Incorporating Geospatial Capacity within Clinical Data Systems to Address Social Determinants of Health

Karen Frederickson Comer, MLA[a]
Shaun Grannis, MD, MS[b,c]
Brian E. Dixon, MPA, PhD[c]
David J. Bodenhamer, PhD[a]
Sarah E. Wiehe, MD, MPH[b,c]

ABSTRACT

Linking electronic health record (EHR) systems with community information systems (CIS) holds great promise for addressing inequities in social determinants of health (SDH). While EHRs are rich in location-specific data that allow us to uncover geographic inequities in health outcomes, CIS are rich in data that allow us to describe community-level characteristics relating to health. When meaningfully integrated, these data systems enable clinicians, researchers, and public health professionals to actively address the social etiologies of health disparities.

This article describes a process for exploring SDH by geocoding and integrating EHR data with a comprehensive CIS covering a large metropolitan area. Because the systems were initially designed for different purposes and had different teams of experts involved in their development, integrating them presents challenges that require multidisciplinary expertise in informatics, geography, public health, and medicine. We identify these challenges and the means of addressing them and discuss the significance of the project as a model for similar projects.

[a]Indiana University-Purdue University Indianapolis, School of Liberal Arts, The Polis Center, Indianapolis, IN

[b]Indiana University, School of Medicine, Indianapolis, IN

[c]Regenstrief Institute, Inc., Indianapolis, IN

Address correspondence to: Karen Frederickson Comer, MLA, Indiana University-Purdue University Indianapolis, School of Liberal Arts, The Polis Center, 1200 Waterway Blvd., Indianapolis, IN 46202; tel. 317-274-2296; fax 317-278-1830; e-mail <kfrederi@iupui.edu>.

©2011 Association of Schools of Public Health

Electronic health record (EHR) systems have the potential to improve the quality of care and decrease overall health-care utilization costs.[1,2] By augmenting clinical data captured in a health information exchange (HIE) with spatially enabled community data, these systems also can more effectively identify and characterize public health trends and events, predict future public health outcomes, and help devise more effective health interventions.[3,4] In this article, we discuss the role of spatially enabled data and community information systems (CIS) in the context of health care.

Spatial data describe the geospatial location(s) of patients and associated geographic entities, such as neighborhoods, census tracts, or counties. These data also may include attributes associated with the patient or the geographic entities in which the patient lives. Residential street address is commonly recorded in electronic patient records. Addresses are translated into spatial data via a geocoding process called address matching. This process involves matching the input address with addresses in a digital reference map and extracting the associated geographic coordinates (latitude and longitude) to define the position of the associated point on the earth. Once geographic coordinates are defined for a patient record, they can be used to identify any other place that shares this location or any catchment area associated with it (e.g., ZIP code or neighborhood). As health disparities are often geographically specific, it is particularly important to consider place to understand and address their causal factors.[5–9]

Community data in this context refer to both compositional and contextual characteristics of the areas, or geographic entities, associated with a location. Compositional data can refer to population characteristics (e.g., adolescent fertility rates or socioeconomic status [SES]) and contextual data can refer to proximity to risk factors (e.g., nearness to high-crime areas or affordable clinical care).[10–15] Contextual data can also refer to qualitative data, such as written histories of a place or interviews with residents. Community data often describe well-known geographic entities, such as neighborhoods, census tracts, and counties. Alternatively, community data may be defined by specific criteria, such as distance zones around a point location. Depending on the analysis and the theorized geographic level of influence, areas of interest may include the associated neighborhood, primary care service area, and/or county, among others.[16]

Data from the U.S. decennial censuses are commonly used to describe demographic, socioeconomic, and housing characteristics of a place. The annual American Community Survey data promise to provide population and housing data more regularly, although these data often have insufficient sample sizes to analyze the context of small geographic entities.[17] In addition, census geographic entities, such as census tracts, may not be the most relevant to examine social processes influencing health.[5,8]

CIS, an ideal source of compositional and contextual community data, typically are developed by local stakeholders interested in assembling data to help assess local issues. In addition to U.S. census data, CIS commonly integrate data from a wide variety of state and local sources[18] that provide more detailed and varied information not covered by the census, such as crime incidence or availability of community resources. Although some CIS focus primarily on neighborhood-level indicators, others provide data at multiple geographic levels to support a wider range of uses, including multilevel analysis, and/or allow data to be aggregated to custom boundaries of interest to the user. Once local administrative datasets are incorporated into a CIS, these data are typically updated on a recurring basis and made publicly available.

