PERSPECTIVE

Drivers of Emerging Infectious Disease Events as a Framework for Digital Detection

Sarah H. Olson,[1] Corey M. Benedum,[1] Sumiko R. Mekaru, Nicholas D. Preston, Jonna A.K. Mazet, Damien O. Joly,[2] John S. Brownstein[2]

The growing field of digital disease detection, or epidemic intelligence, attempts to improve timely detection and awareness of infectious disease (ID) events. Early detection remains an important priority; thus, the next frontier for ID surveillance is to improve the recognition and monitoring of drivers (antecedent conditions) of ID emergence for signals that precede disease events. These data could help alert public health officials to indicators of elevated ID risk, thereby triggering targeted active surveillance and interventions. We believe that ID emergence risks can be anticipated through surveillance of their drivers, just as successful warning systems of climate-based, meteorologically sensitive diseases are supported by improved temperature and precipitation data. We present approaches to driver surveillance, gaps in the current literature, and a scientific framework for the creation of a digital warning system. Fulfilling the promise of driver surveillance will require concerted action to expand the collection of appropriate digital driver data.

Unusual infectious disease (ID) events occur when an underlying mix of antecedent epidemiologic drivers provide the necessary conditions for a pathogen to emerge in susceptible populations. These conditions may be driving emergence through a wide variety of mechanisms, such as climate change, industrial development, ecosystem change, and social inequality (*1*). Public health policy has traditionally targeted well-described socioeconomic drivers, such as lack of sanitation, lack of hygiene awareness, and poor access to health care and disease prevention services (e.g., bed nets, vaccinations, and treatments), but researchers have increasingly evaluated the complex interactions among drivers related to globalization, political issues, human susceptibility, and biophysical environmental change (*1*–*8*) (Table).

Whereas early ID research primarily focused on pathogen identification and specific disease ecologies (*9*), researchers are now exploring the multifactorial causes of emergence. No longer is the question "What causes Ebola?" but rather, "Why does an Ebola outbreak occur at a particular time or location?" As a result of this transition in research, global disease event data have grown. The World Health Organization Global Burden of Disease Reports, commissioned in 1992, first demonstrated the feasibility of measuring both global risk and disease occurrence data (*10*). Scientists built on such initial global platforms and began to develop tools to improve reporting and awareness of disease outbreaks among local and global health workers. In the 1990s, digital systems such as ProMED and Global Public Health Intelligence Network demonstrated the utility of real-time digital disease event detection (*11*,*12*). The emergence of these intelligence platforms was followed by a new generation of surveillance tools, such as HealthMap, Biocaster, and MedISys (*13*–*15*).

Behind the development of surveillance tools for ID events, growing research suggests that untapped driver signals could be quantified and monitored to anticipate emergence risk as a new form of epidemic intelligence. Temperature and precipitation data are already used to forecast meteorologically sensitive IDs, but more driver data could support improved predictive models covering a much broader range of IDs. For example, across 397 outbreaks of international concern, as classified by the World Health Organization, nearly 40% were attributed to 1 driver: lack of public health infrastructure (*2*). Further, changes in land use, another known driver, can produce animal–human interfaces ripe for spillover events (*3*,*7*). Indeed, between 1940 and 2005, 60% of emerging ID events were of zoonotic origin and showed a substantial positive correlation with wildlife abundance and diversity (*4*). The logical progression to further strengthen public health infrastructure is

Author affiliations: Wildlife Conservation Society, New York, New York, USA (S.H. Olson); University of Wisconsin Madison, Madison, Wisconsin, USA (S.H. Olson); Boston University School of Public Health, Boston (C.M. Benedum); Boston Children's Hospital, Boston, Massachusetts, USA (C.M. Benedum, S.R. Mekaru, N.D. Preston, J.S. Brownstein); University of California, Davis, California, USA (J.A.K. Mazet); Metabiota, Nanaimo, British Columbia, Canada (D.O. Joly); Harvard Medical School, Boston (J.S. Brownstein)

DOI: http://dx.doi.org/10.3201/eid2108.141156

[1]These first authors contributed equally to this article.

[2]These authors were co-senior authors of this article.

Table. Disease drivers identified in the literature and examples of data availability*

Driver theme (references)	Global data examples†	Regional data examples†
Human susceptibility to infection (*1,2,4*)	Vaccine rumor surveillance, product distribution data from manufacturers, self-reported immunization status	US influenza vaccination rates, measles vaccination rates from the Mozambique Health Information System
Climate and weather (*1,2,4*)	Numerous satellite products, National Oceanic and Atmospheric; Administration, Climatic Research Unit, Center for Sustainability and the Global Environment, vulnerability to climate change	Climate data, social media reports of climate and air pollution effects on Twitter and Sina Weibo
Human demographics and behavior (*1,2,4*)	Night time lights, Gridded population of the world, mobile phone operator data	National census data products, Twitter, world population
Economic development (*1,2,4*)	International Monetary Fund, World Bank	National departments of economics
Land use and ecosystem changes (*1,2,4*)	Global agricultural lands, Center for International Earth Science Information Network, Global Forest Change 2000–2012, Global Forest Watch, global livestock distribution densities	National departments of agriculture, croplands in western Africa, Africa mining digital news reports, IMAZON Deforestation Alert System
Technology and industry (*1,2,4*)	Digital news, United Nations Global Pulse	NA
Human wildlife interaction (*2,4*)	Species distribution grids, digital news reports	State-level hunting data
Breakdown of public health measures (*1,2,4*)	Natural disaster hotspots	News of impending natural disasters (i.e., predicted hurricane landfall)
Poverty and social inequality (*1*)	Center for International Earth Science Information Network, Global Observatory	National census data
War and famine (*1,2,4*)	Famine early warning system, digital news and social media	Syria Tracker
Lack of political will (*1*)	Historical records, Transparency International, Cline Center for Democracy	NA
International travel and commerce (*1,2,4*)	Flight and shipping data	Regional distribution data of food products

*The table is purposely not exhaustive but provides a survey of types of available digital data that are associated with different drivers. NA, not applicable.
†See online Technical Appendix Table 1 (http://wwwnc.cdc.gov/EID/article/21/8/14-1156-Techapp1.pdf) for available references.

to expand surveillance to monitor the full spectrum of ID emergence drivers (Figure 1) (*2*,*16*,*17*).

