the HDSS

Discussion

Despite the limitations of the methodology (that includes the fact that the baseline between hrs2 and openHDS was not exactly identical, and this did not allow matching of some of the events in round 15 between the two systems, and that for the time saved we only have an oral statement of the managerial staff), we found that quality and costs improved moving from HRS2 to openHDS, but still more could be done.

In particular for cost we assessed that the most of it is attributable to personnel (Figure 5.6) and that moving from HRS2 to openHDS the saving in personnel costs was due to the a cut on the 3 data clerks that led alone to a save of 11855.2 USD (row 11 on Figure 5.7) . Fine-tuning the system in the future could potentially reduce the number of interviewers and possibly of field supervisors that are the highest part of the personnel cost (row 1 and 2 of Figure 5.7). These together make up 49.5% of the total personnel cost (47124.3 USD).

Some issues on slowing down the openHDS system were the change of data manager during the round that led to a 2-3 months with no data manager able to deal with the cleaning procedure of openHDS. The data transfer stalled for some time and there was a need for a training period once the new data manager arrived, before he could start.

Many of the issues that could make the EDC system much better are linked to the structure/organization of the HDSS itself. People still adhere to the procedures used with PDC, and there are insufficient staff with higher skill levels, like IT technicians, data managers with relational database knowledge and some IT technology skills.

Training should be provided to the people in these roles and this translates into an increase in investments (costs) on IT helpdesk and data managers (row 4 and 10 in Figure 5.7).

The tendency to continue to work in the same way as with the paper based system can dramatically limit the speed of an EDC system like openHDS. New technologies need in parallel an "update" in the working methods. In particular, the skill-sets of data managers, familiar with manual data entry and Excel or old databases (e.g. Foxpro), need to be upgraded to the use of new systems. A proper training should be provided to fieldworkers, supervisors and data managers. A standard operating procedure (SOP) that specifies all possible cases of conduct during the survey should be provided to fieldworkers (even in electronic format in the tablet), to avoid different approaches to collecting data depending on the mood of the fieldworker (e.g. clear instructions on cases like empty houses, or no events in a household: should the visit form always be filled? The coordinates recorded?).

It is conceivable that since the fieldworkers knew that the data was collected using the two systems they would take more care than normal on filling the paper forms. But we also know that a large proportion of errors arise on the transfer of the data from the paper to the database due to data clerks. On the basis of this hypothesis, even though the fieldworkers perform better during this study, the EDC proves to provide better quality and this could certainly be better in normal conditions once the system is well established (conservative hypothesis).

Timeliness is improved and we should benefit from the possibility of real-time access to the data to check data quality and the work of the fieldworkers. The architecture of the new system allows well-staffed central helpdesk to be setup. This could possibly lead to substantial changes in the organization of data collection. In particular, adjusting the data collection and providing feedback to field workers during data collection time could reduce errors and reduce the load of mistakes accrued by the end of a DSS round. We strongly suggest following up with a study on how real time feedback could improve the data collection process. Currently HDSS data managers generally wait until the end of a survey round before looking the data, making it impracticable to resolve many errors arising from data that may have been collected up to 3-4 months previously. If a fieldworker is queried on something he submitted the previous day, it is much easier to correct errors and ensure accrual of complete data. Few hours per day on data cleaning and feedback to fieldworkers could lead to better quality data and data

available on near real time, and would avoid at the end of the round the need of rushing on data entry because a new round will start in a month or less.

A proper programmed electronic questionnaire can avoid many errors. It is possible to use constraints, regular expressions to check specific formats (e.g. a phone number, a national ID etc…), relevancies, calculated checks, required fields, images or audio to help the interview, selecting IDs instead of typing (pre-populated fields, csv pre-loaded in the device), give more choices to select instead to provide free text fields. But if the new system is not supported in parallel by new working approaches from the HDSS entourage, this will reduce the benefits.