Equally important, selected data and associated CIS indicators reflect local concerns and interests, which can be informative to the researcher studying social determinants of health (SDH). Additionally, because CIS commonly incorporate geographic information systems to geocode, integrate, and visualize data, these systems can provide a good source of geocoding expertise, tools, and reference data.

METHODS

We demonstrate the challenges and means of leveraging EHR systems and CIS by integrating two well-established information systems in central Indiana. The interdisciplinary Indiana Center of Excellence in Public Health Informatics manages a large EHR system called the Indiana Network for Patient Care (INPC). The Polis Center, also at Indiana University-Purdue University Indianapolis, has developed and manages the SAVI Community Information System (hereafter, SAVI).

Existing systems

INPC is one of the nation's most comprehensive and longest-running HIEs. It is operated by the Regenstrief Institute, an internationally recognized informatics and health-care research organization dedicated to improving health through research, development, and education. In addition to providing clinical data at the point of care to more than 14,000 physicians, INPC provides statewide syndromic surveillance, public

health case detection, and physician alerting services to local and state public health. Its data repository contains more than one billion coded standardized clinical observations dating back more than 30 years and receives 350,000 to one million clinical transactions daily from more than 200 data sources, including nearly 80 emergency departments and 35 hospitals, more than 100 clinics, local and state health departments, and multiple ancillary care data sources.[19] In addition to offering daily access to community-wide clinical data to providers in routine health-care settings and supporting real-time public health surveillance, INPC offers a rich source of clinical data for researchers to study pediatric obesity, adolescent and young adult sexually transmitted infections (STIs), and asthma, among other health topics.[19–29]

SAVI is one of the leading CIS noted by the U.S. Government Accountability Office.[30] SAVI was developed and is managed by The Polis Center, which is dedicated to using collaboration, interdisciplinary research, and knowledge of advanced spatial technologies to provide reliable information for improving communities in Indiana and beyond. SAVI collects, geocodes, organizes, and presents integrated data on communities in the 11-county Indianapolis metropolitan statistical area drawn from more than 30 federal, state, and local providers, all linked to the lowest available geographic level (often, the street address). It is the nation's largest CIS, with more than 10,000 time-series variables from 1980 to the present, including welfare, education, health, public safety, housing, and demographics. SAVI also includes information on the locations of health facilities, health and human services, community facilities, and associated service areas. In addition to providing compositional and contextual data for local public health research, SAVI provides data for cross-site (multiple city and institution) studies on public health and other community issues.[24–29]

Until recently, researchers who wanted to link patient and community data from INPC and SAVI had to do so manually on a project-by-project basis. This ad hoc approach was inefficient and lacked the flexibility for data analysis that an integrated system could provide. Overlapping datasets would be extracted for geocoding by different researchers, with the results not returned for subsequent use. Also, when researchers who had geocoded their own datasets shared their data, there was often uncertainty about the relative accuracy of the geocodes, particularly because there was not a standard method for capturing spatial metadata or documenting the associated methodology and reference data used. In addition to being redundant, this manual approach was time-consuming. To address this problem, an INPC-SAVI team is augmenting the clinical data with geospatial attributes by designing, implementing, deploying, and evaluating a near real-time geocoding process capable of handling high-transaction volumes. Within this system linkage, all current and incoming patient records are geocoded, which allows the clinical data to be spatially associated with extensive, locally developed datasets about the social, economic, and physical environment.

Requirements for the initial version of this system were defined based on a relatively simple administrative use (i.e., generation of aggregate-level counts of notifiable disease cases per county). The accuracy and completeness of geocoding required for this administrative use are not as stringent as needed for many clinical and research uses. Additional use cases have been and will continue to be defined to guide the ongoing refinement and expansion of system requirements.