In the historical case of bromeliad malaria (see Drivers in Action and Hindsight section), actions were taken only after astute clinicians recognized the pattern of an ID event, malarial symptoms around cacao farms. Had a driver surveillance system been available, the elevated risk for an outbreak might have been indicated by reports of agricultural land use changes and human movement in conjunction with the underlying poverty and lack of disease prevention practices. Ideally, a warning system would then trigger an active surveillance program, a preemptive investigation to reduce risk factors, or even control measures (Figure 1).

An integrated driver surveillance system has the potential to be an integral tool for analysts and decision makers at 2 stages. First, whereas standard surveillance methods were designed to detect an outbreak, a driver-centric system will provide situational awareness of potentially unhealthy conditions before and following an outbreak. At the pre-outbreak stage, decision makers will have a tool that summarizes risk across data streams for multiple drivers of IDs. Second, at the postoutbreak stage, driver surveillance could result in more efficient resource allocation. Interventions could be tailored to local needs and capacity based on the knowledge of underlying drivers that will vary over space and time (e.g., infrastructure, vaccine coverage, and public health capacity) (*18*).

A warning and response system will require improved understanding of the relationships among specific drivers and ID emergence events. Advancements must also be made in terms of driver data collection. Well-developed datasets regarding climate, land cover change, and population density already exist (e.g., Center for International Earth Science Information Network, Climate Research Unit, and Google Earth Engine), but well-developed datasets are not readily available for drivers associated with human behavior (e.g., open-source curated data on immunization coverage, public health breakdown, sanitation and hygiene, and vector control). Well-developed, readily available datasets are those that provide subcountry level data or higher resolution at regular and frequent intervals with documented and standardized tools that are published and freely available online. Through curation and accessibility, these data and an expanded knowledge of drivers could greatly enhance mathematical models that describe ID transmission and epidemic occurrence. Herein, we survey available digital resources, present a conceptual framework for such a digital disease driver surveillance platform, and discuss opportunities for and obstacles to its successful implementation.

Drivers in Action and Hindsight

In the 1940s, a malaria epidemic began when economic pressures and poverty led the agriculture sector of Trinidad

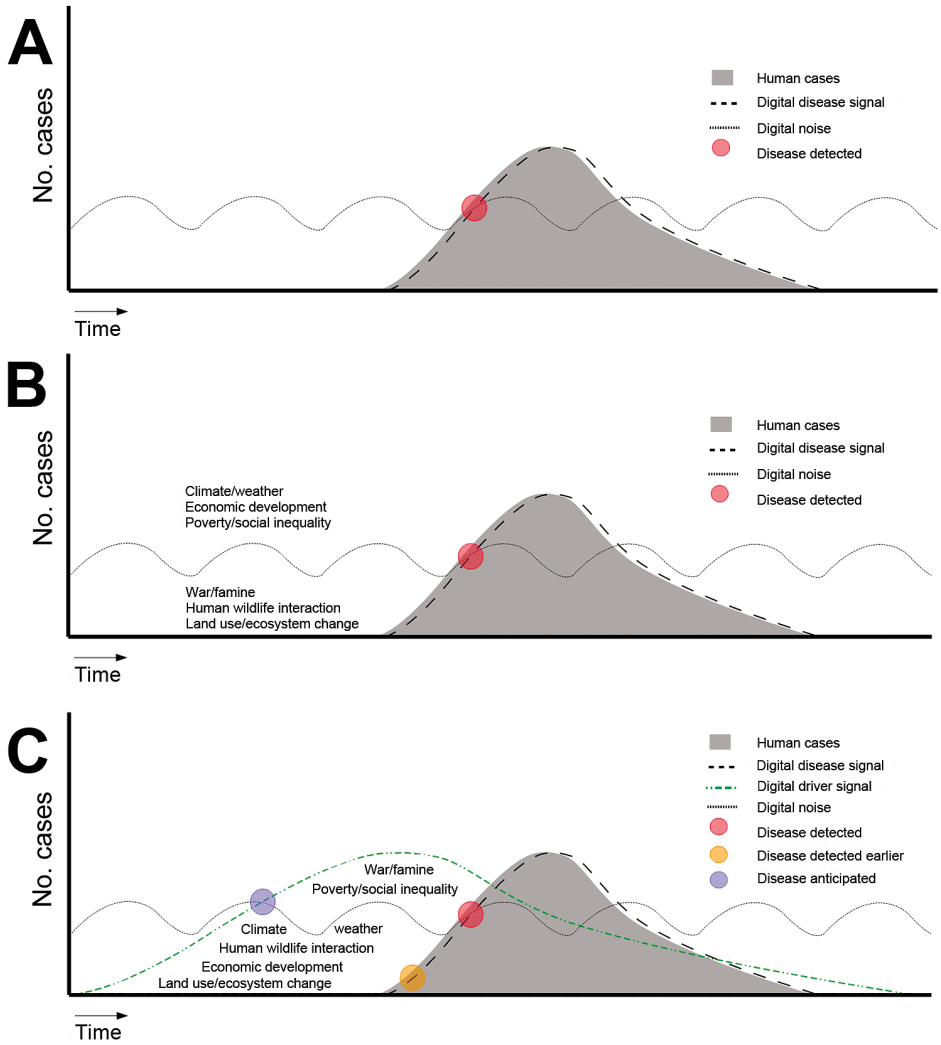


Figure 1. Surveillance and detection of disease by traditional (A, B) and digital (C) detection systems. A) Traditional disease detection, in which a close association exists between the number of cases and the digital disease signal. Disease is detected when the signal exceeds the noise. B) Disease emergence or outbreaks often occur following a driver. Examples of such drivers include climate and weather, economic development, poverty and social inequality, war and famine, human–wildlife interactions, land use and ecosystem changes. C) Detection of disease by using digital techniques. In this system, drivers of disease (not disease) are monitored, essentially to monitor for conditions suitable for disease emergence. Hypothetically, the careful surveillance of drivers that have been separated from digital noise could shorten the time to disease detection (as indicated by the orange dot).

