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Smartphone geospatial apps for dengue control, prevention, prediction, and education: MOSapp, DISapp, and the mosquito perception index (MPI)

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Abstract India has the largest number of dengue cases in the world, contributing approximately 34% of the global burden. The framework for a geospatially enabled early warning and adaptive response system (EWARS) was first proposed in 2008. It was meant to be a decision support system for enhancing traditional surveillance methods for preventing mosquito-borne diseases in India by utilizing remote sensing data and fuzzy logic-based mathematical predictive modeling. This conceptual paper presents a significant evolution of EWARS such that it synthesizes inputs from not only traditional surveillance and reporting systems for dengue but also from the public via participatory disease surveillance. Two smartphone-based applications have been developed to support EWARS. The first—MOSapp—allows field health workers to upload surveillance data and collect key data on environmental parameters by both direct observation and via portable microclimate stations. The second—DISapp—collects relevant information directly from the community to support participatory disease surveillance. It also gives the user a real-time estimate of the risk of exposure to dengue in proximity to their home and has an educational component that provides information on relevant preventive measures. Both applications utilize a new mosquito abundance measure—the mosquito

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perception index (MPI)—as reported by the user. These data streams will feed into the EWARS model to generate dynamic risk maps that can guide resource optimization and strengthen disease surveillance, prevention, and response. It is anticipated that such an approach can assist in addressing gaps in the current system of dengue surveillance and control in India.

Keywords Dengue · *Aedes* · Geospatial applications · Participatory disease surveillance · Public health · Environment

Introduction

Dengue is a viral infection transmitted to humans through the bites of infected *Aedes* mosquitoes (ECDC 2017) with some estimates suggesting an incidence of 390 million infections annually (Singh et al. 2014; Shepard et al. 2016). Among the environmental factors impacting dengue transmission are temperature, rainfall, humidity, etc. (LaDeau et al. 2015). There are also varying sociodemographic factors that contribute to dengue such as unplanned urbanization, high population density, and erratic garbage collection (Lima et al. 2016).

India is the seventh largest country in the world by land mass and the second by population (Worldatlas 2018). The geography is diverse with the north being relatively drier and arid compared with the south. Unfortunately, India has the highest dengue burden in the world, contributing 34% of the global total (Mutheneni et al. 2017). While there are existing government programs for control and prevention, there have been concerns raised about their effectiveness (Kakkar 2012; Shepard et al. 2014). Reporting mechanisms have been largely dependent on paper-based primary data collection from field workers, clinicians, and laboratories though there have been increasing efforts to use information technology for summarizing data and providing online reports. There are ambitious plans to do a great deal more in various areas of e-governance including healthcare. India is now globally recognized for its prowess in information communication technology (ICT) (World Economic Forum 2018). In 2015, the Indian government rolled out a Digital India initiative encouraging public-private partnerships (Digital India 2015). One of the nine identified "pillars" of the program is provision of universal access to mobile connectivity (PIB 2015). India has the second highest number of mobile phone users in the world (Mashable Australia 2017). According to International Telecommunication Statistics (ITU 2017), there were 87.3 mobile cellular subscriptions per 100 inhabitants in India as of 2017. It has been estimated that India has approximately 300 million smartphone users (Iyengar 2017). As the surge of smartphone users continues, "Fast Track Task Force"—a body within the Ministry of Electronics and IT—has announced that they will produce 500 million smartphones in India by 2019 (Economic Times 2018).

In recent times, there have been initiatives around the world to harness ICT for disease surveillance and prevention, including in dengue (Lwin et al. 2014, 2016a, b, c, 2017). Given this juxtaposition of events and technological developments, the time seems right to visualize efficient and effective approaches to creatively using ICT to enhance surveillance and control of dengue in India.

The southern state of Kerala has been a trendsetter in several areas including healthcare and literacy and its success has been internationally recognized (Bhutta et al. 2004). It has recently launched an E-health project with an investment of approximately 15 million US dollars (TOI 2017). It is anticipated that over time, the health records of every resident in the state would be captured by the system. One of the stated objectives of the project is to promote disease surveillance (Ehealth Kerala 2018). Despite these commendable accomplishments, Kerala has also been plagued by dengue. In 2017, it was reported that Kerala had 19,776 cases with 37 fatalities—both totals being the second highest in the country out of 36 states and union territories (NVBDCP 2018). The major impact of dengue on India and the prominent position of Kerala State among affected areas were important factors that led the study team to focus on dengue control in India and conduct the majority of pilot work for our project in Kerala.

This conceptual paper presents the current status of a theoretical framework for an early warning and adaptive response system (EWARS) to help in strengthening existing dengue control programs in India through geospatial decision support and participatory disease surveillance. At the outset, current dengue control mechanisms in India are reviewed. Next, the conceptual framework for our work is presented. The key attributes of participatory disease surveillance and the EWARS concept are outlined. A novel mosquito abundance measure entitled the mosquito perception index (MPI) is described, and two newly developed smart phone application prototypes—MOSapp and DISapp—are detailed. The discussion that ensues elaborates on the relevance

of these tools to the EWARS framework and how these interventions might assist in filling existing gaps in data collection and application in India. Relevant literature is highlighted to compare and contrast our work to contemporary global efforts in participatory disease surveillance and informatics-based dengue control programs.

Dengue control in India

The existing surveillance mechanism in India for dengue centers around the National Vector Borne Diseases Control Program (NVBDCP 2018). It includes prevention, treatment, and surveillance components in addition to the promotion of research and capacity building strategies. It is a passive surveillance system (Mutheneni et al. 2017) where dengue cases are diagnosed by healthcare professionals. Case definitions of dengue are based primarily on clinical indicators and positive laboratory tests (Deen et al. 2006). The number of laboratory-confirmed dengue cases is forwarded to the state government through the district level medical officer. The disease surveillance system is managed by the state government in conjunction with the NVBDCP which monitors dengue-related data around the country (Mutheneni et al. 2017). The NVBDCP also provides technical assistance, funding, and resources to endemic states and union territories.

The NVBDCP program is complemented by the Integrated Disease Surveillance Program (IDSP) which is a standardized surveillance program uniformly implemented across India covering major infectious and non-infectious disease conditions. It has a computerized network that extends down to the mid-level administrative divisions across India and even beyond to the primary health center level, in certain states. Clinically suspected as well as laboratory-confirmed cases of dengue reported from health institutions and referral laboratories are captured by IDSP. It should be noted that most of the collected data arise from government health centers and the participation of the private sector—which provides a majority of the health care in the country—is quite limited.

Recent research has highlighted the likelihood of substantial underestimation of dengue in India. In 2012, 37,070 cases of dengue had been reported as of 26th November of that year (Kakkar 2012). It was opined that a considerably larger proportion was at risk though India reported only an average of 4.2% of the total cases reported in the World Health Organization South East Asia region between 2000 and 2010. Shepard et al. (2014) have stated that between 2006 and 2012, there was an annual average of 20,474 dengue cases reported in India. They believed that after correction for under-reported statistics, India would likely have had approximately 6 million dengue cases. It was concluded from these figures that the NVBDCP successfully captured only 0.35% of the clinically diagnosed dengue cases in India. The annual number of dengue cases was thus projected to be 300 times higher than officially reported (IANS 2014; SNS 2014; NVBDCP 2018). For 2017, there were a total of 153,635 cases of dengue reported in the country according to the NVBDCP with 226 fatalities. Numbers have increased steadily since 2014 when 40,571 cases were reported (NVBDCP 2018) thereby reflecting a greater case burden, improved reporting or a combination of both.