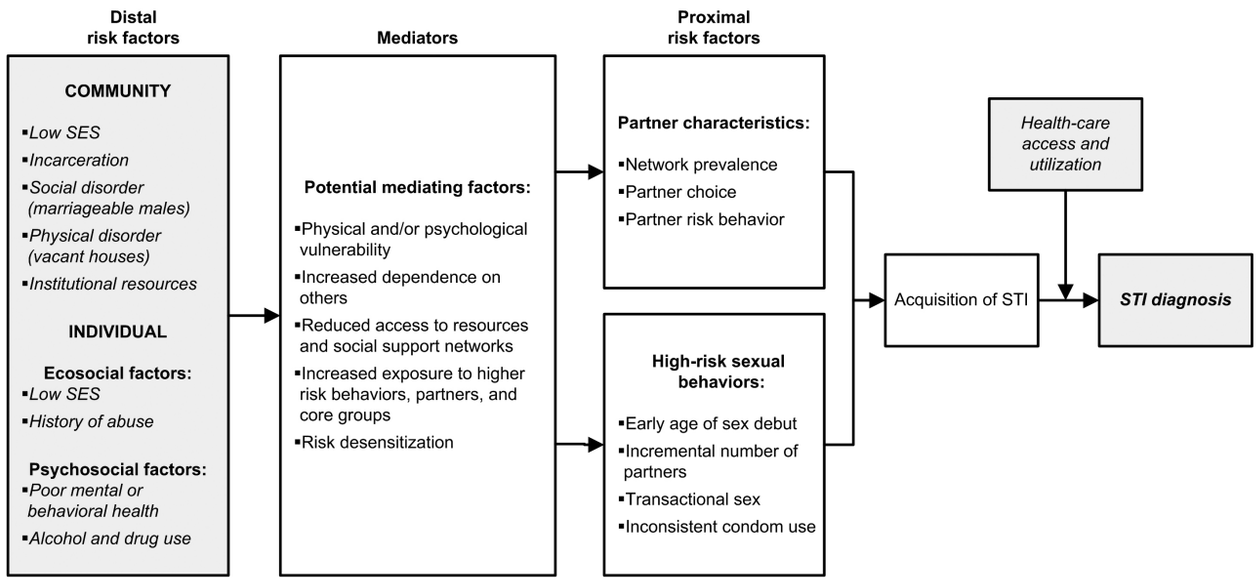
Example use case

To help demonstrate the opportunities and challenges associated with systemized integration of data from INPC with geospatial attributes and associated community data of SAVI, we describe an example use case—disparities in the social determinants of STIs.

Despite dramatic health disparities in STI rates by race/ethnicity and SES, previous work has recognized the limitations of individual-level and behavioral approaches in effectively targeting STI risk factors[31,32] and has called for further investigation of social[33] and structural[34] characteristics as potential factors for contributing to the geospatial clustering of STIs.[12,30,33,35–42] Investigation of how STI cases cluster geographically may identify key associations with the social and physical environment and, thus, inform research on STI prevalence and disparities. Considering geographic context and subsequently addressing characteristics of core areas contributing to spatial heterogeneity of STIs is crucial in effectively tailoring and implementing interventions.[33] Furthermore, determining significant "areas of exposure" may be important in targeting prevention efforts and understanding mechanisms of local sexual networks.

In considering how to integrate community-level exposures and STI risk, we have added to a conceptual model recently presented and discussed by Buffardi et al. (Figure).[43] In this model, ecosocial and individual psychosocial factors (distal risk factors) contribute to STI risk via altered partner characteristics and high-risk sexual behaviors (proximal risk factors). We have modified this model by adding another layer to the distal risk factors box, which includes compositional and contextual measures. We hypothesize that these

Figure. Conceptual model based on Buffardi et al.[a] in which distal risk factors, including community measures, contribute to STI risk via proximal risk factors



[a]Buffardi AL, Thomas KK, Holmes KK, Manhart LE. Moving upstream: ecosocial and psychosocial correlates of sexually transmitted infections among young adults in the United States. Am J Public Health 2008;98:1128-36.

STI = sexually transmitted infection

SES = socioeconomic status

factors may also modify partner characteristics and high-risk sexual behaviors, thus increasing STI acquisition and diagnosis.

For the use case, we are interested in assessing associations between an individual's disease risk (occurrence of a particular STI during that year) and the selected community measures (low SES, incarceration rates, marriageable males, percentage of vacant houses, and institutional resources) at different geographic levels to evaluate significance of exposure proximity. We use incarceration as an example case because STIs have been well-documented in incarcerated populations and among arrestees,[44–48] including adolescents.[49–55] In addition, area-level incarceration has been linked to area-level STI rates. Researchers have suggested that associations between STI prevalence and incarceration rates may reflect the impact of ex-offenders on the general population.[56] Incarceration may also produce a change in network structures while community members are incarcerated.[32,56,57] Communities with high incarceration rates may also carry disproportionate risk through contact with individuals with high STI risk prior to their incarceration.[58]

Most studies of community risk factors rely on commonly available administrative boundaries, such as census-tract boundaries, to define a patient's area of exposure. This is likely a decision of convenience rather than a scientifically based one. While we are interested in developing measures at the census-tract level for comparison with previous studies, we are also interested in developing measures for zones around a patient's residence (e.g., 200 meters, 400 meters, and 800 meters). As such, we identified the following data-processing and integration steps for our example use case.

