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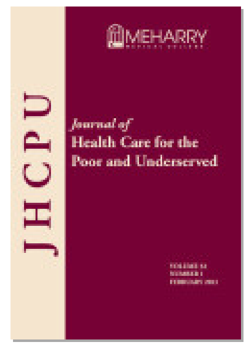

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ORIGINAL PAPER

Fine Scale Replicable Risk Mapping in an Informal Settlement: A Case Study of Mathare, Nairobi

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Abstract: Slums and informal settlements continue to pose considerable health challenges, mostly associated with the unavailability of basic amenities and proper waste management. While mapping where risks occur, such as the location of features associated with disease is obviously beneficial, the spatial data required is frequently not available, especially on a continuous basis. In this paper, we employ a robust, cost-effective, and efficient means of monitoring for these types of environments, using the Mathare SIS in Kenya as an illustration. We show how spatial videos can be used to capture microenvironments around homes or other key features such as toilets and water points, to show localized environmental risks such as standing water and mud. We also show the utility of this approach to capture longitudinal change. The objective of this paper is to illustrate how this method can map changes in the spatial variability of health risks in a challenging environment.

Key words: Environment monitoring, spatial videos, GIS, Mathare Kenya, risk mapping.

Even with advances in medical technologies, availability of vaccines, widespread education, and public health intervention strategies, slum and informal settlements (SIS) continue to stretch local public health capacity, resulting in high rates of infectious and chronic disease, and generally poor health outcomes.[1,2] From a spatial data perspective, while these environments can be mapped at coarse scales using remotely sensed imagery, fine scale (the home and its environs) data that can determine on-the-ground risks, and how they change over time are far harder to acquire.[3,4] Typical logistical impediments to such data collection include cost and skillsets.[5,6] However, if this data challenge can be solved, then fine spatial scale preventive solutions can be developed,

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such as near-real-time monitoring of key components of the water, sanitation and hygiene (WASH) landscape including water points, toilets, and drainage channels.[5,7,8,9] At the same time, researchers would benefit from these data, which would allow for a more geographically accurate modeling of disease.[10,11,12,13]

Even when fine-scale surveys of the WASH landscape are attempted, the same logistical challenges usually result in cross-sectional snapshots that soon become outdated. Adding further cause for concern is the lack of social, behavioral, or environmental context attached to these data characterizing the nuances of daily life in the community.[14] To address this data deficiency, a fine-scale, multi time period contextualized surveillance system is required—but one that is logistically appropriate so that local actors can take ownership of data collection, interpretation and dissemination. Conceptually, the local team can oversee all data collection while the research team provides (and updates) technology and a custom-made software.

In this paper, we present an on-the-ground spatial technology, and associated software, that can be used to collect fine-scale data by local researchers, professionals, or community groups. Secondly, we show how a multi-year data collection in collaboration with local participants, revealed changes in fine-scale environments and especially health risks. For illustration, we used the Mathare SIS in Nairobi, Kenya as our research setting.

Study area. Mathare is the second oldest and largest SIS in Nairobi after Kibera.* The Mathare Valley lies approximately 6 kilometers to the northeast of Nairobi's central business district and is bordered by Thika Road to the north and Juja Road to the south (Figure 1). The Mathare valley consists of 13 main villages: 3A, 3B, 3C, 4A, 4B, Gitathuru, Kiamutisya, Kosovo, Kwa Kariuki, Mabatini, Mashimoni, No. 10 and Village 2.[15] Data collected for this paper were mostly from the Kosovo village.

Mathare is typical of a data poor SIS, with few geographic layers and little understanding of localized population distribution.[16,17] The area also varies in terms of housing quality, including both temporary structures built with repurposed materials (such as corrugated metal sheets) and more permanent well-maintained brick structures (Figure 2). However, the lack of a proper land tenure system[18] makes residents in even the most robust structures fearful of evictions. For many residents, the poor quality of these homes exposes families to a variety of disease-causing vectors including rodents that thrive on the area's poor sanitation. Added to these environmental risks are other social stressors, and health and economic challenges including marginalization, underemployment, high prevalence of communicable diseases, and general inaccessibility to essential services, such as sanitation, water, and electricity.[15] Open trenches adjacent to narrow footpaths and even around homes often contain raw sewage, which adds another level of risk for unsupervised children at play. The quality of the toilet system[19] also varies, with human waste draining or spilling into streets, paths, play spaces and homes, especially during the rainy season.[20] The global standard recommendation of having no more that 20 people per latrine[21] is exceeded in many of the villages in Mathare with ratios ranging from 17:1 to 232:1.[16] More than 83% of the residents must pay to use the toilet, the typical cost being about five (5) Kenyan shillings per use (approximately

*There are variations in the reported population at least in part due to the mobility of the people who live or pass through Mathare.

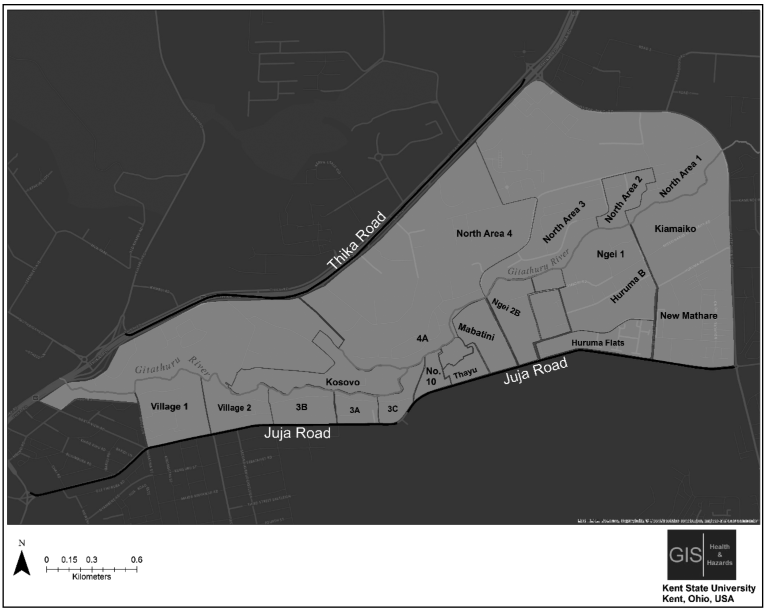


Figure 1. The villages in the Mathare valley and the boundary roads.
Shapefiles and names of villages were obtained from the map Kibera project (http://mapkibera.org/mapmathare/download/).