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Conclusions and recommendations: The way forward for the system

6. General discussion

Summary of results

The rapidity of technology changes, including new ways of capturing data in electronic format, the decreasing costs of devices and continuous interest from many research fields in standardising collection and analysis of data. This inevitably leads to interest in EDC from all kind of organizations (private or public) and has made EDC the quasi-default choice for almost all research activity(1–3). This development has been so rapid in recent years that there have unfortunately been little time for a proper assessment of how these new technologies bring added value to research (4,5).

It appears obvious that new technologies for electronic data collection, using central databases on a centralized server should perform better than old paper based systems. However, the rational for this, needs to be made explicit and proof that this is the way forward for research fields to collect their data is needed, as is evidence that quality, cost, and timeliness are really improved by EDC.

A technology can be considered as progress if it improves and simplifies daily work and, when we talk of research, if it provides advantages in quality, in accessibility, or in timeliness of the data. It should also be also sustainable, and it is important to understand the impact on costs of using EDC compared to PDC (6).

This project looks at those questions and contributes to understanding, assessing and evaluating how EDC performs compared to the previously- used PDC systems, focusing attention on population-based surveillance of vital events.

The first chapter gives an historical background and the rational for the project. It summarises the history of Demographic Surveillance Systems, the need of these and the importance of them for health related questions, which justify the use of the HDSS acronym (rather than simply DSS). It explains how the need for an improved way to collect, store and analyze data led to the development of the OpenHDS system, designed to provide a higher quality data that DSS needed as a basis for health related projects. Starting from the first DSS that used a structured way to capture data, and considering developments up to the latest one, this chapter looks at the technology used and developed during the years in parallel with ICT advances. It describes a set of conjectured data management best practices, and for each of these best practices it uses

a literature review to assess if there is evidence to support it, while also considering whether OpenHDS follows these practices, giving evidence of how this can be feasible and implemented in the field. The conclusion of this chapter explains how the OpenHDS system, using the latest mobile technologies and following data management best practices, manages to be a valid solution to the HDSSs shortcomings. It demonstrates the feasibility in implementing this system both in newly created HDSS sites and already established ones through a data migration process.

Chapter 2 and 3 look at the example of a newly established HDSS, Rusinga Island in Western Kenya. In Rusinga the SolarMal project started in the first quarter of 2012 with the aim of eliminating malaria from the island, by using the nationwide adopted strategy of malaria prevention (insecticide-treated bed nets and case management) augmented with the introduction of odour-baited traps [OBTs] for trapping malaria mosquitoes. Real time health and demographic data of the study population of 24,000 individuals are constantly being accumulated, and were instrumental in informing the study design and project logistics.

This HDSS was one of the first to introduce Android tablet computers to collect data and incorporated a near real time database with integrated quality checks. OpenHDS was chosen as the data management platform, following guidance from the INDEPTH Network due to its anticipated cost effectiveness and organizational efficiency.

However, this piloting of OpenHDS, raised many questions and issues that needed to be addressed; mainly the missing tangible proof of its advantages over a paper-based method. Some of the general key challenges of such HDSSs were addressed like the sharing of data, the harmonization and generalizability of health data collection methods and the logistical management.

Another issue coming out from this first pilot was still the need for an IT and database expert to help the local data manager on the daily routine activities. There was a clear need for a new data manager figure with more technical and relational database expertise. After support of from a software developer in the initial phases, and the training of the data manager to use the system, less support from the software developer was required in the follow up rounds. Training was also needed for the fieldworkers and so an initial effort was made in term of cost and organizational time.

The results from this study showed how this system performed well and that it was a key point for the success of the Solarmal project.

The Rusinga pilot showed the feasibility of implementing this system in new established HDSSs but did not demonstrate whether there were data quality improvements, or indicate the relative cost of implementing such a data platform for a HDSS.

The Majete Malaria Project in Malawi provided an opportunity to confirm the feasibility of setting up such a system in a new setting. The MMP (Majete Malaria Project) HDSS, in Malawi, started in 2014 to support a project with the aim of studying the reduction of malaria using an integrated control approach by rolling out insecticide treated nets (ITNs) and improved case management supplemented with house improvement and larval source management. In order to support the monitoring of the trial, an HDSS was set up in the area that surrounds the Majete Wildlife Reserve (1600 km2), and OpenHDS was chosen as a data system.