into the cacao industry, an activity that requires a large human labor force and shade trees. These shade trees supported a bromeliad tank species, a family of plants that contain water-holding structures, creating an ideal breeding site for *Anopheles bellator* mosquitoes and new niches for different mosquitoes within the forest canopy (*19*,*20*). During the epidemic, medical doctors first noted an increase in the prevalence of splenomegaly, an indication of malaria, among schoolchildren correlated with areas cultivating cacao, and that *A. bellator* mosquitoes were only found near the cacao farms. Removal of the bromeliads reduced *A. bellator* mosquito populations and returned malaria rates to prior endemic levels (*20*). In hindsight, the outbreak resulted from the convergence of poverty, commerce, and agricultural and land-use changes; lack of malaria prevention and treatment services; and resulting shifts in local mosquito ecology. Building on our accumulating knowledge of drivers and the digital streams of data that now exist, the public health sector can be provided with early warning tools to recognize when conditions are ripe for disease emergence events, tools that could not have existed in the mid-20th century.

Identifying Existing Optimal Spatial Data System Components

Driver monitoring requires access to data from multiple domains at sufficient resolution and scale to correlate with known disease events and overcome potential biases. To build a driver surveillance system, issues with data availability and compatibility must be addressed in conjunction with temporal resolution and spatial scale.

Data availability categorized by drivers of interest is shown in Figure 2. The data were collected for the Health Scapes Project (http://healthscapes.io), an initiative launched in 2009 to assemble and collaboratively curate global open data of relevance to the global health research community. Of note, datasets were not readily found for certain drivers (i.e., human wildlife interaction and breakdown of public

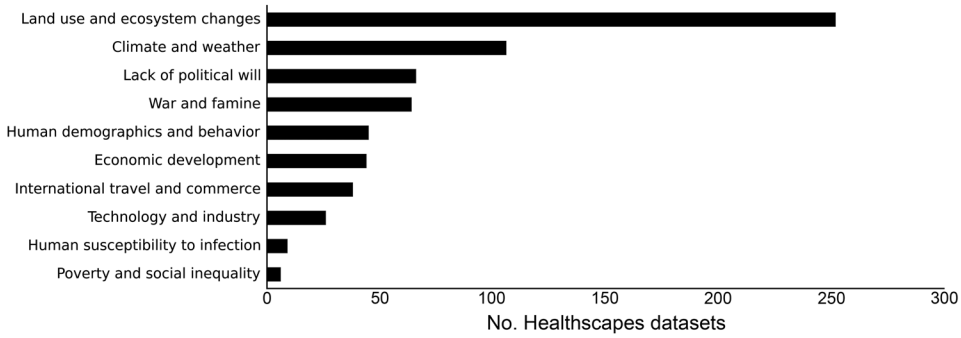


Figure 2. Number of datasets, by disease driver, available globally. The data were collected for the HealthScapes Project (http//:healthscapes.io).

health measures), and few datasets were found for other drivers (i.e., human susceptibility to infection and poverty and social inequality).

Availability

The global volume of data is doubling every 2 years (*21*). Although this trend presents an opportunity for analysts, much of the data are either unreduced big data that have become stored at major institutions or transient data that are not stored. Although potentially applicable to geographic, ecologic, and sociologic driver detection, only a fraction of these data have been processed for analysis on current research infrastructure, and even less is publicly accessible. Despite efforts to make data available, few providers have adopted provenance or metadata standards or leveraged mechanisms to facilitate collaboration, such as web services and application programming interfaces.

Compatibility

Technology trends, software development practices, and disciplinary preferences have resulted in a mosaic of data types and formats. Despite increasing interoperability, propriety obstacles persist, and innovations have isolated valuable legacy data in archaic formats.

Temporal Resolution

The distribution of data is generally skewed to the present because of increased digitization, the emergence of the Internet, and widespread instrumentation of systems. Research funding levels, political cycles, disruptive events, research trends, individual efforts, and the evolution of organizations all contribute to temporal variability in data resolution.

Spatial Scale

Few driver datasets of interest have complete global coverage. When considering data storage location as a proxy for spatial coverage, 50% is in North America, 30% in Europe, and 14% in the Asia–Pacific region; the Middle East, Latin America, India, and Africa account for the remaining 6% (*22*). This uneven distribution presents a challenge for monitoring disease in underdescribed regions. Furthermore, when attempting to grid, or rasterize, data at the global scale, researchers may codify incorrect assumptions through interpolation or by applying bias corrections for research effort. The distribution of data is evolving rapidly; if we consider submarine cable traffic rather than storage volume, intra-Asian connections have surpassed trans-Atlantic bandwidth (*23*). It is not yet determined how this shifting flow of information may influence driver coverage and effect digital media surveillance.

Leveraging Digital Media Reports

Digital media reports already provide a rich source of information on disease outbreaks (*24*) and, likewise, may be useful in monitoring disease drivers to identify periods of increased risk for outbreaks (e.g., news articles about breakdown of public health infrastructure, conflict, and vaccine programs). However, this driver surveillance resource presents a unique mix of opportunities and challenges. On the opportunity side, only a handful of languages account for most content on the Internet, resulting in a distilled set of global languages (*25*). If this pattern continues, only a subset of languages will need surveillance. Furthermore, the ability of natural language processing tools to parse reports for contextual data, such as location information, is improving. On the challenge side, digital media is fleeting and curated datasets are limited. For example, Google News, a popular digital media aggregator, does not provide a list of the sources used in its feed, and, thus, its content could change with time (*26*). Digital media can also miss nondigital disease-related news reports and details due to language or source (e.g., print and audio) limitations (*27*).