1US dime),* compeling many to practice open defecation and flying toilets (defecating into plastic bags and throwing them into any open space).[8,16] Access to reputable health care is also limited,[18]** which causes additional data accuracy problems, making medical interventions as well as day-to-day monitoring of typical infectious and chronic diseases difficult.[8,13,20]

Mapping risks and how they change over time, such as fluctuating outbreak patterns, should be a public health goal in any SIS.[22,23,24] To achieve this, accurate geocoded data are needed, meaning places and spaces that can be placed on a digital map.[25] There have been some novel mapping approaches adopted in the different Nairobi SIS, which have been useful in locating key structures and facilities.[4,15] In Mathare, mapping has focused on infrastructure rather than environmental monitoring or creating health or epidemiological geographical layers. To address this gap, we employ the use of spatial videos, which are video media synchronized with a global position system (GPS) to capture environmental data. These cameras, which can be mounted on a vehicle (such as a car, bike, or boat), or hand-carried, have been used in a variety of similar

*More than 71% of Mathare residents have to walk in excess of 50m for a toilet. Few of these paths and facilities are well lit, meaning that women and girls feel unsafe, especially at night.[16]

**SIS dwellers in Nairobi experience poorer health outcomes than their urban counterparts. For example, child mortality in Nairobi was found to be 62 per 1,000 births compared with 151 per 1,000 in the city SIS.[45]

A) The bridge crossing the Mathare River.

B) Narrow paths between housing units in Kosovo.

C) Other building types

Figure 2. Different housing types identified from the SV.
A) Housing units are tightly packed in Kosovo with many alleys only being big enough for pedestrians. Typical building material often involves repurposed aluminum and plywood sheets. The footbridge shown is used as a link between two villages and provides a safe crossing point over the river, which can swell during the rainy season. B) The structures do not create a sealed interior and there is plenty of opportunity for disease vectors to enter. C) In some sections, houses are more solidly constructed made of brick and concrete.

SIS environments.[7,26,24,27,28,29] Along with the custom-made software developed both to visualize these data and to correct for errors in the GPS signal,[29] these methods provide a means to map fine scale risks by using the video image as a digitizing source. As this equipment is relatively cheap and easy to use, the method has also proven useful for local collaborations and for multi-time period monitoring.[7,29]

Typically, a local team walks through the SIS, collects visual data using spatial videos, and then maps risks from it.[24] These paths can be easily retraced by the field team to see how environments change, or how effective interventions are. The geographies of interest include environments around homes, along paths, where externalities such as flooding might occur, or in the micro spaces surrounding critical infrastructure such as water points. In this paper, we use key locations as examples to show how such changes can be identified and mapped. Finally, this paper includes images extracted from the spatial video. While these are used to illustrate each point being raised, it should also be remembered that each has an associated GPS coordinate, and in effect can be considered as an entry point into the map. By layering multiple spatial videos, three-dimensional view of the SIS can be created.

Methods

Spatial videos were collected using portable GPS-enabled video cameras, being carried by hand or clipped to clothing, and navigating the alleys and corridors of Kosovo by walking. The typical "team" included a local researcher and a resident guide. This approach was similar to that employed by the authors in Haiti and Tanzania.[26,24,28] There was no predetermined path prior to the spatial video collection; they were chosen based on their safety and walkability. The local resident was integral in determining which routes should be taken and which places visited. This resident also served as a mediator between the research team and Kosovo residents especially in terms of explaining the purpose of the mapping exercise. Subsequent spatial video collection tried, whenever possible, to recapture these initial routes. The first set of videos were collected during 2013–2015. The initial spatial videos became the locational guide for subsequent collections in 2017–2018 to monitor change along the pathways and around key locations. The spatial videos were used as a digitizing source to identify key WASH locations, map environmental risks along the paths, around homes, and in proximity to key locations. Mapped risks included trash, stagnant water, mud, overgrowth, and street vendors selling food, all factors found important in previous health studies.[24,26] All mapping utilized the custom-made software (Fig. 3) developed by the team to synchronize the video and GPS stream, while ArcGIS 10.5.1 (ESRI)[30] was used for more sophisticated GIS analysis and cartographic display. To provide additional spatial guidance, a GIS shape file of public toilet and water facilities (WASH) were downloaded from the map Kibera project.* These facilities were used as reference points to determine change across the study years.