1. Geocoding patient addresses with documented positive STI test results. Residential address indicates where the individual likely spent a significant portion of his/her time, although other relevant exposures may include those associated with place of work, school, and other daily activities.[59,60] Multiple residential addresses can be stored if a patient changed residence between clinical visits. Access to these time-series address data allows analysis of effects of residential mobility and longitudinal exposures. Once geographic coordinates are defined for a patient record, they can be used to identify the associated areas (i.e., census tracts) for which compositional and contextual data are available.

2. Geocoding residential addresses associated with individual incarceration cases. We are interested in where convicted criminals lived vs. where crimes occurred. While crime event data are collected and geocoded by SAVI, incarceration data currently are not. As such, individual-level incarceration data must be collected from other agencies and geocoded.

3. Aggregating geocoded incarceration data to geographic areas of interest. Using the generated geographic coordinates of each positive STI, we will be able to calculate incarceration rates for various geographies, including census boundaries or buffer zones.

4. Linking STI cases with other community variables based on geographic units of interest. The remaining community variables of interest are available from SAVI at the census-tract level. We will be able to readily link these variables to the STI cases using census-tract identification as the joining field. For analysis using our buffer zones of interest, we will be able aggregate the available record-level data in SAVI to the generated buffer zones.

BARRIERS TO INTEGRATION

While the integration of spatially enabled EHR systems with CIS holds great promise for understanding health disparities, the automated integration of these data presents challenges.

Differing user requirements

The list of use cases that could potentially be supported by such an integrated system is endless. Also, the output of spatial data integration and analysis will need to be translated into formats useful for a wide range of public health users and accessible to multiple agencies and jurisdictions. Prioritizing use cases and associated system requirements is important for project planning and managing stakeholder expectations.

Varying geocoding methodologies and reference data

Geocoding capabilities are available via a wide range of geographic information system tools and services. In addition, there are multiple types of reference data (e.g., street address centerlines, property parcels, and address points) and sources (e.g., federal, commercial, and academic) for any given geographic area. Different reference data may produce different geospatial attributes. Thus, appropriate selection depends on the use case and an associated assessment of available data, including the cost and associated data types, geometries, accuracies, and resolutions. Finally, geocoding technology and reference layers will continue to evolve.

Managing data-sharing partnerships

Both INPC and SAVI had to develop relationships and trust among their data-sharing partners; INPC and SAVI must continuously demonstrate that their partners are getting value from sharing their data and that their interests are being protected. This sociocultural component is a greater challenge than the technical design and implementation of such a system. Data-sharing memoranda of understanding include oversight provisions, guarantees of confidentiality, and guides on allowable data use. Only aggregate data at a geographic level that appropriately protects the confidentiality of an individual's data are publicly released. In addition to assurances of data security, many stakeholders seek the greatest community benefit possible from their data-sharing efforts. To increase the possible uses of the integrated data while maintaining individual confidentiality, we have discussed the future integration of geomasking techniques into the system.

ADDRESSING THE CHALLENGES

Multidisciplinary approach

To meaningfully facilitate interdisciplinary research of SDH, the integration of clinical and community data systems requires active collaboration among information scientists, geographers, data providers, clinicians, and public health investigators experienced in using clinical, as well as community, data. Specifically, the collaboration helps to accomplish the following tasks.

Define needs. The productive synthesis of geospatially enabled clinical and community data requires careful consideration of the data needs and uses associated with different groups, including, but not limited to, data system administrators, clinicians, public health researchers, public health agencies, and nongovernmental public health organizations. Multidisciplinary collaboration on system design can require extensive communication efforts due to different theoretical frameworks and terminology. Clear documentation of agreed-upon data classifications, standards, and processes is essential.

Identify standards. To develop integrated data systems that meaningfully facilitate exploration of SDH, we need input from all collaborators experienced in using clinical and community data. The coordinated integration of an EHR system with a CIS provides the opportunity to build consistency in geocoding methods and reference data. Use of consistent methods and reference data for geocoding clinical and community datasets is necessary to avoid varying assignment of geographic coordinates biasing subsequent analysis.

As such, choice of geocoding technology and reference maps requires expert knowledge of geographic information science and an understanding of use cases.