An objective evaluation of digital media for driver surveillance will ultimately require an unbiased dataset that links media reports of disease drivers to actual outbreaks that enable determination of the specificity and sensitivity of the system. Notably, it will be difficult to develop such a system because of the circular nature of these data (i.e., the system would be evaluated based on the system used to collect the data). In the absence of independently collected gold standard data, one cannot determine the degree to which unknown unknowns are missed. In summary, more

research is needed in evaluating digital media systems and the influence of these potential limitations.

New Data Technology Solutions for Drivers

Numerous projects have been established as hubs for collecting, cataloging, and sharing global data on a wide variety of potential drivers. Underlying these streams is an increasingly open-data ethic. Numerous repositories of existing data specialize in distributing accessible data formats (e.g., World Organisation for Animal Health's World Animal Health Information Database, Global Biodiversity Information Facility, Center for International Earth Science Information Network, Google Earth Engine, Gapminder World, European Union BioFresh project, and HealthScapes). Recent Digital Disease Detection conferences have highlighted numerous new data sources, including mobile phone and Internet technology that has enabled real-time syndromic and resource monitoring from social media (Twitter and Facebook), active surveillance (e.g., Flu Near You and Influenzanet), and participatory surveillance (Opendream, SMS for Life, and Saude Na Copa 2014). On the ground and at the source, data loggers and sensors are decreasing in cost and are supported by open-source platforms (e.g., Mataki, Arduino, and Onset HOBOs).

HealthMap is one example of emerging digital surveillance technology that uses a flexible architecture and an automated processing system to target ID events and the wildlife trade (*13*,*28*). This framework could be applied to identify any driver of interest as dictionaries for different languages and subject areas are used; the platform is fundamentally subject- and language-agnostic. This structure enables for inclusion of data not distributed digitally, resulting in the ability to expand overall media coverage. In the near future, developments in optical character and audio language recognition offer the potential for the rapid processing of nondigital media, such as photographs of print media and audio news sources.

Coinciding with the growing number of data sources has been an explosion of visualization, analytical, and hybrid tools, often fueled by the open-source community. Once data are collected, these tools will provide new ways for analysts to convey complex data and ideas, such as driver surveillance trends, to decision makers in a clear and logical format (e.g., Hans Rosling's Trendalyzer, online Technical Appendix Table 2, http://wwwnc.cdc.gov/EID/article/21/8/14-1156-Techapp1.pdf). Cloud-based platforms have evolved from desktop-based Esri software and leverage the open-source framework, social coding, and collaboration to provide researchers new opportunities to combine complex multisource big data with newly created virtual forums (e.g., Google Earth Engine and social modeling platforms). In addition to new analytic techniques, digital driver surveillance can build on advances in the way science is conducted. One example is the Open Science Framework, which has pioneered online project spaces that enable others to make changes or add on to the project without affecting the original (https://osf.io/). Another example is rOpenSci (https://ropensci.org), an effort funded by the Sloan Foundation to wrap scientific application programming interfaces in a manner that is readily accessible to analysts and researchers. This new approach sets the groundwork for collaborative, iterative, and adaptive management of ID driver surveillance models.

Application of Driver Surveillance for a Novel ID

The emergence of Nipah virus (NiV) on the global scene can be linked to several drivers, all of which could have been monitored and potentially recognized, resulting in quicker containment of outbreaks. The first human NiV cases were reported in 1998 in Malaysia. This initial spillover event has been linked to agricultural intensification where mango trees were planted in close proximity to pigsties (*16*,*29*). This change in practice led to increased contact between pigs and the natural reservoir for NiV, the flying fox, and subsequent introduction of NiV into the pig population (*29*). The continued contact between the bats and pigs resulted in NiV establishment within the pig population and increasing exposure of pig workers to NiV (*29*,*30*).

Perhaps NiV emergence could have been anticipated if a system existed that raised warnings about the coincident land-use change and agricultural intensification. Scientists were eventually able to match the unknown disease affecting humans with NiV and identified risk factors and modes of transmission, but the key connections might have been recognized sooner. Although an isolated change in agricultural practices would not typically warrant an intervention, the emergence of a new porcine respiratory disease in conjunction with the change could have led to closer monitoring. When the initial spillover into the human population occurred, the knowledge of a new porcine disease, changes in driver activity, and the identification of a new virus in bats all occurring within the same region could have individually triggered heightening alerts.

After emergence, driver surveillance would have provided valuable situational insight. In the early stages of the outbreak, there was a mass sell-off of pigs in response to the cluster of cases and the perceived link among farmers between the sick pigs and the cluster (*29*,*31*,*32*). This sell-off resulted in the spread of NiV to southern regions of Malaysia, where there is a dense pig population (*29*). As the outbreak spread southward, the international pig trade moved the virus to Singapore (*32*). Market monitoring could have potentially identified the increase in pig sales, as well as the regional sources and endpoints of traded pigs. If supply chains and the locations that sit at high-risk critical nodes could be identified, increased active surveillance

or even preemptive interventions, such as animal culling, could have been deployed.