*The map Kibera project is an initiative to generate spatial data for the SIS (Mathare, Kibera and Mukuru) in Nairobi, Kenya. It employs young Kenyans to create digital maps of their communities

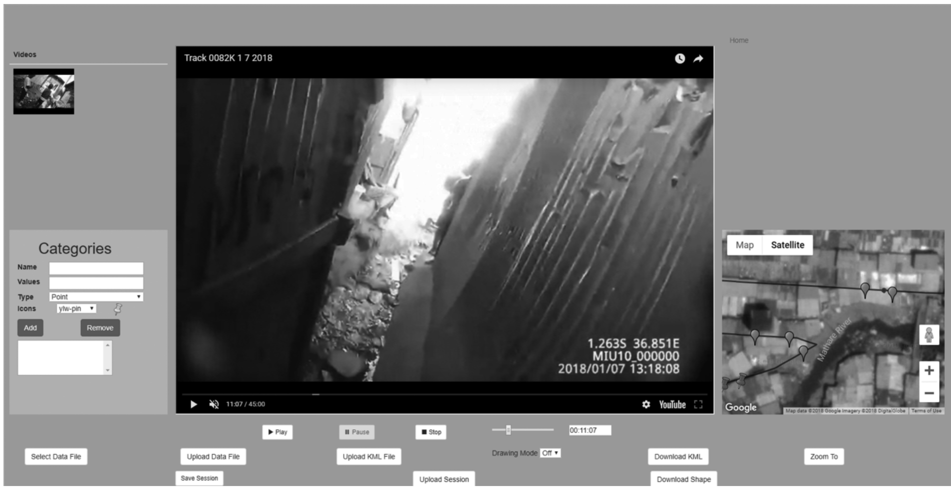


Fig 3: Software interface for digitizing risks

The software used in digitizing environmental risks within Mathare. The line on the map window shows the corrected GPS path and the pin markers are the digitized environmental health risks. The dot corresponds to the geographic location of the video frame being displayed.

For each spatial video, the video was either physically transported by the project team from Kenya to the United States on an external drive or uploaded to a website for analysis at the GIS Health & Hazard Lab at Kent State University. The spatial videos were downloaded as videos in mp4 format and the coordinate information were extracted into Comma Separated Values (CSV) file and GPS Exchange (GPX) file using the custom-made software. Post-processing of the GPS data was required due to the tight corridors with overhangs and reflective surfaces leading to considerable spatial error. This GPS correction approach has previously been described for this project,[2] but in summary, a combination of Google Earth imagery and the video itself was used to identify features such as buildings, vegetation, roads, and turns, and these were used as references to correct or create a new GPS path that could be synced back to the original video. These "new" spatial video files became the source to digitize environmental risks. Figure 3 displays the custom-made software used for both this correction and then as the tool to digitize environmental risks along the route. The dot in the map window on the bottom right shows the position where the video was taken, named pin markers were used to locate the digitized risks by category type, each of which also has a time stamp (from the video) and an associated geographic coordinate. The output map layer was then downloaded as a Google Earth KML file for sharing back with the team in Kenya or a GIS shape file for further geographic or cartographic manipulation, analysis, and visualization.

using hand-held devices. GIS data for Mathare was obtained from their website http://mapkibera.org/mapmathare/download/

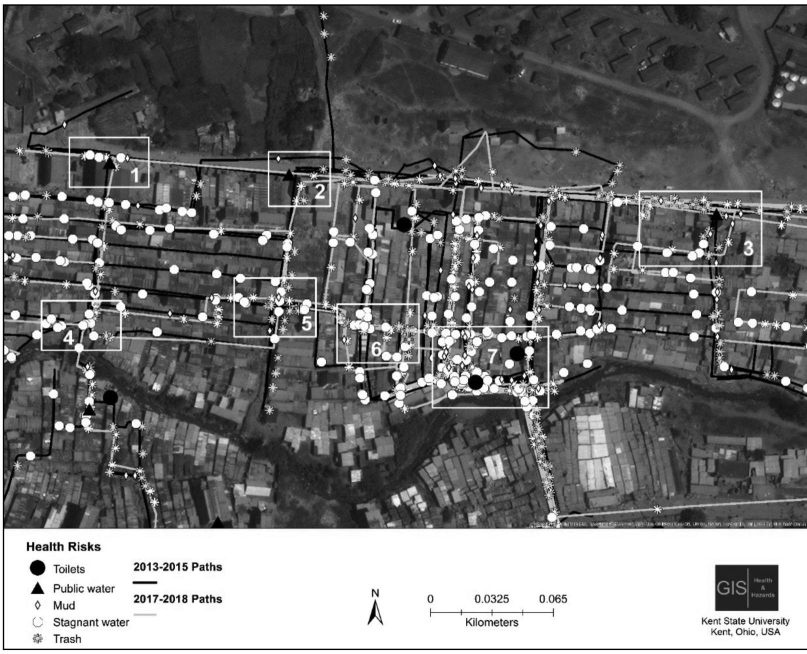


Fig 4: Digitized risks for all paths intersecting the seven sample areas.
Areas 1, 2, 3 and 7 are chosen because they contain WASH features and the GPS paths from each of the data collection time periods. Areas 4, 5 and 6 did not have any WASH features. Unfortunately, though area 4 is also close to the river just like 7, SV coverage and quality was more limited* making it difficult to visually identify change. WASH shapefiles were obtained from http://mapkibera.org/mapmathare/download/.
*One of the main considerations during data collection was research team security, and for some sections the camera was hidden because of safety concerns resulting in both GPS and video problems.[36]

Results

A total of 71 useable spatial videos were obtained for 2013, 2014, 2015, 2017, and 2018. These were further broken into four time periods: 2013, 2014, 2015, and 2017–2018, with 2017–2018 being collapsed together as collection occurred during December 2017 through March 2018.*

Out of the 71 spatial video paths collected, 35 fell within seven sample areas which are further described in this paper (Figure 4). These areas were selected because they contained data from all periods, and typical SIS features: path intersections, river environments, major roads, and a variety of housing types. For ease of visualization, paths were collapsed into either black (2013 to 2015) or grey (2017 to 2018) lines to show the overall extent of data collection. Along these paths visible risks were digitized. Table 1 provides a brief overview of each area and the changes noted within.