The genesis of possible case underestimation will no doubt be multifactorial, including inadequacies of passive surveillance and the modest collection of private sector data by current surveillance programs (Kakkar 2012). Clearly, to arrive at effective improvements the proposed solutions will also need to be multifaceted. From a theoretical position, we propose that tools for increasing the accuracy and timeliness of reporting by government workers as well as having abilities to geotag in real time can increase case detection and reporting. In addition, the engagement of common citizens through crowdsourced social media–based applications enabling participatory disease surveillance (Smolinski et al. 2017) can further assist with deriving more accurate risk estimates and driving community-based interventions. This combination of approaches has the potential to meaningfully address existing gaps in dengue surveillance as well as response and is covered in detail within the conceptual framework for our project that follows.

Conceptual framework

Participatory disease surveillance

An evolving concept known as participatory disease surveillance has been a foundational element in our study framework. Its roots lie in participatory epidemiology which arose in the domain of animal health as a method to foster collaboration between public health entities and the public (Catley 2006). Participatory

disease surveillance has extended this approach to human health as described in a seminal review by Smolinski et al. (2017). It embraces digital connectivity to actively engage the public so that public health entities can aggregate, synthesize, and analyze submitted data for monitoring disease trends, identifying risk factors, and early detection of potential outbreaks. Data of public health utility are collected by directly involving the population at risk via a variety of survey tools such as web portals or smartphone apps. Participatory disease surveillance can thus be viewed as a form of crowdsourcing for public health surveillance. It is also considered a form of citizen science in that it requires engagement with the systems willingly and knowingly to provide information necessary for public health action. Such exchanges can also be an opportunity to provide information to participants about endemic disease risks and enable rapid responses in public health emergencies (Kullenberg and Kasperowski 2016).

Many of the existing participatory disease surveillance systems are centered around reporting syndromic information, i.e., self-reported symptoms of illness suggestive of a particular disease. Some systems also look at other areas such as vector tracking, environmental risk, and animal health. In low and middle-income countries—such as India—where traditional disease surveillance systems may be hampered by limited financial and human resources, participatory disease surveillance has been proposed as a low-cost method for routine monitoring with a sufficient level of specificity (Smolinski et al. 2017).

Early warning and adaptive response system (EWARS)

Babu and colleagues have previously proposed an Early Warning and Adaptive Response System (EWARS) for strengthening public health systems in India to address mosquito-borne diseases, particularly those transmitted by the *Aedes* mosquito (Babu 2008; Babu and Niehaus 2010; Babu et al. 2014). The model was based on the premise that disease control could be achieved if mosquito levels were maintained below epidemic thresholds. An informatics-based temporo-spatial decision support system was conceptualized which would use existing data collected by the public health system along with remote sensing data to generate dynamic risk maps generated with the assistance of fuzzy logic algorithms and geographic information systems (GIS). These maps could provide early warning to the possibility of mosquito-borne epidemics and suggest optimal control responses to enhance the likelihood of epidemic prevention. EWARS would also aid in resource optimization by matching available resources to outstanding needs.

The EWARS model was based on data streams obtained primarily through satellite maps and remote sensing to minimize the dependence on public health workers manually collecting and reporting data. However, it was found that the model was impractical for day-to-day use since satellite data was neither cost-effective nor readily available at the required granularity. With the explosive growth of cell phone penetration in India as well as the advent of crowdsourcing and social media tools such as Facebook and WhatsApp, the focus shifted towards smartphone-based data collection from field workers and participatory disease surveillance from the public as new sources of data to synergize with data already being collected by government surveillance programs.

To further this vision, the team proposes a new mosquito abundance measure—the mosquito perception index (MPI). In addition, the prototypes of two different smartphone-based applications—MOSapp for use by public health workers and DISapp meant for the public—have also been developed. These entities are described in detail below.

The mosquito perception index (MPI)

For dengue infections to arise, it is essential to have an interaction between (1) the mosquito, (2) the virus, and (3) a human host. If any of these factors are absent, an infection cannot occur. Public health control measures have focused largely on reducing mosquito abundance. In theory, if public health authorities have guidance on when and where mosquito abundance is likely to be the highest, they could then focus their efforts on risk mitigation accordingly. Traditional models related to mosquito abundance or disease risk have considered climatic variables such as temperature, humidity, and rainfall; geographical variables like vegetation or built environment; demographic variables such as socioeconomic status or residential location and variables directly related to mosquito abundance such as container index (the percentage of water-holding containers infested with active immatures such as *Aedes* larvae or pupae), Breteau index (the number of positive containers per 100 houses), and ovitrap egg counts (number of *Aedes* eggs laid on the paddle of the ovitrap container).

However, the latter mosquito variables are typically collected on a one-time basis or at most a few times and are not meant for real-time estimation of mosquito abundance. They also have significant limitations for use in comparative analyses between areas as elegantly pointed out by Focks (2004).

Apart from formal public health data collection efforts, individuals routinely make subjective observations about mosquito activity in their daily lives—particularly in their immediate environments at that point in time, and on occasion, also in the recent past. Though this is a widely prevalent process of estimation done by members of a community, there appears to have been little attempt so far as to systematically collect such impressions from community members and public health workers to evaluate their utility in developing predictive models.

The MPI represents a new approach to collect such perceptions of mosquito abundance and activity in real time from public health workers as well as from the general public via crowdsourcing. It can be defined as the number of mosquitos perceived by an observer in their immediate vicinity over a given period of time. The MPI is a subjective assessment in that the observer is reporting their perception—based on "inputs" such as visualized mosquitos, mosquito bites, or buzzing consistent with mosquito activity (even if not directly visualized). An added dimension to the MPI is that it may sensitize participants to mosquito activity and possible determinants that impact its magnitude. The authors believe that the MPI can thus indirectly become a health awareness and promotion tool by making users more conscious of the mosquito abundance in their vicinity, in particular possible *Aedes* species.

Data relating to the MPI will be gathered using MOSapp and DISapp. The collected responses are submitted to a designated database and incorporated into the predictive model. Descriptions of each application along with the specific questions asked in these applications related to MPI are detailed in the following sections. Technical specifications for the two apps are provided in Appendix 1.

MOSapp

MOSapp is an android-based smart phone application utilizing technology developed by Applied Cognition Systems (APCOG), Bangalore, India. It is meant for public health workers (and other authorized users) to upload geotagged information relating to mosquito abundance and environmental factors. Table 1 lists the information collected via MOSapp while Fig. 1 offers a screen shot of the data entry screen.