Field Deployment as a Two-Way Communication Interface

A successful epidemic surveillance platform should leverage the latest web technologies to support global communication among health workers with near–real-time information on the drivers of disease emergence. It is important that the platform have the capability to capture ground-truthed data from field teams to effectively crowd-source data curation to amplify efforts in the global response to disease emergence. Such open data curation and provisioning services would further help democratize data access to those often most affected by IDs. Core features of the system would include the ability to identify relevant drivers for a disease or region of interest as well as the capacity to monitor spatiotemporal trends for these drivers. A user could use this information to make decisions about allocating funding for health control measures or prioritizing health effect assessments of development initiatives. In the field, a mobile interface to the platform could be used to identify future field sampling sites, intervention options, or changes in drivers. It is essential the platform have the capacity to monitor and overlay multiple drivers, in light of known interactions. The utility of the system would be enhanced by being able to set notifications on drivers of interest that could initiate a response, follow up, or further investigation. A truly dynamic web interface would enable the user to simulate different health outcomes under different scenarios, such as economic policies, control strategies, or climate futures. In anticipation of future ID outbreaks, a well-designed system could be used strategically by decision makers to allocate or predeploy limited human and material resources to risk hotspots. Globally, the system could be used to help orchestrate multinational responses to emerging ID threats, identify priorities, and raise awareness of the role of antecedent drivers in global health.

Moving toward a Prototype Platform

For a first-generation analysis platform to prove useful, it must provide insight regarding specific drivers and the drivers' subsequent effect upon current risk. We envision a country-based analysis framework that could comprise 3 components. The first component will measure a nation's risk for an emerging ID event by establishing driver baselines through the use of historical data or published ratings. The hotspots approach used by Jones et al. (*4*) illustrates the potential of this component, which could be extended from using historical events to using historical driver data to identify geographic locations at risk for ID emergence. Together these baselines would provide a Bayesian prior distribution of risk. The second component will introduce existing and new digital alerts as new evidence for a model. The addition of these alerts would build a risk map according to baseline levels; that is, a driver with a low baseline will not contribute much to changing the overall risk with the addition of a few alerts, but for a driver with a high baseline, the addition of a few driver alerts could push it into a higher risk category. By overlaying the digital disease alerts upon the baseline prior distribution of risk, we can then analyze these data for trends and biases to anticipate future emerging ID events. The third component will involve continually updating beliefs about the distribution of risk that is determined on the basis of new evidence.

Despite our positive outlook on digital driver surveillance, we note several caveats, such as the complexity of causal human–environment interactions (*33*) and the use of models to confront imperfect knowledge. For instance, false-positive signals, when a driver system identifies a strong signal but no disease occurs, are inevitable. Without appropriate user sensitization, this result could lead to misallocation of resources and erosion of trust. Conversely, some disease events might lack any warning signals, as may have been the case with the 2009 pandemic of influenza A(H1N1)pdm09 virus infections. Despite the existence of these problems, we believe they will be alleviated through a better understanding of the disease–driver and driver–driver associations. However, some problems will be unavoidable. For example, a potentially strong limitation would be that infrequent updating of driver data could result in either missing a brief signal or not identifying the signal until it is too late to implement control measures. Ultimately, we must recognize that digital surveillance is one tool among many that can help supplement, but not replace, traditional public health surveillance.

Conclusions

A digital driver surveillance platform that improves situational awareness by active monitoring of ID events and associated drivers is an obtainable goal for the public health community. We believe that future surveillance platforms will be able to not only describe driver activity in space and time but also indicate driver thresholds, severity, and likely interactions among drivers. Digital media reporting offers tremendous potential to contribute to existing datasets because of its automated ability to scrape news sources for alerts and provide real-time driver data. Channels of communication need to be opened between the data producers, who may not see the wider utility of what is collected, and data consumers, who may not understand barriers with data collection. In addition, funding agencies that support driver-associated data collection efforts need to require that recipients follow best data practices. We recognize the existence of obstacles to developing a digital driver surveillance platform, but as data become more available, compatible,

and refined, our ability to overcome systematic biases and sources of error to identify driver activity will become easier. This report is a call to action to improve collection of driver and ID event data to rapidly develop the science and our understanding of relationships between drivers and emerging ID events, and move toward driver-based ID surveillance systems.

Acknowledgments

We thank Rachel Chorney for help developing Figure 1 and the 2 anonymous reviewers who provided helpful comments.

This study was made possible by the generous support of the American people through the United States Agency for International Development (USAID) Emerging Pandemic Threats program, PREDICT project. Additional support was provided by the National Library of Medicine of the National Institutes of Health (grant R01-LM010812). Journal access was provided by in-kind support from the University of Wisconsin–Madison Center for Sustainability and the Global Environment and Boston University School of Public Health.