*Data was obtained specifically on August 2013, March 2014, October 2015, and December 2017 through March 2018. No data was collected for 2016. This is because the error in the GPS paths obtained after the 2013-2015 data collection made these data unusable. Hence the data was archived until 2017 when bespoke software was developed to correct the erroneous GPS paths.[29]

Table 1.

PERIODS OF SV COLLECTION FOR THE SEVEN AREAS SELECTED

Area	Date of Paths	Changes
1	March 19, 2014 October 8, 2015 January 7, 2018	This area contained a water point. There were few environmental risks digitized, partly due to fewer SV collection paths. One notable change was that the dusty road that had been visible in 2014 and 2015 had been surfaced with brick by 2018.
2	March 19, 2014 October 8, 2015 January 16, 2018	This contains a large road that borders Kosovo and is suitable for vehicles. One notable change was the once dusty road had been bricked over, and the roadside vendors that had laid food out on the ground and table tops now served from kiosks. Though this was a major structural change that improved both transportation and reduced health risks, there were still piles of visible trash by the side of the road.
3	August 2, 2013 March 19, 2014 October 8, 2015 March 26, 2018 February 5, 2018 January 29, 2018	Early SV routes captured stagnant water along the alleys and around the water point, which was also busy with a lot of human activity including people fetching or carrying water. The major road that ran in front of the water point was dusty and had visible trash along it. In 2014, the position of the camera did not show the water point, but it was again visible in the 2018 SV. In 2018, there was also a lot of human activity at the water point with almost equal amount of moisture on the ground as observed from previous years. Again, the dusty road had been bricked over.
4	March 19, 2014 October 8, 2015 January 7, 2018	Due to security concerns SV data quality was problematic. Most of the SVs were partially concealed making it difficult to assess change.
5	March 19, 2014 October 8, 2015 December 29, 2017 January 16, 2018	This area was an intersection of a crossroad that led to four different alleys. Unofficial drains along the paths were always wet and had open pipes laid in them suggesting a crude drainage system. The residential units were poorly constructed made of salvaged material and they did not visibly change over the SV collection period. The drains with open pipes visible in them did not change through the years of data collection.
6	August 2, 2013 March 19, 2014 October 8, 2015 December 29, 2017 January 7, 2018 January 16, 2018 February 3, 2018	Area 6 and 7 had the most SV collections. Area 6 was comprised of alleys and small unofficial drains. These drains varied between being wet and dry for different SVG collections, but the overall visible structure appeared unchanged.

(*continued on p. 362*)

Table 1. (*continued*)

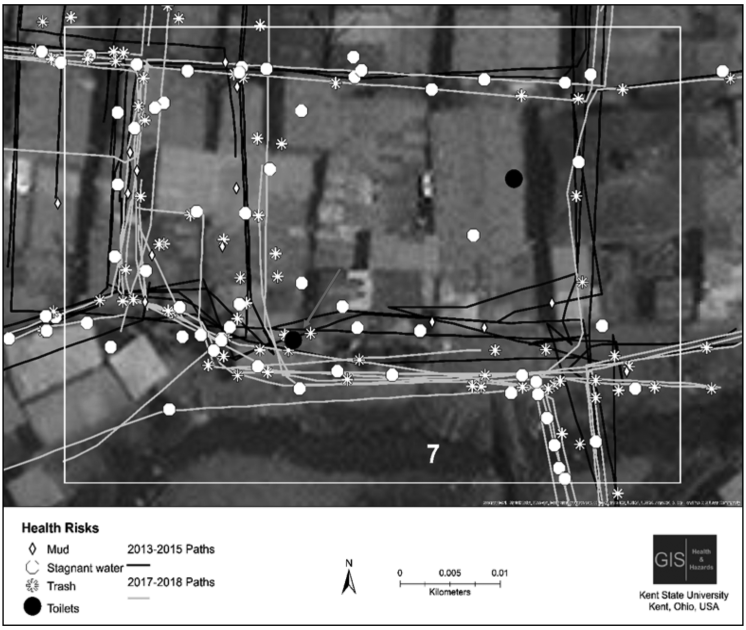
Area	Date of Paths	Changes
7	August 2, 2013 March 19, 2014 October 8, 2015 December 29, 2017 January 16, 2018 February 5, 2018 March 27, 2018	Area 7 was one of the busiest sections covered by the SV. While the alleyways, much as with area 6, remained unchanged, the banks of the Mathare River displayed considerable improvement. During 2013 to 2015 the banks of the river had large amounts of trash (especially plastics), overgrowth and a public toilet. By 2017–2018 the public toilet had been removed and the banks of the river cleaned up.

The next step was to consider change around key locations. Four (1, 2, 3, 7) of the seven areas had WASH features that could be identified in the videos. In general, Areas 4, 5, and 6 were mostly alleys, and as was noted in Table 1, displayed little change across the time periods. To illustrate how change occurred around a key location, one toilet (Figure 5) and one water point (Figure 6) were selected for more detailed description.

Figure 5A displays the spatial video paths in area 7, many of which follow or intersects the river seen at the bottom of the image. The area was visibly busy with foot traffic, especially along the river and across the bridge. The water in the river was discolored (polluted), and the research team noted the foul stench emanating from it. The banks of the river had steep sides and an overhang, possibly a result of erosion from flooding. The banks were also overgrown and littered with trash. Two toilets are shown on the map, with the one by the river being constructed of wood and metal sheets and draining directly into the river. Spatial video collected between 2013 through 2015 (Figures 5B to 5D) captured no apparent change in the toilet. In 2015 (Figure 5D), the spatial video did show earth being moved along the river and the banks being excavated. By December 2017 the toilet had gone, and the riverbank appeared to have been leveled out (Figure 5E).