In Majete, in addition to the normal use of the system for recording vital events in the area, we assessed how the sensory capabilities of the mobile computing devices (in particular the in-built GPS sensor) in combination with auxiliary data source could improve the quality of the data and of the daily routine work in the field. The combination of the electronic data collection component OpenHDS with recent developments in open data availability and data sciences opens various possibilities for improving quality aspects in longitudinal population-based surveillance.

Chapter 4 reports an illustrative example that demonstrated the potential of linking OpenHDS to other data sources to support the MMP HDSS. The complementary data source was Volunteered Geographic Information (VGI) provided by cyber volunteers who were recruited at negligible cost, using publicly available software (PyBossa) to analyze satellite images. VGI and crowd sourced data (geodata) have changed the collection of digital spatial data, and this approach with volunteers recruited over the internet provides a new way to improve the data collection. In general crowdsourcing projects also have an outreach component (citizen, civic or amateur science), and the benefit is probably more than the data because people learn about the research. VGI contrasts with the core HDSS model of survey-based data collection, and the feasibility of combining these data sources illustrates the versatility of the OpenHDS-based system.

The problem addressed by VGI was the validation of the coverage of the HDSS population. Incomplete coverage of the population in an HDSS area can be a problem, because HDSS systems do not contain information about their own completeness. Remote sensed data (i.e. satellite imagery) can serve as an independent source of information about the location of residential structures in areas under surveillance, so we combined satellite imagery with location data routinely collected using the built-in GPS sensors of the tablets to assess completeness of population coverage.

In last 3-4 years computer image recognition has improved significantly, but algorithmic image analysis of remote-sensed images, and especially developing and tuning a new image analysis application is still technically challenging. This kind of technology is limited to the pharmaceutical or military industry, or in general to well-funded research. Crowd sourcing data is relatively straightforward and can be implemented quickly, and so was a logical approach to addressing this, although since the problem of identifying houses on satellite images is recurrent and will not go away because even existing population databases need frequent updating, so it is probably worth investing in automating such systems. If the automated image recognition algorithm is developed, the VGI, combined with the ground-truthing methodology presented in Chapter 4, may contribute to the process of training it.

The approach described in Chapter 4 was to compare the crowd-sourced house position with the maps obtained by the collection of location coordinates through the tablet in the baseline survey conducted by the fieldworkers. We calculated distances between houses on satellite images to the locations collected by the field teams to evaluate the precision of the GPS coordinates collected. A subset of locations was revisited by field supervisors to resolve discrepancies between the two data sets. We also used the map and distances of the house to guide fieldworkers to unregistered structures that appeared in the satellite images for checking if individuals were missed during the round.

The crowd-sourcing provided a convincing check of the coverage of the ground census carried out using OpenHDS, demonstrating that the HDSS achieved a high coverage of the population of the study area, and that the OpenHDS system had good performance in term of data availability, and precision in population enumeration. No occupied house was missed during the baseline. The few buildings indicated in the satellite images by the volunteers that initially could be considered candidates for missing house/individuals were determined to be either empty locations, non-residential buildings (Schools, churches, health facilities, shops), non-building structures (e.g. trees) , or houses with individuals who had refused consent to be enumerated in the baseline survey.

The large number of houses enrolled in the HDSS but not identified was not expected and merits some discussion of possible reasons. It appears that, as implemented, the crowd-sourcing missed many of the inhabited locations and the number of houses identified by the volunteers, deemed "eligible for ground-truthing" was much lower than the houses enrolled in the HDSS census in the same area. One factor that may explain the classification of HDSS-enrolled houses as distant is that for a number of those databases records the reported GPS-accuracy was substantial (up to 50m). A more detailed analysis showed that many of the HDSS houses had close-by analogues in at least one of the task replicates. This was both because close-standing buildings could not always be distinguished on the satellite imagery, and because the algorithm chosen for consolidating groups nearby buildings into single locations. For the application described here this was of no consequence, except that it introduced an asymmetry between the HDSS and volunteer-provided locations which making it difficult to compare some results in absolute numbers. For example, the 455 points identified as distant probably represent a higher number of buildings. It would be scientifically interesting to follow up with a more detailed analysis using a supervised learning algorithm to explore the potential for locating houses in some of the areas from the volunteer provided data, and then test how it works on the other area(s).