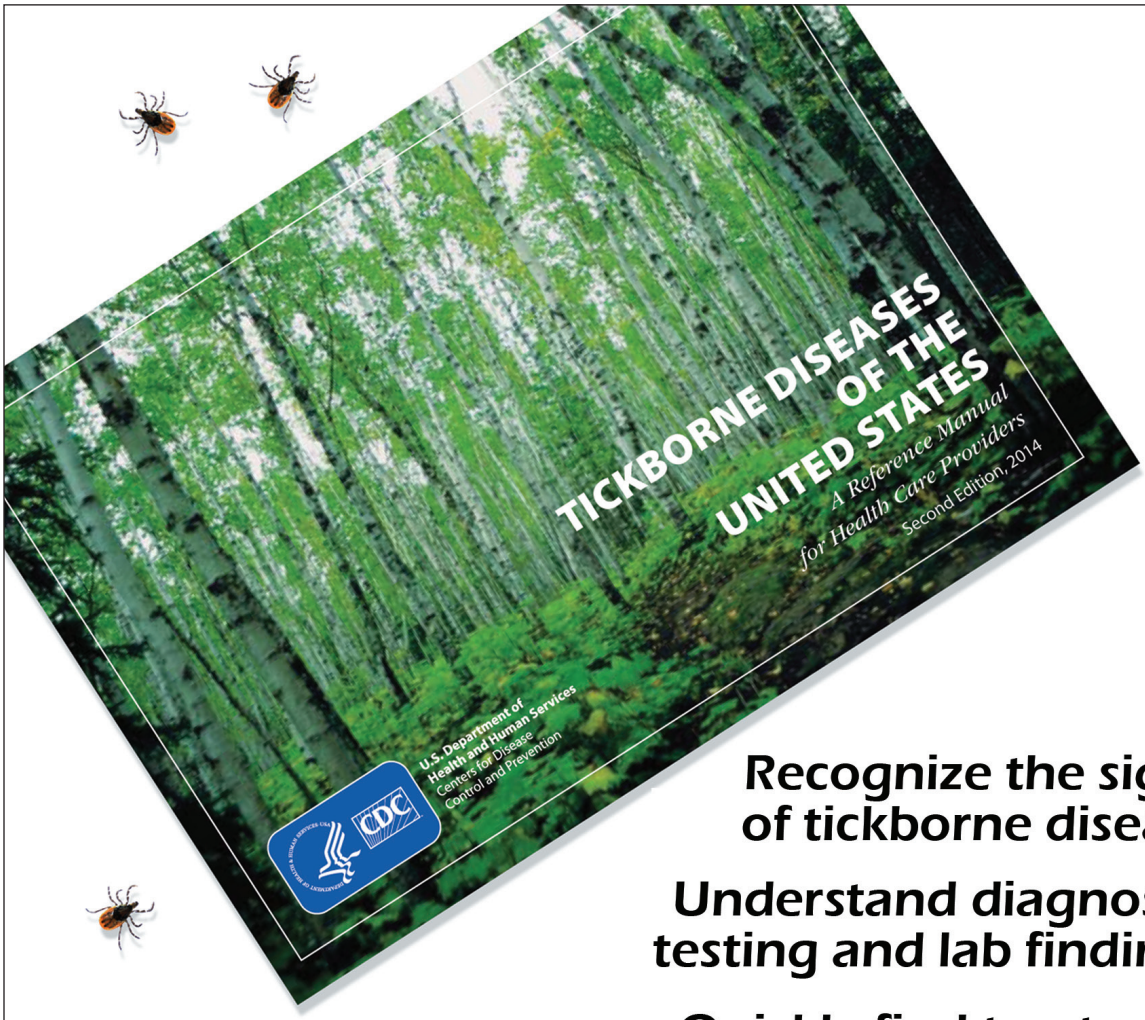
Dr. Olson is a wildlife epidemiologist currently working on the USAID Emerging Pandemic Threats program, PREDICT project; her research focuses on complex ecologic and social factors related to emerging infectious diseases; Mr. Benedum is a doctoral student at the Boston University School of Public Health; his research interests lie in integrating modern technology with infectious disease surveillance.

References

1. Smolinski MS, Lederberg J, Hamburg MA, editors. Microbial threats to health: emergence, detection, and response. Washington (DC): The National Academies Press; 2003.
2. Bogich TL, Chunara R, Scales D, Chan E, Pinheiro LC, Chmura AA, et al. Preventing pandemics via international development: a systems approach. PLoS Med. 2012;9:e1001354. http://dx.doi.org/10.1371/journal.pmed.1001354
3. Daszak P, Cunningham A, Hyatt A. Anthropogenic environmental change and the emergence of infectious diseases in wildlife. Acta Trop. 2001;78:103–16. http://dx.doi.org/10.1016/S0001-706X(00)00179-0
4. Jones KE, Patel NG, Levy MA, Storeygard A, Balk D, Gittleman JL, et al. Global trends in emerging infectious diseases. Nature. 2008;451:990–3. http://dx.doi.org/10.1038/nature06536
5. Lederberg J, Shope RE, Oaks SC Jr. Emerging infections: microbial threats to health in the United States. Washington (DC): The National Academies Press; 1992.
6. Myers SS, Gaffikin L, Golden CD, Ostfeld RS, Redford KH, Ricketts TH, et al. Human health impacts of ecosystem alteration. Proc Natl Acad Sci U S A. 2013;110:18753–60. http://dx.doi.org/10.1073/pnas.1218656110
7. Patz JA, Daszak P, Tabor GM, Aguirre AA, Pearl M, Epstein J, et al. Unhealthy landscapes: policy recommendations on land use change and infectious disease emergence. Environ Health Perspect. 2004;112:1092–8. http://dx.doi.org/10.1289/ehp.6877
8. Weiss RA, McMichael AJ. Social and environmental risk factors in the emergence of infectious diseases. Nat Med. 2004;10:S70–6. http://dx.doi.org/10.1038/nm1150
9. Snow J. On the mode of communication of cholera. 2nd edition. London: John Churchill; 1855.
10. Lopez AD, Mathers CD, Ezzati M, Jamison DT, Murray CJ. Global and regional burden of disease and risk factors, 2001: systematic analysis of population health data. Lancet. 2006;367:1747–57. http://dx.doi.org/10.1016/S0140-6736(06)68770-9
11. Madoff LC. ProMED-mail: an early warning system for emerging diseases. Clin Infect Dis. 2004;39:227–32. http://dx.doi.org/10.1086/422003
12. Mykhalovskiy E, Weir L. The Global Public Health Intelligence Network and early warning outbreak detection: a Canadian contribution to global public health. Can J Public Health. 2006;97:42–4.
13. Brownstein JS, Freifeld CC, Reis BY, Mandl KD. Surveillance Sans Frontieres: Internet-based emerging infectious disease intelligence and the HealthMap project. PLoS Med. 2008;5:e151. http://dx.doi.org/10.1371/journal.pmed.0050151
14. Collier N, Doan S, Kawazoe A, Goodwin RM, Conway M, Tateno Y, et al. BioCaster: detecting public health rumors with a Web-based text mining system. Bioinformatics. 2008;24:2940–1. http://dx.doi.org/10.1093/bioinformatics/btn534
15. Steinberger R, Fuart F, van der Goot E, Best C, von Etter P, Yangarber R. Text mining from the web for medical intelligence. In: Fogelman-Soulié F, Perrotta D, Piskorski J, Steinberger R, editors. Amsterdam: IOS Press; 2008. p. 295–310
16. Daszak P, Zambrana-Torrelio C, Bogich TL, Fernandez M, Epstein JH, Murray KA, et al. Interdisciplinary approaches to understanding disease emergence: the past, present, and future drivers of Nipah virus emergence. Proc Natl Acad Sci U S A. 2013;110(Suppl 1):3681–8. http://dx.doi.org/10.1073/pnas.1201243109
17. Karesh WB, Dobson A, Lloyd-Smith JO, Lubroth J, Dixon MA, Bennett M, et al. Ecology of zoonoses: natural and unnatural histories. Lancet. 2012;380:1936–45. http://dx.doi.org/10.1016/S0140-6736(12)61678-X
18. Cohen ML. Changing patterns of infectious disease. Nature. 2000;406:762–7. http://dx.doi.org/10.1038/35021206
19. Bates M. Observations on the distribution of diurnal mosquitoes in a tropical forest. Ecology. 1944;25:159–70. http://dx.doi.org/10.2307/1930689
20. Downs WG, Pittendrigh CS. Bromeliad malaria in Trinidad, British West Indies. Am J Trop Med Hyg. 1946;s1–26:47–66.
21. Turner V, Gantz JF, Reinsel D, Minton S. The digital universe of opportunities: rich data and the increasing value of the Internet of things. Framingham (MA): IDC; 2014.
22. Report: McKinsey Global Institute. Big data: the next frontier for innovation, competition, and productivity. 2011 [cited 2014 May 15]. http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation
23. TeleGeography 2014. Executive summary. Global bandwidth research service. Washington (DC): TeleGeography, Inc; 2014. p. 6.
24. Keller M, Blench M, Tolentino H, Freifeld CC, Mandl KD, Mawudeku A, et al. Use of unstructured event-based reports for global infectious disease surveillance. Emerg Infect Dis. 2009;15:689–95. http://dx.doi.org/10.3201/eid1505.081114
25. Kornai A. Digital language death. PLoS ONE. 2013;8:e77056. http://dx.doi.org/10.1371/journal.pone.0077056
26. Scales D, Zelenev A, Brownstein JS. Quantifying the effect of media limitations on outbreak data in a global online web-crawling epidemic intelligence system, 2008–2011. Emerging Health Threats Journal. 2013;6:21621. http://dx.doi.org/10.3402/ehtj.v6i0.21621
27. Schwind JS, Wolking DJ, Brownstein JS, Consortium P, Mazet JAK, Smith WA. Evaluation of local media surveillance for improved disease recognition and monitoring in global hotspot regions. PLoS ONE. 2014;9:e110236. http://dx.doi.org/10.1371/journal.pone.0110236