Methodology for use

Three categories of data will be collected: (1) Objective measure of mosquito abundance represented by ovitrap egg counts; (2) environmental factors (both natural and built) that can affect *Aedes* abundance, and (3) microclimate related data—temperature, humidity, soil moisture, and ambient light. The collected data will be processed by a fuzzy logic mathematical model for calibration of the MPI which will be one of the variables considered for prediction of mosquito abundance as well as risk of potential dengue outbreaks.

Ovitrap-based estimation of mosquito abundance

Ovitraps are black containers filled with water into which a wooden ruler wrapped in cloth (ovipaddle) is submerged. This provides an environment which *Aedes* mosquitos find attractive for laying eggs. Ovitraps have been used for decades as an accepted approach for determining *Aedes* abundance in a particular locality. In our project, they are evaluated on a weekly basis for

Table 1 MOSapp data streams

Parameter	Collection procedure
Ovitrap locations	Specific ovitraps identified by assigned number. GPS mapping occurs automatically during data upload
Egg counts	Users input data after manual egg counts from ovitraps
Environmental factors impacting mosquito abundance (vegetation, trash collection, stagnant water, artificial containers, etc.)	Users input data regarding presence/absence of local factors that impact mosquito abundance
Perceived mosquito activity (feeds into MPI)	Users input their perception of mosquito activity at the time of data entry (user-centric)
Microclimate data (temperature, humidity, soil moisture, ambient light)	Users collect microclimate data using a custom-built device which sends collected data to MOSapp upload

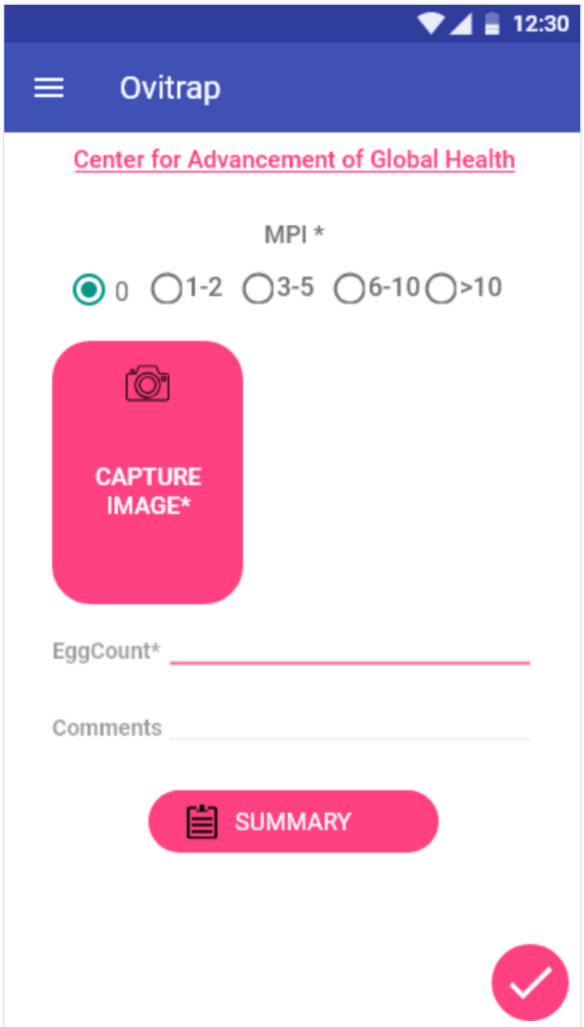

Fig. 1 MOSapp data entry screen

egg counts which are then entered manually into MOSapp.

Environmental factors

MOSapp users can upload observations related to any area where there may be factors promoting mosquito breeding/spread such as trash heaps, stagnant water, and abundant vegetation.

Microclimate data

A microclimate mobile data collection device has been developed by APCOG to specifications provided by the study team. It will be used by MOSapp users to measure local temperature, humidity, ambient light, and soil moisture content at selected areas to given insight into the microclimate in the vicinity. Data once collected is transmitted via MOSapp to the central database for use by the fuzzy model.

MOSapp and MPI

While uploading both ovitrap and environmental data, an MPI statistic, namely the approximate number of mosquitos perceived by the user in the immediate vicinity at the time of data entry (range from "0"; "1–2"; "3–5", "6–10" and "> 10"), has to be concurrently entered as a mandatory procedure (to ensure that an MPI is also being reported by the user) before data uploading can proceed (see Fig. 2).

DISapp

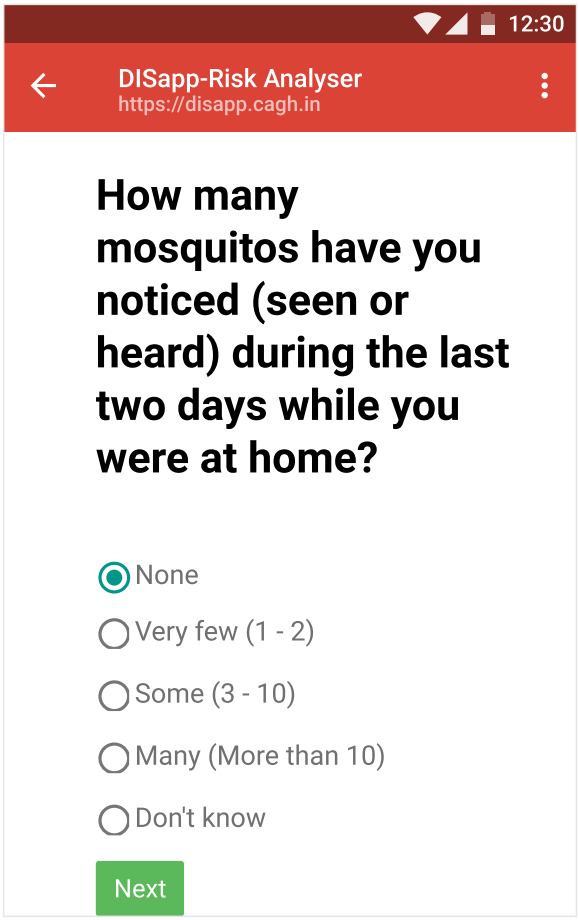

Fig. 2 DISapp Question 1 screenshot

DISapp is an application for use by the general public which can upload geotagged data. It provides a personalized estimate of the risk of exposure to dengue in the vicinity of the user's residence at that point in time. In the initial stage, the prototype is being distributed on an individual basis till it is refined and suitable for general availability and use.

In the long term, DISapp will be made available for public download (e.g., from google play) and can provide users with ongoing risk estimates and specific education/recommendations while giving rise to crowdsourced data that enables participatory GIS.

Methodology for use

The user can download and use DISapp on any smartphone. The user will initially answer five questions asked by the application relating to various risk factors. On submission of answers, the application will provide a risk estimate for that user, at that time and location, ranging from "very low"; "low"; "medium"; "high", and "very high". Table 2 presents the data streams that are conceptually mapped to each question. The collected data will be processed by a fuzzy logic mathematical model for calibration of the MPI (which will be one of the variables considered for prediction of mosquito abundance) and risk of potential dengue outbreaks so that appropriate measures can be taken by the public health system and the general public.