Leverage relationships. Acquisition of administrative datasets, particularly at the individual record level, typically requires memoranda of understanding with the source data provider(s), usually with strict data-handling protocols designed to protect confidentiality. Establishing a memorandum of understanding can be time-consuming. With the explicit, written permission of source providers and Institutional Review Board approval, many of the individual-level data geocoded for CIS inclusion can be made available for research and other public health uses in a de-identified or aggregated format. CIS typically have data advisory committees composed of community stakeholders that recommend datasets for inclusion based on understanding the needs of the local community. These committees provide a valuable source of community perspective.

Supporting use by multiple public health sectors

Ultimately, we want to make our integrated data available for public health uses. An EHR system in combination with a CIS can be used to significantly augment existing community health assessment tools. These tools typically report health outcomes by county or other geographic administrative unit relevant for policymaking but not necessarily for understanding SDH. Our envisioned system will incorporate the generated spatial attributes into existing standards-based, bidirectional communications between public health and clinical stakeholders. For this full potential to be realized, multiple public health sectors must become invested, contributing members of use case development.

SIGNIFICANCE

The benefits of integrating EHR systems with CIS include a better fit between the intended use of clinical, spatial, and community data and the associated geoprocessing options, with the ultimate aim of developing a sound theoretical and practical guide for applying these data for addressing SDH. Benefits also include the opportunity to generate and test new hypotheses to address the social etiologies of health disparities. Our integration work will lead to the identification of nexus elements in system design that will inform the work of other systems' integration efforts and continually improve upon our current efforts. For instance, system integration will address whether geospatial data may improve patient-matching methods that are used to aggregate patient data.

The growth in the number of EHR systems and CIS nationwide holds promise for this type of system integration and the associated benefits to occur in cities and states across the nation. In 2009, there were an estimated 193 initiatives across the U.S. pursuing HIE activities.[61] Additional investment from the American Recovery and Reinvestment Act of 2009 is likely to increase this number.[62] The Centers for Disease Control and Prevention (CDC) has invested in HIE via the Nationwide Health Information Network (NHIN), envisioned to be a network of networks allowing for data integration across states and regions among clinical and public health information systems.[63,64] CDC also has funded initiatives that would connect HIEs to state health departments and state health departments to CDC via NHIN.[65,66]

U.S. agencies are increasingly developing, integrating, and using local data for community building and policymaking, as reflected by the growth and activity of the National Neighborhood Indicators Partnership (NNIP), which grew from six original partner cities in 1995 to 36 in 2011 and has been involved in many multi-city initiatives to advance the development and use of local CIS. All NNIP partner cities have built advanced, spatially enabled data systems on neighborhood conditions. The local specificity of these data systems makes them a valuable resource for those interested in investigating the relationships between health and prevention and social, cultural, and other environmental factors. A 2004 U.S. Government Accountability Office study surveyed such systems for potential inclusion in a national indicators system.[29] These systems serve different purposes, some with comprehensive missions (e.g., SAVI), and others focused on specific topics such as education or housing; however, most use geospatial information technologies and have efficient geocoding mechanisms.[67] Despite the significant potential for geospatial integration with HIE, CIS do not have a standard design, as most have developed *in situ* in response to local interests and needs[68] and, thus, their possibilities and challenges vary.

While it is not uncommon to geocode clinical data for ad hoc analyses and queries, it is uncommon to routinely maintain an up-to-date geocoded patient registry containing billions of clinical data results using operational automated mechanisms. We believe that this type of system will become more common in the future, and our system serves as an example of a novel data-enhancement process that links clinical data to important community-level information. Once the integration of CIS as a core part of HIE infrastructure becomes accepted practice, more in-depth investigation of SDH disparities will be possible.

CONCLUSION

Understanding SDH is critical in addressing health disparities. However, relatively few research projects use individually identified data, tracked longitudinally with point-level address data, possibly contributing to the reason that resulting findings and associated interventions have been inadequate to address the problem. With the nationwide development of HIEs and CIS, there is an increased opportunity for meaningful compositional, contextual, and geographic analysis of SDH. To realize the full potential of this opportunity, several challenges must be met, including the need for (*1*) a multidisciplinary approach; (*2*) research in related fields, such as information science, geoinformatics, informatics, and health geographics; and (*3*) tools that can be used by multiple public health sectors. The benefits, however, clearly outweigh the challenges.

With system integration recently completed, including the geocoding of more than 27 million historic clinical records and an additional 300,000 new clinical records every evening, we are poised to proceed with analysis of the linked data for several local research projects, including the study of STIs, obesity, and diabetes health disparities.

With our advancing technology, interdisciplinary collaborations, and developing experience, we will aptly be able to investigate further and hopefully address fully health disparities resulting from social determinants.