28. Sonricker Hansen AL, Li A, Joly D, Mekaru S, Brownstein JS. Digital surveillance: a novel approach to monitoring the illegal wildlife trade. PLoS ONE. 2012;7:e51156. http://dx.doi.org/10.1371/journal.pone.0051156
29. Pulliam JR, Epstein JH, Dushoff J, Rahman SA, Bunning M, Jamaluddin AA, et al. Agricultural intensification, priming for persistence and the emergence of Nipah virus: a lethal bat-borne zoonosis. J R Soc Interface. 2012;9:89–101. http://dx.doi.org/10.1098/rsif.2011.0223
30. Preston ND, Daszak P, Colwell RR, Preston ND, Daszak P, Colwell RR. The human environment interface: applying ecosystem concepts to health. Curr Top Microbiol Immunol. 2013; 365:83–100.
31. Epstein JH, Field HE, Luby S, Pulliam JR, Daszak P. Nipah virus: impact, origins, and causes of emergence. Curr Infect Dis Rep. 2006;8:59–65. http://dx.doi.org/10.1007/s11908-006-0036-2
32. Lam SK, Chua KB. Nipah virus encephalitis outbreak in Malaysia. Clin Infect Dis. 2002;34(Suppl 2):S48–51. http://dx.doiorg/10.1086/338818
33. Wilcox BA, Gubler DJ. Disease ecology and the global emergence of zoonotic pathogens. Environ Health Prev Med. 2005;10:263–72. http://dx.doi.org/10.1007/BF02897701

Address for correspondence: John S. Brownstein, Children's Hospital Boston, Emergency Medicine, 451 One Autumn St, Boston, MA 02215, USA; email: John.Brownstein@childrens.harvard.edu



Recognize the signs of tickborne disease

Understand diagnostic testing and lab findings

Quickly find treatment recommendations

Order or download at www.cdc.gov/pubs

Article DOI: http://dx.doi.org/10.3201/eid2108.141156

Drivers of Emerging Infectious Disease Events as a Framework for Digital Detection

Technical Appendix

Technical Appendix Table 1. References for available data examples found in the Table in the article text*

Driver theme, data example	Citation
Human susceptibility to infection	
Vaccine rumor surveillance	(*1*)
U.S. influenza vaccination rates	(*2*)
Mozambique Health Information System	(*3*)
Climate and weather	
SAGE (Center for Sustainability and Global Environment)	(*4*)
Vulnerability to climate change	(*5*)
Human demographics and behavior	
World Pop	(*6*)
Economic Development	
International Monetary Fund	(*7*)
World Bank	(*8*)
Land use and ecosystem changes	
Global Agricultural Lands	(*9*)
CIESN (Center for International Earth Science Information Network)	(*10*)
Global Forest Change 2000–2012	(*11*)
Global Forest Watch	(*12*)
Croplands in western Africa	(*13*)
IMAZON Deforestation Alert System	(*14*)
Global livestock distributions	(*15*)
Technology and Industry	
United Nations Global Pulse	(*16*)
Human wildlife interaction	
Digital news reports	(*17*)
State-level hunting data	(*18*)
Breakdown of public health measures	
Natural disasters hotspots	(*19*)
Poverty and social inequality	
CIESEN (Center for International Earth Science Information Network)	(*10*)
Global Observatory	(*20*)
War and famine	
Famine early warning system	(*21*)
Syria Tracker	(*22*)
Lack of political will	
Transparency International	(*23*)
Cline Center for Democracy	(*24*)
International travel and commerce	
NA	NA

*NA, none available.