Table 2 DISapp data streams mapped to each question

Parameter	Questions
Mosquito abundance (feeds into MPI)	How many mosquitoes have you noticed (seen or heard) during the last 2 days while you were at home?
Mosquito bites	Approximately how many mosquito bites have you received in the last 2 days while you were at home?
Mosquito morphology—consistent with *Aedes*?	Have you seen mosquitoes with white stripes on its body and legs during the last 2 days while you were at home?
Dengue incidence in the household	Including you, how many members of your family while staying at home with you have gotten dengue in the last 1 year?
Dengue incidence in the community	Have you heard of any cases of dengue in your neighborhood in the last 1 month, including cases in local hospitals?

DISapp and MPI

The first question in DISapp feeds into the MPI. To answer the question, DISapp users will select from a range of pre-defined ranges for mosquito abundance ranging from none, very few (1–2), some (3–10), and many (10+) over the prior 2 days (see Fig. 2).

DISapp for education

A primary function of DISapp is to serve as an educational tool for creating public awareness regarding the prevalence of *Aedes* mosquitos, their relationship to dengue, and the user's risk of contracting the disease. Through a series of questions in a simple social media type interface, the application renders a risk profile in real time to the user. Thereafter, recommendations for specific actions to protect both themselves and their household environment from dengue are presented (see Fig. 3). Finally, the current pilot version of DISapp has a feedback section that solicits input from the user regarding the usability and utility of the application.

Later versions of DISapp will provide users the ability to do a trend analysis for their own entries/risk reports over time, and also to see map-based anonymized data from their locality to have a better understanding of occurrences in their local community. The user will also be asked about their current use of recommended preventive modalities and/or their intent to use them in the future. Table 3 presents a comparison of the two applications.

Current status and preliminary findings

The status of pilot studies utilizing MOSapp and DISapp are detailed below. Their intent is to evaluate the usability of these apps and assess the consistency and robustness of their function. User feedback is also sought to improve the user experience and functionality. Given the small number of users and limited geographic area covered, no attempt is being made at this time to engage in dengue prediction or to test the predictive performance of the EWARS model.

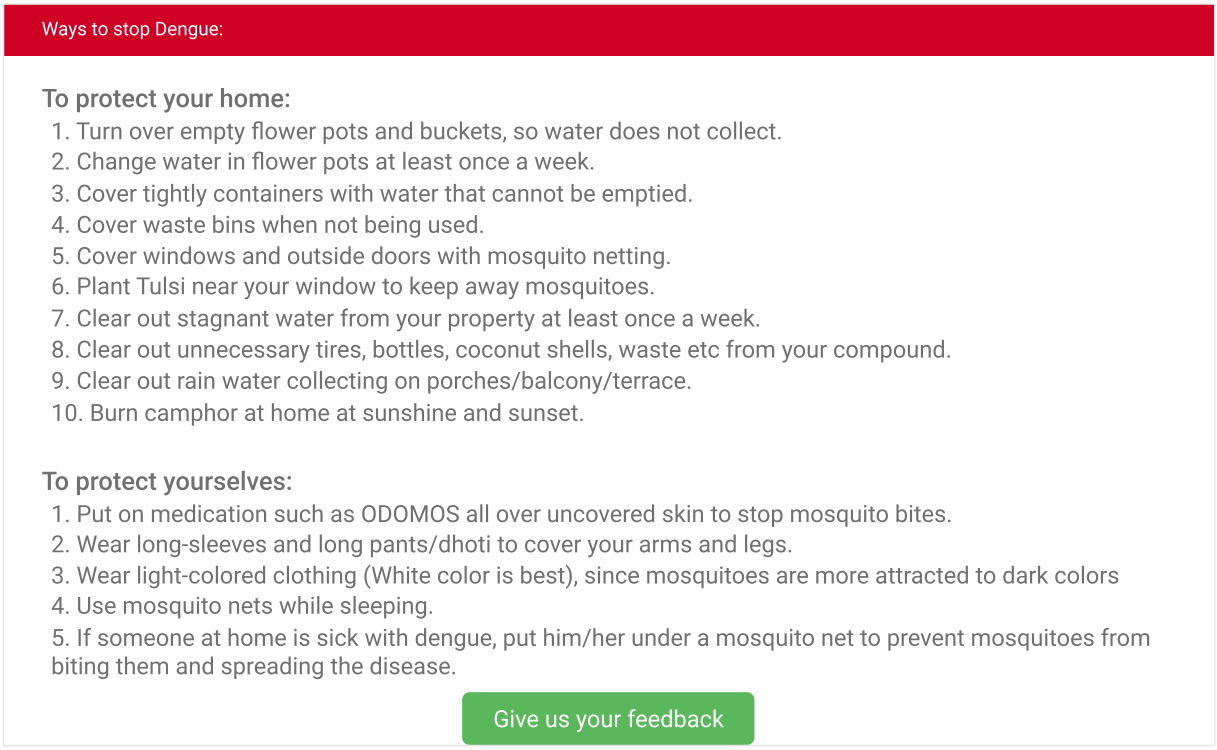

Fig. 3 DISapp recommendations screenshot

MOSapp

Pilot testing commenced in December 2015, and the initial phase of data collection concluded in May 2017. The study team chose two separate areas in Kerala State—Fort Cochin and Aluva. While Fort Cochin is surrounded by sea and backwaters, the town of Aluva is 30 km inland. Both sites are recognized as historically having high incidences of dengue. The Fort Cochin site commenced work in December 2015. Data collection was performed primarily by bachelor of science students from The Cochin College under the supervision of their designated faculty and study staff from the Center of Advancement of Global Health (CAGH) in Cochin. In Aluva, bachelor of science students from St Xavier's College started data collection from June 2016. They were being guided by their supervising faculty and CAGH staff. The collected data was uploaded to the project database and preliminary findings are noted below.

Table 3 Comparison of MOSapp and DISapp

App element	MOSapp	DISapp
Data streams collected	Ovitrap egg counts	User submission relating to mosquito prevalence (e.g., felt, seen, bitten, heard mosquitoes)
	Local environment observations	Presence of *Aedes* mosquitoes
	Micro-climate data	Dengue in the household and surrounding communities
Intended users	Public health workers (including research institutions and academia, government, NGOs)	General public
Intended location	Any location where workers collect data	Home and immediate vicinity
Format of application	Closed application for authorized users	Open application for common citizen engagement

Mathematical analytic procedures involved aggregation of monthly data smoothened with the use of moving average plots. Instead of using absolute values for MPI and ovitrap counts, trends of increase and decrease in counts were encoded by + 1 and − 1 respectively. Fuzzy logic was utilized for trend analysis and Pearson coefficient was applied to the trend encoding. There was a total of 943 records from 30 users relating to 105 ovitraps that had been deployed.

The monthly moving average plots generated demonstrate that much of the time, there was concordance between MPI and Ovitrap counts (see Fig. 4).

Application of Pearson correlation to the trend analysis findings (Fig. 5) gave an R value of 0.5458 which would traditionally be considered a strong correlation. However, due to the inherent limitations of the data, we prefer to avoid such a characterization and instead merely conclude that our initial findings are supportive of a positive correlation between the MPI and ovitrap counts.