This also raises questions about the optimal way of presenting tasks to volunteers. The first concerns the number of replicates needed to provide a more solid foundation for distinguishing reliably located buildings from spurious mouse clicks. There were 164 tasks in which one replicate was submitted with no clicks, but more than 10 clicks in both other replicates, suggesting that a quorum smaller than the replicate number might increase the quality of volunteered data.

The second is related to task size. It may be useful to make the task size (i.e. the area to be inspected as part of a task) smaller. Due to an issue with the PyBossa software at the time of the data collection, we lack information on how long it took a volunteer to process each task replicate. This issue has since been resolved, and we recommend that future applications focus on this metric for optimizing the size of the task. Most of the volunteer work was done by a small number of individuals, whereas most volunteers stopped contributing after a small number of tasks. It is possible that simpler tasks (i.e. smaller area to analyze) would lead to a volunteer contributing more task replicates. Further, it might be possible to identify incentives for those who only contributed a few results to do more, rather than spending effort on recruiting more volunteers.

To our knowledge this is the first time that VGI has been employed in an effort to establish the population coverage in an HDSS, and the approach is an important addition to the tools available to HDSS program managers, allowing them to ensure that the entire population was covered during the census or successive rounds. The approach is easily transferable to other areas, and could be used to estimate coverage in any surveillance system which requires geo-locations of houses.

Beyond using the approach described here for quality control in population-based surveillance, we see further applications in the planning of observational or intervention field studies. Potentially, crowd-sourcing of such images could provide improved sampling frames for household surveys, even in areas where there is no population database. This could even be used for generating samples stratified according to other characteristics identifiable on satellite images (e.g. vehicles, or gardens etc.). Similarly, crowd-sourcing could be used to count or localize the numbers of such features within a research area for comparison between different areas. All of these extra studies could be also decided after the data collection and not predetermined a priori.

The final Chapter (Chapter 5) describes studies carried out in the Nanoro HDSS site situated in Central West region of Burkina Faso (85km from Ouagadougou). This includes: 24 villages with 63’000 inhabitants, 11’500 households at 5’500 distinct locations. In contrast to the Kenya and the Malawi sites, this site already existed and was migrated to the OpenHDS system from the previously used HRS2 in June 2015. The migration of this system provided an opportunity to make a quantitative comparison of the quality, timeliness and cost of the EDC compared with the previously used HRS2 system. Specifically, four of the six data quality dimensions proposed by

DAMA UK (completeness, uniqueness, timeliness, consistency) were compared, as well as the costs for setting up and running a PDC vs. a paper-free data system.

The baseline situation for this study was the migrated and cleaned pre-round 15 databases in OpenHDS and HRS2. For one DSS round, data were collected for a subset of 8 villages with OpenHDS and simultaneously using the traditional paper method. The 8 study villages were selected at random from the full set of 24 (all villages are in rural areas and we hypothesized there were no appreciable differences in data collection data between villages).

During the round, fieldworkers were sent in pairs to the same location to record the vital events with the two data collection instruments. Fieldworkers had same skills and had the same training on data collection for HDSS. To avoid bias introduced by the person the two fieldworkers were alternating during data collection to work 50% with the tablet and 50% with the paper.

We used a bottom-up costing methodology (micro-costing) starting by identifying precisely and measured the inputs required for running the HDSS, and then converted everything into value terms to estimate the cost. This allowed to not only to identify differences in cost of the two programs (EDC-PDC) at the aggregate level but also point to specific activities and resource categories where cost savings are realized. The cost of paper data collection was obtained by reviewing historical program data from Nanoro HDSS site from 2014 (the year before the switch to electronic data collection was implemented). Cost of establishing the openHDS system for data collection, cost of change in policy, as well as operational costs post-implementation was assessed from 2015 accounting records at the same site.