Technical Appendix Table 2. References for web platforms mentioned in the text

Web platform	Web site
FluNearYou	https://flunearyou.org/
Influenzanet	https://www.influenzanet.eu/
OPENDREAM – Thailand	https://www.opendream.co.th/
SMS for Life	http://malaria.novartis.com/innovation/sms-for-life/index.shtml
Saude Na Copa 2014	http://www.saudenacopa.com/dashboard/site/termos
Mataki	http://mataki.org/
Arduino Platform	http://www.arduino.cc/
Onset HOBOs	http://www.onsetcomp.com/
Trendalyzer	http://www.gapminder.org/
Esri	http://www.esri.com/
Google Earth Engine	https://earthengine.google.org/#intro

References

1. HealthMap. Vaccine Sentimeter: Global monitoring of vaccination conversations. 2014 Feb 1 [cited 2014 Jun 25]. http://www.healthmap.org/viss/

2. US Department of Health and Human Services. Interactive mapping tool: live-tracking flu vaccinations of Medicare beneficiaries. 2014 May 23 [cited 2014 Jun 25]. http://www.hhs.gov/nvpo/flu-vaccination-map/

3. World Health Organization. WHO vaccine-preventable diseases: monitoring system. 2014 global summary. 2014 [cited 2014 Jun 25]. http://apps.who.int/immunization_monitoring/globalsummary/estimates?c=MOZ

4. Center for Sustainability and the Global Environment University of Wisconsin–Madison. WHIPS (the Wisconsin Horizontal Interpolation Program for Satellites). 2013 Mar 6 [cited 2014 Jun 25]. http://www.sage.wisc.edu/download/WHIPS/WHIPS.html

5. Wheeler D. Quantifying vulnerability to climate change: implications for adaptation assistance. Washington (DC): Center for Global Development; 2011.

6. GeoData Institute, University of Southampton. WorldPop [cited 2014 Jun 25]. http://www.worldpop.org.uk/

7. International Monetary Fund. Data and statistics. 2014 [cited 2014 Jun 25]. http://www.imf.org/external/data.htm

8. The World Bank. Data. 2014 [cited 2014 Jun 25]. http://data.worldbank.org/

9. LUGE (Land Use and the Global Environment) Lab. Data sets. 2013 May 3 [cited 2014 Jun 25]. http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html

10. NASA's Socioeconomic Data and Applications Center (SEDAC). World Data Center for Human Interactions in the Environment. 2011 [cited 2014 Jun 25]. http://sedac.ciesin.columbia.edu/wdc/datapolicy.jsp

11. Hansen MC, Potapov P, Moore R, Hancher M, Turubanova S, Tyukavina A, et al. High-resolution global maps of 21st-century forest cover change. Science. 2013;342:850–3. PubMed http://dx.doi.org/10.1126/science.1244693

12. World Resource Institute. Global Forest Watch [cited 2014 Jun 25]. http://www.globalforestwatch.org/

13. Ramankutty N. Croplands in West Africa: a geographically explicit dataset for use in models. Earth Interact. 2004;8:1–22. http://dx.doi.org/10.1175/1087-3562(2004)8<1:CIWAAG>2.0.CO;2

14. Institute of Man and Environment in the Amazon. Publications. 2011 [cited 2014 Jun 25]. http://www.imazon.org.br/publicacoes

15. Geo-Wiki. Livestock Geo-Wiki. 2014 [cited 2014 Jun 25]. http://www.livestock.geo-wiki.org/

16. United Nations. United Nations Global Pulse. 2014 [cited 2014 Jun 25]. http://www.unglobalpulse.org/

17. HealthMap. Wildlife Trade. 2014 [cited 2014 Jun 25]. http://www.healthmap.org/wildlifetrade/

18. Illinois Department of Natural Resources. IDNR harvest query. 2014 [cited 2014 Jun 25]. http://www.dnr.illinois.gov/hunting/Pages/IDNRHarvestQuery.aspx

19. Center for Hazards and Risk Research at Columbia University. Core data sets. 2005 [cited 2014 Jun 25]. http://www.ldeo.columbia.edu/chrr/research/hotspots/coredata.html

20. International Peace Institute. Catalogue of indices. 2014 [cited 2014 Jun 25]. http://theglobalobservatory.org/indices.html

21. United States Agency for International Development. Famine Early Warning System Network. [cited 2014 Jun 25]. http://www.fews.net/

22. Syria Tracker [cited 2014 Jun 25]. https://syriatracker.crowdmap.com/

23. Transparency International. 2014 [cited 2014 Jun 25]. http://www.transparency.org/

24. Cline Center for Democracy. Data. 2010 [cited 2014 Jun 25]. http://www.clinecenter.illinois.edu/data/

25. Flunearyou [cited 2015 Mar 3]. https://flunearyou.org/

26. Influenzanet [cited 2015 Mar 3]. https://www.influenzanet.eu/

27. OPENDREAM – Thailand [cited 2015 Mar 3]. https://www.opendream.co.th/

28. SMS for Life [cited 2015 Mar 3]. http://malaria.novartis.com/innovation/sms-for-life/index.shtml

29. Healthy Cup 2014 [cited 2015 Mar 3]. http://www.saudenacopa.com/dashboard/site/termos

30. Mataki [cited 2015 Mar 3]. http://mataki.org/

31. Arduino platform [cited 2015 Mar 3]. http://www.arduino.cc/

32. HOBOs [cited 2015 Mar 3]. http://www.onsetcomp.com/

33. Trendalyzer [cited 2015 Mar 3]. http://www.gapminder.org/

34. ESRI [cited 2015 Mar 3]. http://www.esri.com/

35. Google Earth Engine [cited 2015 Mar 3]. https://earthengine.google.org/#intro