DISapp

DISapp was distributed to beta testers starting in January 2017. At present, there are 25 unique users from various parts of India with the majority being from the state of Kerala. Their feedback is being solicited on the user interface and possible enhancements. No attempt is being made yet to systematically analyze and apply the data users are submitting. Future versions with enhancements are anticipated in both English and various Indian regional languages in the latter half of 2018.

Discussion

Dengue has been a categorized as a public health problem of national significance in India. There are well-established programs, namely the National Vector Borne Diseases Control Program (NVBDCP) and the Integrated Disease Surveillance Program (IDSP) for dengue. The Indian government has evidenced significant interest in moving towards a stronger informatics-based architecture. At present, there is negligible integration between community sourced information and those obtained from public health workers and other official data streams. In this context, participatory disease surveillance offers valuable opportunities for low-cost community-based epidemic prediction, reporting, and prevention. Initial work in this area started around 2003 in Europe and over 20 projects around the globe using ICT to gather disease

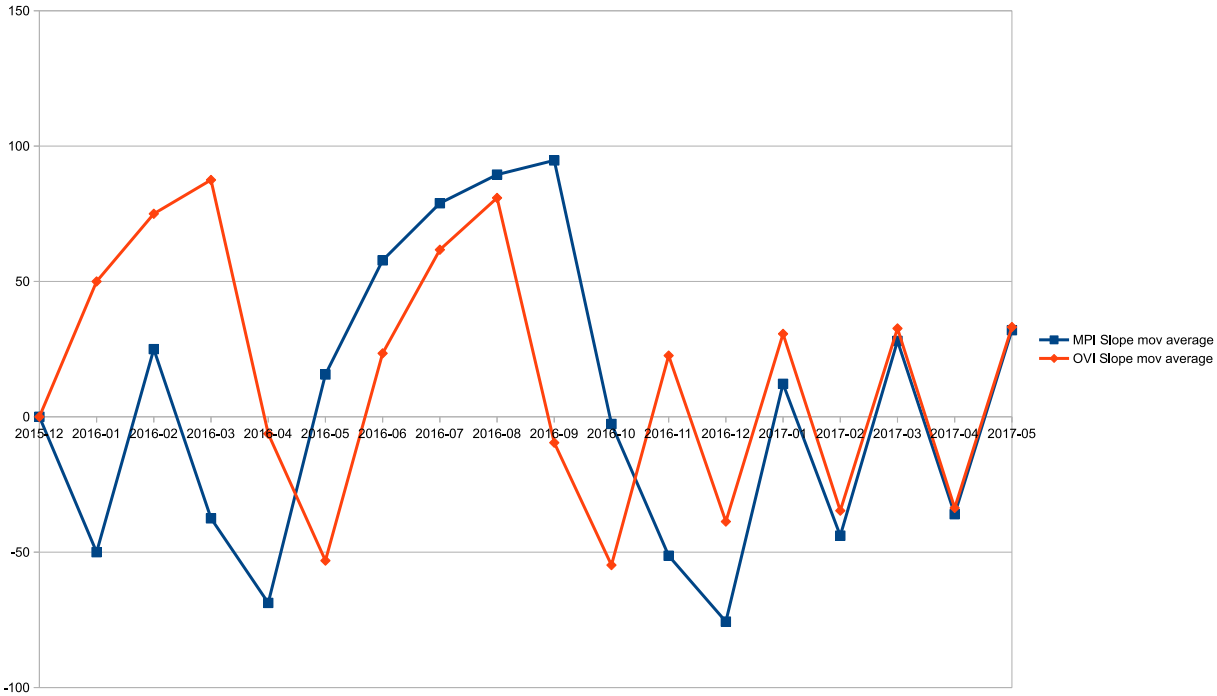

Fig. 4 Monthly moving average plot

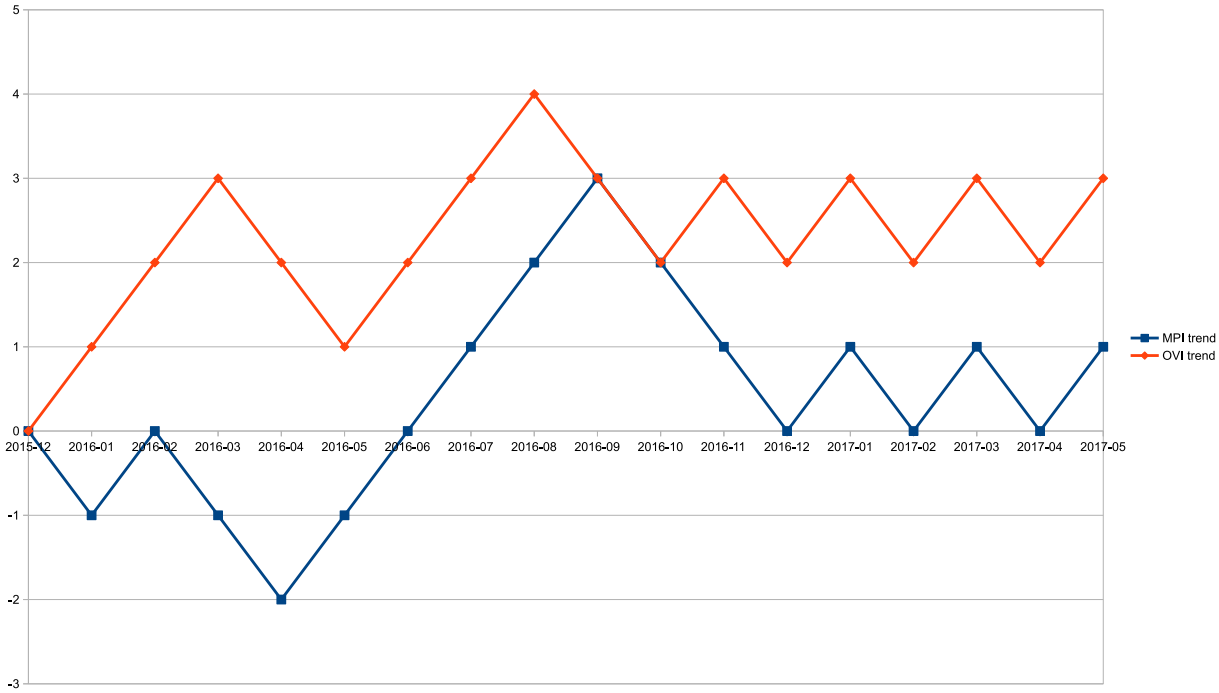

Fig. 5 Pearson correlation and trend analysis

surveillance data from populations have now been reported (Smolinski et al. 2017). Most of these projects have used web interfaces for the public to contribute data. Gathering observations of possible import to public health authorities and compilation of syndromic data have been core elements of many of these programs. There is a great deal that remains to be done to explore possibilities for enhancement of the methodology, validation of its efficacy, and to foster its adoption by both the general public and public health authorities. We believe that an EWARS approach which incorporates GIS-based participatory disease surveillance and real-time inputs from public health workers via smartphone apps can be of benefit in enhancing dengue surveillance and control. Our conceptual paper has outlined the theoretical framework for such an undertaking while reporting some preliminary data as well.