This study confirmed the substantial advantages in efficiency and cost of the OpenHDS system.

Time to availability of a record is on average reduced with OpenHDS (compared to 4 data clerks working full time for data entry). Data transfer from mobile devices plus cleaning of inconsistencies took fewer days to one Data manager compared to 1 month of manual entry done daily from 4 data clerks, plus the data manager time required for sorting out the inconsistencies with the paper-based system.

Fieldworkers take on average 20 minutes less for a visit than with paper forms. This value obtained from supervisors comparing household visits done with paper vs. mobile device.

Financial and Economic costs with OpenHDS are respectively 10 and 6.9% lower. Demographic rates calculated through the IShare2 software (http://www.indepth-ishare.org/index.php/about) show lower error rates 0.55% vs. 0.75% with the OpenHDS ($p < .001$).

The way forward for the system

The results obtained demonstrate that the paperless openHDS system has many advantages compared with the traditional paper-based data collection methods, but at the same time showed some limitations, mainly relating to the need for staff with higher skill levels. These include the need for staff to fill new roles as IT technicians, data managers with relational database know-how, together with some smearing of tech skills. There are significant needs for training of fieldworkers to use computer tablets. There are also new IT infrastructural needs, in terms of availability of mobile devices, charging stations, and internet connections to configure the tablets and to send data

The potential of such a system is also reduced by the tendency of people to continue to work in the same way to work as with the paper based system. New technologies need in parallel an "update" in the working methods. In particular, the skill-sets of data managers, familiar with manual data entry and Excel or old databases (e.g. Foxpro), need to be upgraded to the use of new systems. If new technologies are not introduced in the correct way, or if they are not used properly, instead of being useful for research, could be even be harmful. Analogously to providing a powerful car to someone without a driving license, provision of a powerful data system to unskilled staff can lead to accidents. A proper training should be provided to fieldworkers, supervisors and data managers.

Timeliness is a very important aspect for EDC and the possibility of near-real-time access to the data should be used to check data quality and the work of the fieldworkers. This could possibly lead to substantial changes in the organization of data collection. In particular, adjusting the data collection and providing feedback to field workers during data collection time could reduce errors and reduce the load of mistakes accrued by the end of a DSS round. Currently HDSS data managers generally to wait until the end of a

survey round before looking the data, making it impracticable to resolve many errors arising from data that may have been collected up to 3-4 months previously. If a fieldworker is queried on something he submitted the previous day, it is much easier to correct errors and ensure accrual of complete data.

A system accessible from everywhere through the network, secured with SSL and password protected (7), would give any collaborator of the project the possibility to access the data at any time from any location. This needs an IT skilled person to configure the server with a public IP and setup an SSL certificate. The same person will have also the important duty to set up a backup process that guarantees (in case of any possible problem) the possibility of rollback to a certain configuration or a fixed date and time.

The use of devices could allow extra security checks, which prevent illicit access in case of a theft. It is possible to configure the system so that fieldworkers do not have access to functionality that should not be part of their daily work. The same devices could be also programmed to check that the fieldworker is effectively visiting households (forcing to record GPS coordinates at time of the visit), or to take pictures of the visited houses together with the coordinates.

A proper programmed electronic questionnaire can avoid many errors. It is possible to use constraints, regular expressions to check specific formats (e.g. a phone number, a national ID etc…), relevancies, calculated checks, required fields, images or audio to help the interview, selecting IDs instead of typing (pre-populated fields, csv pre-loaded in the device), give more choices to select instead to provide free text fields. It is worthwhile investing time in designing and piloting questionnaires, to ensure that high quality data are obtained, rather than starting the data collection process and trying to fix possible errors on the go.

HDSS sites, as described in the introduction, have been originally put in place either to overcome the CRVS deficiencies, or as a basis to conduct clinical trials (8), and their utility for other population-based data projects came later. (E.g. district health service delivery research, research related to epidemics). HDSSs until now in general have been just served as a platform for epidemiological studies and health programme evaluation. The concept of Monitoring & Evaluation (M&E) to achieve an improvement of current data collection and management processes, other performance management and learning

tasks to get better future outputs, outcomes and impact is the original and actual basis for HDSSs (9–12).