REFERENCES

1. Tierney WM, Miller ME, Overhage JM, McDonald CJ. Physician inpatient order writing on microcomputer workstations. Effects on resource utilization. JAMA 1993;269:379-83.
2. Tierney WM, Overhage JM, Takesue BY, Harris LE, Murray MD, Vargo DL. Computerizing guidelines to improve care and patient outcomes: the example of heart failure. J Am Med Inform Assoc 1995;2:316-22.
3. Hogan VK. Addressing perinatal health disparities: another place for a paradigm shift. N C Med J 2004;65:159-63.
4. Basara HG, Yuan M. Community health assessment using self-organizing maps and geographic information systems. Int J Health Geogr 2008;7:67.
5. Diez Roux AV. Neighborhoods and health: where are we and where do we go from here? Rev Epidemiol Sante Publique 2007;55:13-21.
6. Mobley LR, Kuo TM, Andrews L. How sensitive are multilevel regression findings to defined area of context?: a case study of mammography use in California. Med Care Res Rev 2008;65:315-37.
7. Henry KA, Niu X, Boscoe FP. Geographic disparities in colorectal cancer survival. Int J Health Geogr 2009;8:48.
8. Diez Roux AV, Mair C. Neighborhoods and health. Ann N Y Acad Sci 2010;1186:125-45.
9. Johnson PJ, Call KT, Blewett LA. The importance of geographic data aggregation in assessing disparities in American Indian prenatal care. Am J Public Health 2010;100:122-8.
10. Diez Roux AV. Investigating neighborhood and area effects on health. Am J Public Health 2001;91:1783-9.
11. Winkleby MA, Jatulis DE, Frank E, Fortmann SP. Socioeconomic status and health: how education, income, and occupation contribute to risk factors for cardiovascular disease. Am J Public Health 1992;82:816-20.
12. Besculides M, Heffernan R, Motashari F, Weiss D. Evaluation of school absenteeism data for early outbreak detection, New York City. BMC Public Health 2005;5:105.
13. Monteiro EF, Lacey CJ, Merrick D. The interrelation of demographic and geospatial risk factors between four common sexually transmitted diseases. Sex Transm Infect 2005;81:41-6.
14. Cole R, Leslie E, Donal M, Cerin E, Owen N. Residential proximity to school and the active travel choices of parents. Health Promot J Austr 2007;18:127-34.
15. Vaidyanathan A, Staley F, Shire J, Muthukumar S, Kennedy C, Meyer PA, et al. Screening for lead poisoning: a geospatial approach to determine testing of children in at-risk neighborhoods. J Pediatr 2009;154:409-14.
16. Mobley LR, Kuo TM, Driscoll D, Clayton L, Anselin L. Heterogeneity in mammography use across the nation: separating evidence of disparities from the disproportionate effects of geography. Int J Health Geogr 2008;7:32.
17. Starsinic DE. Projections of the population of voting age for states: November 1984. Curr Popul Rep Popul Charact 1984;(948):1-10.
18. Howell EM, Pettit KL, Ormond BA, Kingsley GT. Using the National Neighborhood Indicators Partnership to improve public health. J Public Health Manag Pract 2003;9:235-42.
19. Overhage JM, Grannis S, McDonald CJ. A comparison of the completeness and timeliness of automated electronic laboratory reporting and spontaneous reporting of notifiable conditions. Am J Public Health 2008;98:344-50.
20. Grannis SJ, Biondich PG, Mamlin BW, Wilson G, Jones L, Overhage JM. How disease surveillance systems can serve as practical building blocks for a health information infrastructure: the Indiana experience. AMIA Annu Symp Proc 2005:286-90.
21. Mahon BE, Rosenman MB, Kleiman MB. Maternal and infant use of erythromycin and other macrolide antibiotics as risk factors for infantile hypertrophic pyloric stenosis. J Pediatr 2001;139:380-4.
22. Overhage JM, Dexter PR, Perkins SM, Cordell WH, McGoff J, McGrath R. A randomized, controlled trial of clinical information shared from another institution. Ann Emerg Med 2002;39:14-23.
23. Biondich PG, Grannis SJ. The Indiana network for patient care: an integrated clinical information system informed by over thirty years of experience. J Public Health Manag Pract 2004;Suppl:S81-6.
24. Liu GC, Cunningham C, Downs SM, Marrero DG, Feinberg N. A spatial analysis of obesogenic environments for children. Proc AMIA Symp 2002:459-63.
25. Howell EM, Pettit KL, Kingsley GT. Trends in maternal and infant health in poor urban neighborhoods: good news from the 1990s, but challenges remain. Public Health Rep 2005;120:409-17.
26. Liu G. Obesity and environment in Indianapolis: an analysis of neighborhood indicators. A SAVI report. Indianapolis: The Polis Center at Indiana Univeristy-Purdue University Indianapolis; 2005.
27. Yamada I, Comer KF. Exploratory modeling of teenage pregnancy prevalence. Presented at the 102nd Annual Meeting of the American Association of Geographers; 2006 Mar 5–10; Chicago.
28. Mushi-Brunt C, Morrone A, Angermeier L, Ruschhaupt D, Peebles J, Sothmann M. Health knowledge assessment: improving health literacy among adolescents. Presented at the 58th Annual Meeting of the Society for Public Health Education; 2007 Oct 31–Nov 3; Alexandria, Virginia.
29. Sandy R, Liu G, Ottensman J, Tchernis R, Wilson J, Ford OT. Studying the child obesity epidemic with natural experiments. In: Grossman M, Mocan NC, editors. Economic aspects of obesity. Chicago: University of Chicago Press; 2011. p. 181-221.
30. Hayes RM. Informing our nation: improving how to understand and assess the USA's position and progress. Libr Info Sci Res 2006; 28:154-7.
31. De P, Singh AE, Wong T, Yacoub W, Jolly AM. Sexual network analysis of a gonorrhoea outbreak. Sex Transm Infect 2004;80:280-5.
32. Adimora AA, Schoenbach VJ. Social context, sexual networks, and racial disparities in rates of sexually transmitted infections. J Infect Dis 2005;191 Suppl 1: S115-22.
33. Law DC, Serre ML, Christakos G, Leone PA, Miller WC. Spatial analysis and mapping of sexually transmitted diseases to optimise intervention and prevention strategies. Sex Transm Infect 2004; 80:294-9.
34. Jennings JM, Curriero FC, Celentano D, Ellen JM. Geographic identification of high gonorrhea transmission areas in Baltimore, Maryland. Am J Epidemiol 2005;161:73-80.