Putting it all together—the current vision for EWARS

The preceding sections of this paper have reviewed the concept of EWARS and described key components that have been recently developed in the form of two smartphone apps and a new mosquito abundance measure. *How do these entities relate to each other as well as to existing dengue control mechanisms?* Operationally, EWARS would utilize inputs from three sources to support dengue prevention, control and education: (1) The existing governmental dengue surveillance and control programs (NVBDCP and IDSP). MOSapp data relating to field ovitrap data, environmental survey, and microclimate data (none of which are presently collected by the existing system in a routine or systematic way) could also feed into these programs; (2) Data from other governmental and non-governmental sources (such as from private hospitals and clinics) that for the most part have not been integrated into cross-program or cross-disciplinary analytics at present; and (3) DISapp data coming from the public. Over time, if the app-related data gathering process is demonstrated to be robust and adding incremental value, it is possible that it could replace elements of processes that are currently paper-based. An overview of the current vision for EWARS is shown in Fig. 6.

Data streaming in from these three data torrents would be processed by a fuzzy logic predictive model (detailed in appendix 2) which is at the heart of EWARS. Risk maps showing hot spots at appropriate levels of granularity would then be generated for use of public health authorities. EWARS will also provide decision support relating to resource allocation for enhancing outcomes in dengue prevention, control, and

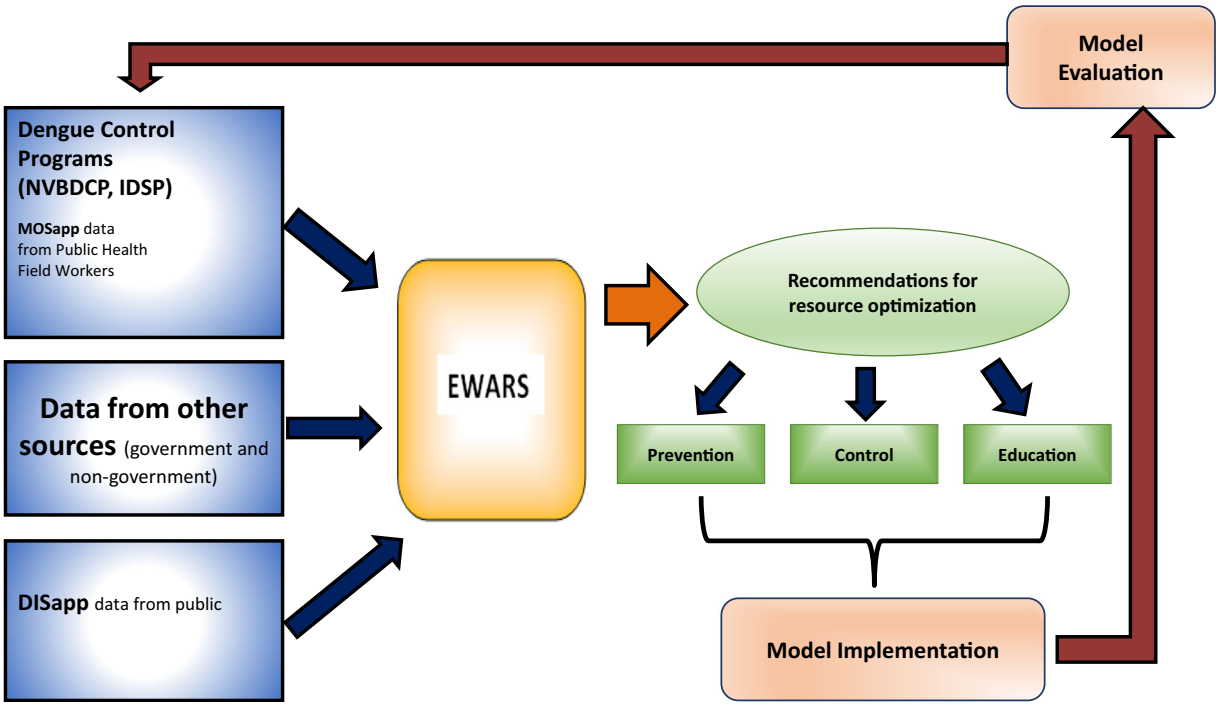

Fig. 6 Early warning and adaptive response system (EWARS) operational overview

community education. Following implementation, evaluation would occur on an ongoing basis with findings feeding back to the governmental surveillance programs. In addition, at an individual level DISapp creates a real-time, personalized assessment of the risk of dengue exposure for a given user based on their responses to DISapp questions.

The MPI supplied by MOSapp and DISapp users is an additional, non-traditional data element. *How does it fit into EWARS*? The MPI is a subjective evaluation by an observer of mosquito abundance in a given location over a defined period. It is a means for the public to report their impressions in a quantifiable manner to the public health system—providing a variable that is presently not systematically gathered. It is likely that in many instances the "perceived" number of mosquitos may differ from the "actual" number in the vicinity. The observer may miss seeing certain mosquitos, particularly those that are dormant and staying in concealment. They may also double count mosquitos. *With this being the case, how can the MPI potentially add useful information*? The answer lies in the use of a fuzzy logic modeling approach. Combing the attributes of a neural network with fuzzy logic can give rise to a neuro-fuzzy controller. A fuzzy-controller embedded in an app describes the individual's perception of mosquito abundance. The information can be complemented by other measurements like ovitrap egg counts which can supply objective evidence for the mosquito abundance in a region. Reports of confirmed dengue cases can provide in time series a delayed signal of disease risk.

Borel's law of large numbers in mathematics postulates that an increasing number of samples provide a stochastic convergence towards the unknown probability of an event. Assuming that individuals have an individual perception rate of mosquitos in their environment, the individual fuzzy truth of perceiving mosquitos can be calibrated using more objective measures of probability. For example, if observer A systematically underestimates risk and observer B systematically overestimates risk, the fuzzy-controller calibrates these individual risk perceptions of the MPI using validated risk measures determined by classical means.

The proposed EWARS model remains largely theoretical at this point other than for the components of the dengue surveillance mechanism (NVBDCP and IDSP) that are already in place. It is worth considering at this juncture whether relevant work has been implemented in India or elsewhere and if so, what the outcome has been.

None of the projects reported by Smolinski et al. (2017) are from India and our literature review (at the

end of 2017/early 2018) revealed no mobile applications with geotagging and social media enablement being used in India for dengue prevention and control. However, there have been some international projects germane to our work and among them, those of greatest relevance are considered below.

A notable project with thought-provoking similarities to our work is by Lwin et al. (2014) who reported a contemporary approach to dengue control in Sri Lanka, using crowdsourced surveillance, predictive mapping, and tailored communication. They presented the application Mo-Buzz, an integrated mobile- and desktop-based dengue communication system. It has three components—predictive surveillance, civic engagement, and health communication. The predictive surveillance uses algorithms and computer simulations (based on weather, vector and human data) to predict dengue outbreaks and disseminate the information in the form of hotspot maps to health officials and the public. The civic engagement element enables citizens to use their mobile smart phones to inform health authorities regarding (1) breeding sites, (2) symptoms, and (3) mosquito bites through interactive forms on websites and social media (eg., Twitter). The information is also reflected in hotspot maps. Using crowdsourced information, the intelligent system disseminates health alerts and tailored messages to individuals/communities living in respective geographic zones. The system is designed to share information on individual social media networks. Later reports from this group (Lwin et al. 2016a, b, c, 2017) have presented the results of their initial implementation in Colombo both with the public health professionals and with the general public. The uptake by the workers was low in the beginning (less than 10%) but increased to 76% after incentives for use (such as considering the number of reports submitted as a factor for determining yearly performance bonuses and pay increments) were put in place. The public component of Mo-Buzz also struggled initially with getting users following which they are pursuing additional avenues for incentivizing users and marketing the app. Despite these hurdles, the authors reported a decrease in the number of dengue cases in Colombo by approximately one-third which they have attributed to Mo-Buzz (Lwin et al. 2017).