The use of EDC in HDSSs should bring a change in its purpose. The real time possibility to monitor the system and a real access to results of a certain degree of quality should make this system not anymore a platform with the goal of evaluation for review, but have the potential for something more.

The future move, the way forward for this system should be Surveillance & Response (S&R) (13,14). Surveillance as a continuous systematic collection, comparison, analysis and interpretation of data and then provide the information to those people who need to know in order to provide an appropriate Response, take an action to react to a problem. This scenario could be necessary for example in a situation of near elimination of a pathogen (15,16) or to react in case of a pandemic of an infection disease(17–19).

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Curriculum vitae

First names: Aurelio Di Pasquale

Date of birth: 26.08.1973

Nationality: Italian

Civil status: Married, 1 child

Education:

September 2015 to current: Epidemiology Department at the University of Basel	PhD candidate: Thesis: “Improving quality, timeliness and efficacy of data collection and management in population-based surveillance of vital events”
September 1993-July 1999 Università degli Studi di Palermo	MSc Electronic Engineer in Telecommunication

Membership of professional bodies: 2011 Member: Swiss Society of Tropical Medicine and Parasitology (SSTMP), Member of Technical Steering Committee of ODK (Open Data Kit: opendatakit.org)

Present position: Swiss Tropical and Public Health Institute: Software project coordinator Scientific Computing

Years within the firm: 9 yrs

Key qualifications:

Software/Database design and development, Data Analysis

Specific country experience:

Country	Date: from (month/year) to (month/year)
Kenya	August 2011 to August 2015 (offsite and onsite)
Tanzania	August 2011 to August 2015 (offsite and onsite)
Malawi	October 2013 to present (offsite and onsite)
Mali	May 2014 to present (offsite and onsite)
Burkina Faso	June 2014 to November 2017 (offsite and onsite)
Ethiopia	July 2015 to November 2016 (offsite and onsite)
Italy	January 2000 to February 2009
Switzerland	March 2009 to present

Professional experience record:

Date from - Date to	Location	Company& reference person (name & contact details)	Position	Description
August 2015 to present	Basel, Switzerland	Swiss Tropical and Public Health Institute Dept. Epidemiology and Public Health / Health Systems Research and Dynamical Modelling	Software project coordinator Scientific Computing	• **Technical Advisor** for the INDEPTH network on HDSS systems implementation. • **Software coordination and implementation of** electronic data capturing systems in various projects
August 2011 to August 2015	Basel, Switzerland	Swiss Tropical and Public Health Institute Dept. Epidemiology and Public Health / Health Systems Research and Dynamical Modelling	Software project coordinator Scientific Computing	• **Software coordination,** Solarmal Project: Solar power for malaria eradication Health and Demographic surveillance systems (HDSS) implemented to support a malaria intervention study in Kenya, in the Rusinga Island. • **IHI OpenHDS**: Coordination of data migration for the HDSS data on site to the new OpenHDS/ODK system. Implementation of forms, pilot of the new system.

Apr 2009 to Aug 2011	Basel, Switzerland	Swiss Tropical and Public Health Institute Dept. Epidemiology and Public Health / Health Systems Research and Dynamical Modelling	Technical Project Leader and Senior Software Engineer	• Project “SAPALDIA3” (Swiss study on Air Pollution and Lung Disease in adults) a cohort study in the Swiss population, which studies the effects of air pollution on the respiratory and Cardiovascular health in **adults providing web interfaces to databases and software to perform statistical analysis and entry data.** • **Provision of web interfaces to epidemiological databases** and other software held by the Department of Public Health and Epidemiology
July 2003 to March 2009	Palermo, Italy	Sispi S.P.A	**Software Engineer**	• Solutions and software development of WEB applications in a development team.
Feb 2000 to Dec 2002	Palermo, Italy	Nortel Networks	**Software Engineer**: Client Server	• Developer of a monitoring and maintenance tool of GSM/GPRS networks, Support on Server for the same tool, Manage the version coding

Publications:

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