35. Rothenberg RB. The geography of gonorrhea. Empirical demonstration of core group transmission. Am J Epidemiol 1983;117:688-94.
36. Potterat JJ, Rothenberg RB, Woodhouse DE, Muth JB, Pratts CI, Fogle JS 2nd. Gonorrhea as a social disease. Sex Transm Dis 1985; 12:25-32.
37. Rice RJ, Roberts PL, Handsfield HH, Holmes KK. Sociodemographic distribution of gonorrhea incidence: implications for prevention and behavioral research. Am J Public Health 1991;81:1252-8.
38. Becker KM, Glass GE, Brathwaite W, Zenilman JM. Geographic epidemiology of gonorrhea in Baltimore, Maryland, using a geographic information system. Am J Epidemiol 1998;147:709-16.
39. Blanchard JF, Moses S, Greenaway C, Orr P, Hammond GW, Brunham RC. The evolving epidemiology of chlamydial and gonococcal infections in response to control programs in Winnipeg, Canada. Am J Public Health 1998;88:1496-502.
40. Aral SO, Padian NS, Holmes KK. Advances in multilevel approaches to understanding the epidemiology and prevention of sexually transmitted infections and HIV: an overview. J Infect Dis 2005;191 Suppl 1:S1-6.
41. Kerani RP, Handcock MS, Handsfield HH, Holmes KK. Comparative geographic concentrations of four sexually transmitted infections. Am J Public Health 2005;95:324-30.
42. Bush KR, Henderson EA, Dunn J, Read RR, Singh A. Mapping the core: chlamydia and gonorrhea infections in Calgary, Alberta. Sex Transm Dis 2008;35:291-7.
43. Buffardi AL, Thomas KK, Holmes KK, Manhart LE. Moving upstream: ecosocial and psychosocial correlates of sexually transmitted infections among young adults in the United States. Am J Public Health 2008;98:1128-36.
44. Bickell NA, Vermund SH, Holmes M, Safyer S, Burk RD. Human papillomavirus, gonorrhea, syphilis, and cervical dysplasia in jailed women. Am J Public Health 1991;81:1318-20.
45. Holmes MD, Safyer SM, Bicknell NA, Vermund SH, Hanff PA, Phillips RS. Chlamydial cervical infection in jailed women. Am J Public Health 1993;83:551-5.
46. Puisis M, Levine WC, Mertz KJ. Overview of sexually transmitted diseases in correctional facilities. In: Puisis M, Anno BJ, Cohen RL, Heyman B, King LN, May JP, et al., editors. Clinical practice in correctional medicine. St. Louis: Mosby; 1998. p. 129-35.
47. Hammett TM, Harmon MP, Rhodes W. The burden of infectious disease among inmates of and releases from U.S. correctional facilities, 1997. Am J Public Health 2002;92:1789-94.
48. National Commission on Correctional Health Care. The health status of soon-to-be-released inmates: a report to Congress. Chicago: National Commission on Correctional Health Care; 2002.
49. Oh MK, Cloud GA, Wallace LS, Reynolds J, Sturdevant M, Feinstein RA. Sexual behavior and sexually transmitted diseases among male adolescents in detention. Sex Transm Dis 1994;21:127-32.
50. Morris RE, Harrison EA. Health risk behavioral survey from 39 juvenile correctional facilities in the United States. J Adolesc Health 1995;17:334-44.
51. Widom R, Hammett TM. HIV/AIDS and STDs in juvenile facilities. NIJ Res Brief 1996;4:1-11.