Mwangungulu et al. (2016) reported an innovative crowdsourcing approach, which relied on simple knowledge and experiences of residents to rapidly predict areas where there would be increased mosquito abundance. Guided by community champions (resources), they mapped boundaries and physical features in three rural villages in Tanzania. Sixty community members were selected and taught basic map reading skills. They were offered grid maps to identify locations where they believed mosquitoes were abundant and rank them according to high and low densities. The ranks were interpolated in ArcGIS-10 using inverse distance weighting (IDW) method and reclassified to depict areas. Finally, odor-baited mosquito traps were used to compare and verify actual outdoor mosquito densities in the same areas. This process was repeated for 12 months with different groups of 60 residents. All entomological surveys revealed similar geographical stratification of mosquito densities in areas classified by community members as high, medium, and low vector abundance. The study makes an important contribution in demonstrating that community knowledge and experiences can assist in identifying mosquito abundance.

The University of Arizona recently launched a mobile application to track the zika virus (UA News 2016). Kidenga is a community-based disease detection system that allows a team of public health investigators to track day-biting mosquito populations within a community and to identify people who have exhibited symptoms of illness. The application provides users with country-level, confirmed case information, educational materials, and up-to-date news on mosquito activity (Kidenga 2017).

Hernández-Ávila et al. (2013) have reported on the use of Dengue-GIS in Mexico whereby a reporting system that was initially based on paper-based primary data collection, and forwarding to higher authority was transformed to a web-based, GIS-enabled system that complemented existing information systems facilitating a high degree of acceptance from health officials and other users. Ovitrap-based geotagged data collected as a surrogate for entomological risk was correlated with dengue case distribution to derive transmission risk. Since our project has also used ovitraps as an objective measure of *Aedes* abundance, and EWARS is visualized as an informatics-based decision support system that integrates both existing as well as new streams of data, the successes reported by this group are especially pertinent.

It is evident from the above discussion that a number of international projects of potential have already employed geospatial information technology resources

to tackle *Aedes*-related diseases. However, our work adds value in three important respects. First, unlike the other projects highlighted, our approach is targeted to India—the country with the highest dengue burden in the world. Second, our MPI concept allows the user-friendly collection and application of crowd-sourced data, thereby creating a channel to leverage social media and ICT to empower communities. Third, the EWARS approach provides a framework for integrating both governmental and non-governmental data to support decision making and resource optimization. Our phone apps and the EWARS inputs were designed to support these unique attributes while retaining sufficient flexibility to allow for their application to other contexts and countries as well, if desired.

Challenges and limitations

The studies cited above have particularly informed our work as reported in this paper. In addition, there have been a number of praiseworthy efforts which are building a body of evidence and laying a durable foundation for future work in dengue as well as the evolving field of participatory disease surveillance. The report from Sri Lanka by Lwin and colleagues highlighted challenges faced in field testing and adopting ICT tools for participatory disease surveillance while at the same time illustrating the possibilities. As exemplified by their experiences, real-world implementation of a participatory disease surveillance program can face difficulties in acceptance by public health workers and participation by the public. It can be expected that similar circumstances may arise in Kerala State, given the parallels between the two regions. They have both succeeded in achieving excellent health care indices to the extent that they have been highlighted as models for other parts of Asia (see for example, Bhutta et al. 2004).

It is likely that Kerala which has traditionally been a leader within the states in providing high quality of primary health care (Dandona 2017) may outperform other parts of the country should a national level implementation of EWARS be attempted. Nevertheless, when seeking early adopters for public health innovation, it is logical to start with a bellwether state. The project by Lwin and colleagues has reached significant maturity while we are still in the prototype refinement phase. As such, their experiences will be of immense value as we move forward. There are also important differences in our work such as the MPI and our approach to fuzzy logic modeling. The concept of the MPI is something unique that we have created on the basis of a simple question—*if our goal is to predict and prevent a mosquito-borne disease like dengue, could not community reports of their own exposure to mosquitos and their perception of disease penetration in the community add value?* We believe the answer to be in the affirmative but acknowledge that substantial work remains to evaluate, validate and refine the measure.

Conclusion and future directions

Smartphone-based apps can be useful in participatory disease surveillance for dengue prediction, prevention, control, and education in India. An integrated disease surveillance and response system can incorporate provisions for geospatially tagged, real-time data from both the community and front-line public health workers for inclusion along with traditionally collected systemic surveillance data and health system responses to dengue outbreaks. Such an approach has the potential to improve data collection and provide new streams of data that can add greater insight into relevant findings at the grass roots level. This conceptual paper details the mosquito perception index (MPI) and the functionality of two new smart phone apps namely, MOSapp and DISapp. In addition, the role of the generated data in informing an integrated disease surveillance and response model—EWARS—is described. Future work will evaluate the validity and utility of the MPI concept, the impact of these apps once deployed for large scale use, and the value of the EWARS model for dengue surveillance and risk mitigation. If these are shown to be of value, they could find application not only in India but also in other resource-poor parts of the world where dengue is a problem. It is also possible—and indeed desirable—that an EWARS architecture could be used for surveillance and response of other diseases as well, thereby enlarging the user base and enhancing cost-effectiveness.

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Appendix 1

Technical considerations of MOSapp and DISapp

MOSapp is an android-based application, enabling users to log different types of data which are geotagged by default (Latitude and Longitude Coordinates). Apart from screen-based user inputs, the app enables the user to capture images of the environment and ovitraps at a given location using the phone camera. It also wirelessly acquires data from a companion microclimate sensing device. MOSapp logs the acquired data through wireless Internet streaming into a backend MOSapp server. The server aggregates and stores data from multiple smart phones and provides utilities to extract, view, map and export the data into other applications as needed.

DISapp uses a service oriented architecture with RESTful web services designed using a Python-based framework - Flask with a MySQL database, all hosted on a digital ocean droplet with a Django-based UI to cater to the survey needs. The APIs are dynamic and can be corrected from the backend to update the statistical model and give the users an enriched experience related to prediction, survey questions, and available questionnaires. Flask is hosted using Gunicorn servers and a nginx reverse proxy. It has token-based authentication to add a certain amount of security along with SSL encryption. DISapp will be made available in multiple languages to engage more respondents. It is location aware and logs in user data, which would be useful for demographic surveys and risk mitigation.