In area 3 (Figure 6), the water point (an above ground cistern and a kiosk—Figure 6B) was by the side of a busy road that ran along the edge of that portion of the SIS, and people carrying containers and drawing water were clearly visible. The road that ran in front of the water point was dusty with considerable amounts of trash (Figure 6B). Interestingly in 2014, (Figure 6C), the road environment had been improved with much of the trash removed, leaving just some loose litter, and then by 2015 (Figure 6D) the road surface itself changed. This can be clearly seen in Figure 6E as the once dusty road is now bricked over. Further change occurred with the vendors, who in the first time periods sold wares directly by the roadside now moving into stores. These vendors mostly had ready to eat food, and could easily be contaminated as it was on the ground. This informal selling culture had now been moved to possibly more sanitary booths. However, while change had occurred with the road surface and vendor locations, the water points appeared to remain unchanged across the study period (2013–2018).

A) A detailed view showing the location of two toilets



B) The toilet is still in the same location and the river still has an undercut bank in 2013. Raised edges of the riverbank and the toilet just by the riverbank. Note also the amount of trash in and around the river.

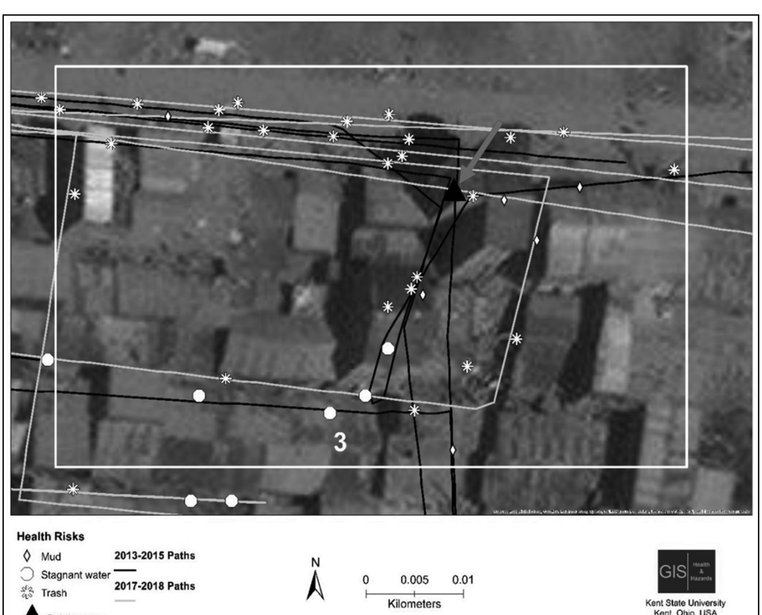
C) View on 2014; The pronounced riverbank is still visible.

Figure 5. Area 7—showing the environment around the river.
(*continued on p. 363*)

D) View in 2015. The bank of the river has been changed though the toilet remains (right).

E) View in 2017–2018. The toilet has been removed, and the riverbank smoothed out.

Figure 5. (*continued*)



A) A detailed view of Area 3.

Figure 6. Area 3—capturing change around a water point.
(*continued on p. 364*)

B) View in 2013 (above)
The position of the water point and the nature of the path that runs in front of it. There is considerable trash on the side of the road.

C) View in 2014 (left)
The position of the camera did not show the water point, just the path in front of it.

D) View in 2015 (left)
People with containers at the water vending point. The water point appears unchanged though the road looks improved.

E) View in 2017–2018 (below)
Notice the trash on the side of the road. The once dusty road is now bricked over.

Figure 6. (*continued*)

Discussion

Disparities in health are never better illustrated than with the situations found in SIS environments, many of which border wealthier neighborhoods where basic infrastructure and access to services is a daily right.[31] However, the SIS is often characterized by uncertainty, poor or no services, violence, and disease.[32,33,34] Added to this is a lack of data, including spatial information, that makes plotting disease cases, or even following up on a clinic visit difficult as even simple maps are not available.[27] "Streets" are often unnamed, there are no address ranges, and movement occurs along organically grown paths that snake between the poorly constructed residences, while standing water, mud and in some cases open sewage wash along the ground.[35] Wires and pipes wind together both on the ground and overhead. Places to get clean water, go to the toilet, and dispose of trash, can be found, but they vary dramatically in terms of their health safety.[20,36,37] A map of this space is vital; knowing where safe water can be found, for example, is paramount. While the mapping of these environments has occurred, especially in Kenya, there is still a lack of features important for health intervention, and especially in an ongoing basis. In this paper, we have shown how a combination of a spatial video camera and custom-made software make such fine scale multi period mapping possible. The technique is cheap (approximately \$130 per camera), easy to use, and allows for basic map making including temporal updating without need of GIS skills.

In this paper, we have presented the utility of the spatial video method using illustrations of fine-scale environmental changes witnessed along multiple paths in the Mathare SIS of Kenya. However, these examples should only be placeholders for other research ideas. Spatial video presents us with the opportunity for virtual surveys, meaning other researchers can re-walk these same paths again with a different perspective. For example, all the images presented in this paper are not just snapshots, but entry points into the map. We know where each image was taken, and by consulting our archive, can see how features have changed over time. Using these data, other diseases, or infrastructure changes, or even intervention evaluations can be considered. In this regard, there is no restriction in terms of staying within the silo of the original data collection purpose. These data do not die. Indeed, we did not originally collect these data with any specific project in mind, and because of initial GPS errors, these videos were archived for years. However, with an advance in technology, and in this case the functionality of spatial programming developed to the point of easily being able to correct and relink GPS paths, these spatial videos again became a resource. In the same way other projects collected by the team in locations such as pre-Ebola Liberia and Haiti during a cholera outbreak, can all be repurposed to further investigate those environments, or even to start cross-site comparisons. In this way it is possible to compare mosquito environments (where the standing water is and how stable across time it is), other environmental risks (such as trash accumulations), and social activity or gathering points (for education dissemination).