52. Nesmith JD, Klerman LV, Oh MK, Feinstein RA. Procreative experiences and orientations toward paternity held by incarcerated adolescent males. J Adolesc Health 1997;20:198-203.
53. Pack RP, Diclemente RJ, Hook EW 3rd, Oh MK. High prevalence of asymptomatic STDs in incarcerated minority male youth: a case for screening. Sex Transm Dis 2000;27:175-7.
54. Kahn RH, Mosure DJ, Blank S, Kent CK, Chow JM, Boudov MR, et al. *Chlamydia trachomatis* and *Neisseria gonorrhoeae* prevalence and coinfection in adolescents entering selected U.S. juvenile detention centers, 1997–2002. Sex Transm Dis 2005;32:255-9.
55. Centers for Disease Control and Prevention (US). STD surveillance, 2006. Special focus profiles: persons entering corrections facilities [cited 2011 May 4]. Available from: URL: http://www.cdc.gov/std/stats06/corrections.htm
56. Thomas JC, Sampson LA. High rates of incarceration as a social force associated with community rates of sexually transmitted infection. J Infect Dis 2005;191 Suppl 1:S55-60.
57. Thomas JC, Levandowski BA, Isler MR, Torrone E, Wilson G. Incarceration and sexually transmitted infections: a neighborhood perspective. J Urban Health 2008;85:90-9.
58. Bernstein KT, Chow JM, Ruiz J, Schacter J, Horowitz E, Bunnell R, et al. *Chlamydia trachomatis* and *Neisseria gonorrhoeae* infections among men and women entering California prisons. Am J Public Health 2006;96:1862-6.
59. Kwan MP. From place-based to people-based exposure measures. Soc Sci Med 2009;69:1311-3.
60. Wiehe SE, Carroll AE, Liu GC, Haberkorn KL, Hoch SC, Wilson JS, et al. Using GPS-enabled cell phones to track the travel patterns of adolescents. Int J Health Geogr 2008;7:22.
61. eHealth Initiative. Results of 2009 Survey of Health Information Exchange: state of the field. Washington: eHealth Initiative; 2009.
62. American Recovery and Reinvestment Act of 2009, Pub. L. No. 111-5, 123 Stat. 115, H.R. 1 (Feb. 17, 2009).
63. Halamka J, Overhage JM, Ricciardi L, Rishel W, Shirky C, Diamond C. Exchanging health information: local distribution, national coordination. Health Aff (Millwood) 2005;24:1170-9.
64. Rishel W, Riehl V, Blanton C. Summary of the NHIN prototype architecture contracts. Washington: Department of Health and Human Services (US); 2007.
65. Dobbs D, Trebatoski M, Revere D. The Northwest Public Health Information Exchange's accomplishments in connecting a health information exchange with public health. Online J Public Health Inform 2010;2(2).
66. Grannis SJ, Stevens K, Merriwether R. Leveraging health information exchange to support public health situational awareness: the Indiana experience. Online J Public Health Inform 2010;2(2).
67. Bodenhamer DJ, Colbert JT, Frederickson Comer K, Kandris SM. Developing and sustaining a community information system for central Indiana: SAVI as a case study. In: Sirgy MJ, Phillips R, Rahtz D, editors. Community quality-of-life indicators: best cases V. New York: Springer; 2011. Volume 3, p. 21-46.
68. Harrison TM, Zappen JP, Adali S. Building community information systems: the Connected Kids case. Computer 2005;38:62-9.