Appendix 2

The fuzzy logic mathematical model

In general (if other things remain equal), the risk of contracting dengue will depend on the mosquito abundance in each region. Risk for dengue will depend on geospatial factors and individual factors. To create an appropriate risk profile, the modeling methodology must deal with identified risk factors and link them automatically. For example, the geospatial patterns of mosquito abundance must be linked with recommended applications of risk mitigation strategies, based on the geospatial database of variables affecting the risk, such as temperature, humidity, etc. The geospatial database would be compiled as part of the system with an adaptive "fuzzy-logic" methodology to support geospatial decision making (see Metternicht 2001 applied for salinity as risk).

Classical mathematical logic operates with statements and rules that can be evaluated as "true" or "false" (1 or 0 respectively). For mosquito abundance at the certain geolocations the classical evaluation for the statement "abundance of the *Aedes* mosquito" will lead to:

- true (1) "mosquito can be identified at geolocation (x,y)" or
- false (0) "mosquito cannot be found at geolocation (x,y)".

However, a difference between 1 mosquito or 1000 cannot be represented by the classical approach of logic. Rule-based systems in the public health sector typically have to deal with statements that have a degree of truth ranging between 0 and 1.

Fuzzy logic methodology (Zadeh 1973, 1979) is a scientific approach to implement decision support in complex environments and integration of expert knowledge into the decision support (see Bui et al. 2012, with application on landslide risks). The importance of spatial modeling and application of spatial rules in geographic information systems leads to the representation of spatial properties (e.g., the availability of health care services at a geolocation). These spatial properties are mathematically represented by membership function mapping a property a (abundance of mosquitos) to a degree of truth ranging between 0 and 1. On a mobile

device with GPS at a geolocation (x, y), the evaluation reports back $a(x, y)$ to the owner of the geolocation and transforms $a(x, y) = 0.52$ to "at your geolocation (x, y) there is a 'medium risk' according to *A. aegypti* or *A. albopictus* mosquito abundance." The "or" in the statement indicates that fuzzy logical rules are applied to spatial risk factors as well. The areas under surveillance would be stored in GIS and field ovitrap data are reported on a defined schedule to determine mosquito abundance. The data collected by ovitraps are randomly assigned to training data (70%) and validation data (30%), as proposed by Bui et al. (2012). The training data is used to calibrate the mosquito abundance for the locations and validation data is used for checking the risk models for mosquito abundance.

Temporal mathematical representation needs a definition of time. Similar to Lwin et al. (2014) and Jones (1981), we discretize the time in steps of 1 day. The natural numbers 0,1,2,… represents the elapsed day, since the start of data collection $t = 0$. Old data is less relevant than data that is recent. Therefore, aging of data is represented in fuzzy membership functions on the data as well. If the data are getting "older" the fuzzy value converges from 1 towards 0. Let D be a dataset $t_{0,D}$ is the collection date of D (i.e., Time span of days between the start of the study and let it be the time span of days between the start of the study and current date. The fuzzy representation of the fuzzy age is defined by $\mathrm{age}(D) = 1/(1 + ((t - t_{0,D})\mathrm{s})^2)$. The positive real value s, determines the speed of aging. High values of s imply that the data is aging rapidly and therefore the datasets have less impact for decision support than "younger" data. The temporal similarity is represented by the distance to the corresponding season of the year, i.e., if collected data from January 27th, 2016 has a higher similarity to a data set from February 15th, 2017, than to a dataset that is collected in July 29th, 2016 due to seasonal weather conditions. The seasonal distance of two collection dates t_1 and t_2 in days is calculated by:

$$\boldsymbol{sd}(t_1, t_2) := \boldsymbol{min}\{|365\ \mathrm{k} + t_1 - t_2| : k \text{ whole number}\}$$

The corresponding fuzzy value is;

$$\mathbf{f}\boldsymbol{sd}(t_1, t_2) := 1/\left(1 + (\boldsymbol{sd}(t_1, t_2)\ s)^2\right).$$

The positive real number s indicates the "speed" at which temporal similarity will decrease the fuzzy value along with the increasing seasonal distance of two collection dates t_1 and t_2 in days. As mentioned earlier, identified risks are dependent on individual risk factors such as risk literacy (i.e., knowledge about risk and the skills to apply risk mitigation strategies). This knowledge and skill contributes to calculated risk as well because applied risk mitigation strategies and awareness of risks can reduce the impact of dengue on the public health system. Knowledge about risk literacy could also be used wherever feasible to trigger public awareness and educational interventions in schools and colleges when skills are identified as poor. At the same time, crowdsourcing data derived risk scoring would change automatically and dynamically based on updated abundance data from ovitraps. Old validation data becomes training data and new input data then becomes fresh validation data. The ratio between training data (70%) and validation data (30%) remains constant when new input data is fed into the decision support system. The success of the risk mitigation options that were recommended by the system can be later assessed according to the impact of the interventions on mosquito abundance and disease cases in that area.

The application of fuzzy logic permits a comprehensive decision support system because it allows the use of linguistic values. For example, the use of risk mitigation option: "often", "sometimes" and "never" and its fuzzification into values between 0 and 1 for mathematical processing by fuzzy rules and its comprehensive defuzzification of calculated values between 0 and 1 into linguistic representation (e.g. "the application of risk mitigation strategy X does not make sense at this time of year at your geolocation"). At the same time, the collected data supports health service administration in risk evaluation, allocation of resources and initiation of educational programs based on risk scores. Feasibility and acceptance of risk mitigation strategies reported by users are relevant at the level of administration, because theoretically effective strategies that are not practically applied by users do not have a risk mitigation impact. This leads to the requirement of systematic integration of quantitative geospatial representation of mosquito abundance and disease cases together with qualitative methods incorporating risk literacy and education of citizens. The community-led development theory and constructivism theory along with more traditional approaches of data collection are combined by the application of spatial fuzzy logic (see Babu and Niehaus

2010; Platz et al. 2014). The core functionalities of MOSapp and DISapp were developed keeping these key concepts in consideration.

According to epidemiological modeling, we build on the susceptible-exposed-latent-infected-recovered (SELIR) model which is similar in some respects to the modeling methodology followed by Lwin et al. (2014). The difference in our approach is that we incorporate spatial proximity on a grid and SELIR transition from day t to day $t+1$ with the infection of citizens being dependent on the spatial connectedness in grid, rather that applying SELIR on administrative territories like Lwin and colleagues. Each cell k on the grid (map) has a strength of connectedness $c(k,m)$ to another cell m. Cells have a unique ID with k resp. n. With the fuzzy-value 1, e.g., the infection of susceptible has same impact on the connected cell as if the infected were located in connected cell of the grid, while fuzzy-value 0 means that there is no impact on the cell. This implies that the transition for the number of infected population is not only depended on the number of infected population $I_k(t)$ at cell k, but also from all other cells n (not equal k) by $c(k,m) \cdot I_m(t)$. At the same time the concept of connectivity supports the extrapolation from grid cells with data to grid cells with less or no data. Collected data populates the connectivity matrix if observed data correlates in time for two grid cells k and m.

The described mathematical model is at the core of the EWARS concept wherein data streams from governmental databases, field workers, and the general public will be used to generate dynamic risk maps and recommendations for resource allocation.

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