These data can also play an important role in addressing emerging disease outbreaks. For example, in Haiti, a similar approach when combined with water quality testing has identified which water points are the safest, which to avoid, and which can be in flux.[24] During a cholera outbreak (for example), the team knows which water points should be targeted first in terms of intervention. Similarly, by mapping out the location of toilets and open drains, connections are established between sewage flow and drinking water which could prove valuable in predicting disease spread once the location of the first cases are mapped. These data layers not only provide valuable insight during an outbreak, but could also be used to help predict where future vulnerabilities are greatest. For instance, in Figure 4, we can say the area in box 7 is most likely to be the greatest at risk for a disease outbreak or need the first attention if disease cases start to emerge in the area.

Returning to our Mathare example, the contribution this paper makes is that it showcases how spatial video has been used for a multiyear fine scale change detection to determine how microenvironments that might have impacts on human health have changed. In our chosen examples, there were some notable improvements as some of the main streets had been paved, making them less "dusty" and likely to cause either respiratory problems or drop contaminants on food or water. Street vendors had been relocated to kiosks, meaning their food should be safer and less prone to animal, ground, or water contamination.[38,39] One of the biggest environmental and health threats to the neighborhood is the river (especially during the rainy season)[35,40] as houses would be washed away, and excess flood water containing pathogens washing around living quarters and contaminating food and water. The spatial video showed that the riverbank environment had been levelled out and a nearby toilet, which almost certainly would have spilled over during flooding, had been removed.* This leads to the question of whether these changes occurred as part of a flood prevention strategy and general efforts to improve the health[41] in what is still "officially" an illegal area. To answer this additional context is required. This could be acquired using a variant of the technique presented here, the spatial video geonarrative.[42,43,44] This is a simultaneously collected narration which can be mapped using bespoke software that spatializes transcribed interviews. In this way, we could add context in terms of what happens or happened at a location, when, and why. Such a geonarrative could have helped explain why these changes occurred and whether they had been effective, if they were the result of a planned intervention. This all leads to the empowerment of residents who now have a means to collect data that can be turned into a quantifiable output (a map) to help both understand, plan and evaluate their local needs, and be used as a tool to convey those needs to higher officials. Future work will use machine learning to automatically identify and then map key features, such as WASH locations on the video. This would further reduce costs and reliance on outside expertise for mapping. In this regard, what has been described in this paper should be seen as part of a multi-step process leading to local health mapping in the most challenging environments entirely by local actors.

In addition, this will help empower the locals as they would feel as a part of contributing to avert the prevailing societal ills. Spatial videos and spatial video geonarratives are citizen centered. That is to say, a local researcher or resident can employ the

*This area had a lot of plastic contamination prior to our observation in the 2018 data. Interestingly, less plastic contamination was visible in 2018, which we believe are in line with the recent effort in Kenya to ban the use of plastic bags towards healthier communities.[41]

method to help provide the visual evidence needs to address existing issues within the community. This helps the researchers gain the trust of the locals as well as empower them to be participants and not spectators.

This is not to say that the spatial video method does not have limitations. Unlike other environments that have been collected by car[27] or by foot,[7,28] Mathare presented the most challenging environment encountered by the authors. Safety[*] issues meant that video quality was often compromised as the camera had to be hidden, which in combination with the narrow paths and metal walls and roofs caused considerable error in the GPS signal. Technology and software is always improving and offers solutions to most problems; the camera is now smaller and less obtrusive (a police body camera is the new tool—images in this paper showing a coordinate at the bottom are taken using this camera) and spatial programming software has made mapping easier. As a result, this technique can now be used on a regular basis by community health workers, either on planned surveys or just accompanying day-to-day activities. In this way, the SIS can be continuously mapped, almost organically, in an ever-expanding archive that can be accessed when the need arises.

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References

1. Simiyu S. Determinants of usage of communal sanitation facilities in informal settlements of Kisumu, Kenya. Environ Urban. 2016;28(1):241–58. https://doi.org/10.1177/0956247815616732
2. Corburn J, Sverdlik A. Slum upgrading and health equity. Int J Environ Res Public Health. 2017 Apr;14(4):342. https://doi.org/10.3390/ijerph14040342 PMid:28338613 PMCid:PMC5409543
3. Xu M, Cao C, Wang D, et al. Identifying environmental risk factors of cholera in a coastal area with geospatial technologies. Int J Environ Res Public Health. 2015 Jan;12(1):354–70. https://doi.org/10.3390/ijerph120100354

*While it is always importance to gain the trust and permission of local authorities, it is unlikely they could have helped reduce the potential for violence during data collection. Our local data collaborators were familiar with the neighborhood, knew how to "read" local conditions, and well versed in explaining the objects of the work being done. In this regard, as with all SV projects, a local collaborator or guide is necessary in bridging language and social barriers.

PMid:25551518 PMCid:PMC4306866

4. Mahabir R, Croitoru A, Crooks A, et al. A critical review of high and very high-resolution remote sensing approaches for detecting and mapping slums: trends, challenges and emerging opportunities. Urban Sci. 2018;2(1):8. https://doi.org/10.3390/urbansci2010008
5. Karanja I. An enumeration and mapping of informal settlements in Kisumu, Kenya, implemented by their inhabitants. Environ Urban. 2010;22(1):217–39. https://doi.org/10.1177/0956247809362642
6. Aditya T, Sugianto A, Sanjaya A, et al. Channelling participation into useful representation: combining digital survey app and collaborative mapping for national slum-upgrading programme. Appl Geomatics. 2019 Aug;12:133–48. https://doi.org/10.1007/s12518-019-00284-5
7. Curtis A, Squires R, Rouzier V, et al. Micro-space complexity and context in the space-time variation in enteric disease risk for three informal settlements of Port au Prince, Haiti. Int J Environ Res Public Health. 2019 Mar 5;16(5):807. https://doi.org/10.3390/ijerph16050807 PMid:30841596 PMCid:PMC6427463
8. Corburn J, Hildebrand C. Slum sanitation and the social determinants of women's health in Nairobi,Kenya. J Environ Public Health. 2015;2015:1–6. https://doi.org/10.1155/2015/209505 PMid:26060499 PMCid:PMC4427764
9. Panek J, Sobotova L. Community mapping in urban informal settlements: examples from Nairobi, Kenya. Electron J Inf Syst Dev Ctries. 2015;68(1):1–13. https://doi.org/10.1002/j.1681-4835.2015.tb00487.x
10. Townes LR, Mwandama D, Mathanga DP, et al. Elevated dry-season malaria prevalence associated with fine-scale spatial patterns of environmental risk: a case-control study of children in rural Malawi. Malar J. 2013;12(1):407. https://doi.org/10.1186/1475-2875-12-407 PMid:24206777 PMCid:PMC3833815
11. Zhou G, Munga S, Minakawa N, et al. Spatial relationship between adult malaria vector abundance and environmental factors in western Kenya highlands. Am J Trop Med Hyg. 2007 Jul;77(1):29–35. https://doi.org/10.4269/ajtmh.2007.77.29
12. Hagan JE, Moraga P, Costa F, et al. Spatiotemporal determinants of urban leptospirosis transmission: four-year prospective cohort study of slum residents in Brazil. PLoS Negl Trop Dis. 2016;10(1):1–16. https://doi.org/10.1371/journal.pntd.0004275 PMid:26771379 PMCid:PMC4714915
13. Reis RB, Ribeiro GS, Felzemburgh RDM, et al. Impact of environment and social gradient on Leptospira infection in urban slums. PLoS Negl Trop Dis. 2008;2(4):11–8. https://doi.org/10.1371/journal.pntd.0000228 PMid:18431445 PMCid:PMC2292260
14. Mwakalinga VM, Sartorius BKD, Mlacha YP, et al. Spatially aggregated clusters and scattered smaller loci of elevated malaria vector density and human infection prevalence in urban Dar es Salaam, Tanzania. Malar J. 2016;15(1):1–11. https://doi.org/10.1186/s12936-016-1186-9 PMid:26931372 PMCid:PMC4774196
15. Corburn J, Ngau P, Karanja I, et al. Mathare Valley, Nairobi, Kenya: 2011 collaborative upgrading plan. Berkeley, CA: University of California, 2011.

16. Corburn J, Karanja I. Informal settlements and a relational view of health in Nairobi, Kenya: sanitation, gender and dignity. Health Promot Int. 2016;31(2):258–69. https://doi.org/10.1093/heapro/dau100 PMid:25421267
17. Kamau N, Esamai FO. Determinants of immunisation coverage among children in Mathare Valley, Nairobi. East Afr Med J. 2001;78(11):590–4. https://doi.org/10.4314/eamj.v78i11.8949 PMid:12219965
18. Republic of Kenya Ministry of Housing. Background document : the national slum upgrading and prevention policy. Kenya: Republic of Kenya Ministry of Housing, 2013 May:1–14.
19. Wegelin-Schuringa M, Kodo T. Tenancy and sanitation provision in informal settlements in Nairobi: revisiting the public latrine option. Environ Urban. 1997;9(2):181–3. https://doi.org/10.1177/095624789700900208
20. Corburn J, Riley L. Slum health: from the cell to the street. Berkeley, CA: Univ of California Press, 2016. https://doi.org/10.1525/9780520962798
21. The Sphere Project. The Sphere handbook: humanitarian charter and minimum standards in humanitarian response (3rd ed.). Geneva, Switzerland: Sphere Association, 2011. Available at: https://spherestandards.org/wp-content/uploads/Sphere-Handbook-2018-EN.pdf. https://doi.org/10.3362/9781908176202
22. Latif ZA, Mohamad MH. Mapping of Dengue outbreak distribution using spatial statistics and geographical information system. In: 2015 2nd International Conference on Information Science and Security (ICISS). Soeul, Korea: 2015 Dec 14–16:1–6. https://doi.org/10.1109/ICISSEC.2015.7371016
23. Rodriguez-Morales AJ, Bedoya-Arias JE, Ramirez-Jaramillo V, et al. Using geographic information system (GIS) to mapping and assess changes in transmission patterns of chikungunya fever in municipalities of the Coffee-Triangle region of Colombia during 2014–2015 outbreak: implications for travel advice. Travel Med Infect Dis. 2016;14(1):62. https://doi.org/10.1016/j.tmaid.2015.06.009 PMid:26165455
24. Curtis A, Blackburn JK, Smiley SL, et al. Mapping to support fine scale epidemiological cholera investigations: a case study of spatial video in Haiti. Int J Environ Res Public Health. 2016;13(2). https://doi.org/10.3390/ijerph13020187 PMid:26848672 PMCid:PMC4772207
25. Sasaki S, Suzuki H, Igarashi K, et al. Spatial analysis of risk factor of cholera outbreak for 2003–2004 in a peri-urban area of Lusaka, Zambia. Am J Trop Med Hyg. 2008;79(3):414–21. https://doi.org/10.4269/ajtmh.2008.79.414 PMid:18784235
26. Curtis A, Blackburn JK, Widmer JM, et al. A ubiquitous method for street scale spatial data collection and analysis in challenging urban environments: mapping health risks using spatial video in Haiti. Int J Health Geogr. 2013;12(1):21. https://doi.org/10.1186/1476-072X-12-21 PMid:23587358 PMCid:PMC3685559
27. Curtis A, Quinn M, Obenauer J, et al. Supporting local health decision making with

spatial video: Dengue, Chikungunya and Zika risks in a data poor, informal community in Nicaragua. Appl Geogr. 2017;87:197–206.
https://doi.org/10.1016/j.apgeog.2017.08.008
28. Smiley S, Curtis A, Kiwango J. Using spatial video to analyze and map the water-fetching path in challenging environments: a case study of Dar es Salaam, Tanzania. Trop Med Infect Dis. 2017;2(2):8.
https://doi.org/10.3390/tropicalmed2020008
PMid:30270867 PMCid:PMC6082071
29. Curtis A, Bempah S, Ajayakumar J, et al. Spatial video health risk mapping in informal settlements: correcting GPS error. Int J Environ Res Public Health. 2019 Jan;16(1):33.
https://doi.org/10.3390/ijerph16010033
PMid:30586861 PMCid:PMC6339035
30. ArcGIS Desktop. 10.5. 1 quick start guides. Redlands, CA: Esri, 2017.
31. Bell MG. Historical political ecology of water: access to municipal drinking water in colonial Lima, Peru (1578–1700). Prof Geogr. 2015;67(4):504–26.
https://doi.org/10.1080/00330124.2015.1062700
32. Unger A, Riley LW. Slum health: from understanding to action. PLoS Med. 2007;4(10):1561–6.
https://doi.org/10.1371/journal.pmed.0040295
PMid:17958462 PMCid:PMC2039756
33. Kimani-Murage EW, Schofield L, Wekesah F, et al. Vulnerability to food insecurity in urban slums: experiences from Nairobi, Kenya. J Urban Heal. 2014.
https://doi.org/10.1007/s11524-014-9894-3
PMid:25172616 PMCid:PMC4242851
34. Unger A. Children's health in slum settings. Arch Dis Child. 2013;98(10):799–805.
https://doi.org/10.1136/archdischild-2011-301621
PMid:23899920
35. Salles A, Wolff DB, Silveira GL. Solid wastes drained in an urban river sub-basin. Urban Water J. 2012;9(1):21–8.
https://doi.org/10.1080/1573062X.2011.633612
36. Waweru S, Kanda E. Municipal solid waste management in Kenya : a comparison of middle income and slum areas. In: International Conference on Disaster Risk Reduction & Conflict Resolution for Sustainable Development. Masinde Muliro University of Science and Technology, Kakamega, Kenya, Aug 2012. Available at: https://www.researchgate.net/profile/Edwin_Kanda/publication/309180645_Municipal_Solid_Waste_Management_in_Kenya_A_Comparison_of_Middle_Income_and_Slum_Areas/links/5803659008ae6c2449f949d8/Municipal-Solid-Waste-Management-in-Kenya-A-Comparison-of-Middle-I.
37. Kimani-Murage EW, Ngindu AM. Quality of water the slum dwellers use: the case of a Kenyan slum. J Urban Heal. 2007;84(6):829–38.
https://doi.org/10.1007/s11524-007-9199-x
PMid:17551841 PMCid:PMC2134844
38. Debela TH, Beyene A, Tesfahun E, et al. Fecal contamination of soil and water in sub-Saharan Africa cities: the case of Addis Ababa, Ethiopia. Ecohydrol Hydrobiol. 2018;18(2).
https://doi.org/10.1016/j.ecohyd.2017.10.003
39. Shields KF, Bain RES, Cronk R, et al. Association of supply type with fecal contamination of source water and household stored drinking water in developing countries: a bivariate meta-analysis. Environ Health Perspect. 2015;123(12):1222–31.

https://doi.org/10.1289/ehp.1409002
PMid:25956006 PMCid:PMC4671240

40. Thorn J, Thornton TF, Helfgott A. Autonomous adaptation to global environmental change in peri-urban settlements: evidence of a growing culture of innovation and revitalisation in Mathare Valley Slums, Nairobi. Glob Environ Chang. 2015;31:121–31. https://doi.org/10.1016/j.gloenvcha.2014.12.009
41. Reality Check team. Has Kenya's plastic bag ban worked? London, United Kingdom: BBC News, 2019. Available at: https://www.bbc.com/news/world-africa-49421885.
42. Curtis A, Curtis JW, Shook E, et al. Spatial video geonarratives and health: case studies in post-disaster recovery, crime, mosquito control and tuberculosis in the homeless. Int J Health Geogr. 2015;14:22.
https://doi.org/10.1186/s12942-015-0014-8
PMid:26253100 PMCid:PMC4528811
43. Krystosik AR, Curtis A, Buritica P, et al. Community context and sub-neighborhood scale detail to explain dengue, chikungunya and Zika patterns in Cali, Colombia. PLoS One. 2017;12(8):1–26.
https://doi.org/10.1371/journal.pone.0181208
PMid:28767730 PMCid:PMC5540594
44. Ajayakumar J, Curtis A, Smith S, et al. The use of geonarratives to add context to fine scale geospatial research. Int J Environ Res Public Health. 2019;16(3).
https://doi.org/10.3390/ijerph16030515
PMid:30759776 PMCid:PMC6388256
45. Emina J, Beguy D, Zulu EM, et al. Monitoring of health and demographic outcomes in poor urban settlements: evidence from the Nairobi urban health and demographic surveillance system. J Urban Heal. 2011;88(Suppl 2):200–18.
https://doi.org/10.1007/s11524-011-9594-1
PMid:21713553 PMCid:PMC3132229