Geospatial Data Science and Health Geography

TEXAS STATE GEOGRAPHY

Texas Center for Geographic Information Science
Department of Geography, College of Liberal Arts

TEXAS STATE COLLEGE OF LIBERAL ARTS

Project 1: Individual-based Air Pollution and Health Risk Study

This study models **health risk of ozone pollution at the individual level**. Traditional population-level studies assume all people in the same place (a city or a county) are exposed to the same level of air pollution and health risk. This study models air pollution level by considering land use, weather, and human activities through much finer spatial and temporal scales (**Fig. 1.1**).

A space-time air pollution cube supported by a large database was constructed. Individual trajectories can be plugged into **the space-time cube**, and personal level physical activities and physiological characteristics can be considered to predict individual level pollution exposure and health risk, tailored to particular travel time, route, and other patterns (**Fig. 1.2**).

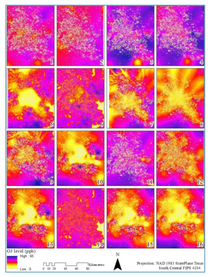

Fig. 1.1 Hourly Prediction of Ozone Pollution Level in Houston Region (Dec 27th - 28th, 2010).

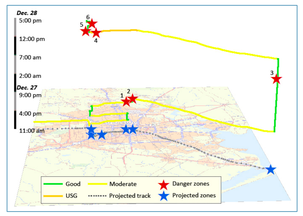

Fig. 1.2 The personal air pollution danger zones for a volunteer in Houston on Dec 27th-28th, 2010.

Selected Publications

Brender JD, Shinde MU, Zhan FB, Gong X, Langlois PH. Maternal residential proximity to chlorinated solvent emissions and birth defects in offspring: a case-control study. *Environ Health*. 2014 Nov 19;13:96. doi: 10.1186/1476-069X-13-96. PubMed PMID: 25406847.

Fang TB, Lu Y. Constructing Near Real-time Space-time Cube to Depict Urban Ambient Air Pollution Scenario. *Transactions in GIS* 2011 15(5): 635-649.

Fang TB, Lu Y. Personal real-time air pollution exposure assessment methods promoted by information technological advances. *Annals of GIS*. 2012 18(4): 279-288.

Hanford EJ, Zhan FB, Lu Y, Giordano A. Chagas disease in Texas: recognizing the significance and implications of evidence in the literature. Soc Sci Med. 2007 Jul;65(1):60-79. PMID: 17434248

Jin H, Lu Y. 2016. The relationship between obesity and socioeconomic status among Texas school children and its spatial variation. *Applied Geography*. 2016 79:143-152.

Lin Y, Zhan FB. Geographic variations of racial/ethnic disparities in cervical cancer mortality in Texas. *South Med J*. 2014 May;107(5):281-8. PubMed PMID: 24937725.

Lu Y, Fang TB. 2015. Examining personal air pollution exposure, intake, and health danger zone using time geography and 3d geovisualization. *ISPRS International Journal of Geo-Information*. 2015 4(1): 32-46.

Suarez L, Brender JD, Langlois PH, Zhan FB, Moody K. Maternal exposures to hazardous waste sites and industrial facilities and risk of neural tube defects in offspring. *Ann Epidemiol*. 2007 Oct;17(10):772-7. Epub 2007 Aug 6. PubMed PMID: 17689262.

Project 3: Spatially Informed Strategies for Cancer Intervention

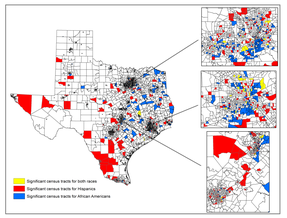

Fig. 3.1 Disparities of advanced-stage cervical cancer at diagnosis in Texas: Hispanics and African Americans, 1995-2008.

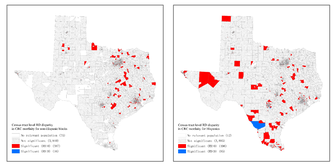

Fig. 3.2 Colorectal cancer mortality disparities in African Americans (left) and Hispanics (right) in Texas when non-Hispanic whites is used as a reference group, 1995-2003. (Note: Red census tracts are areas where African Americans/Hispanics have significantly higher mortality rates. Pink census tracts are areas where non-Hispanic whites have significantly higher mortality rates)

With more than 10 million new cases every year worldwide, cancer poses an enormous burden on society and affects almost all families. The burden can be disproportionally higher in certain underserved population groups and communities. This disproportionate burden is called **cancer disparity** and must be addressed.

This project develops **spatially informed cancer intervention strategies** to reduce cancer disparities. The strategies will make targeted and personalized delivery of cancer intervention programs in underserved population groups and communities possible. The two example maps at the left show the census tract level disparities of **cervical cancer** (**Fig. 3.1**) and **colorectal cancer** (**Fig. 3.2**) in Texas.

Where we live matters to our health. Physical environment, socioeconomic conditions, and accessibility to healthcare services affect the health of an individual. Geospatial data science employs spatial analytics methods to analyze massive geographically-referenced data. It helps us gain insights about how location, place, community characteristics, accessibility to healthcare services, delivery of healthcare, and individual behaviors contribute to various health disparities. These insights can be used to develop better healthcare policies and enhance healthcare practices to improve the overall health of all citizens in the nation.

Project 2: Overweight and Obesity among Texas School Children

More than one-fifth of Texas children are overweight or obese. In the 2012-13 school year, more than 60% of Texas students were considered economically disadvantaged. Using campus level physical fitness data, this study investigates if and how the prevalence of obesity among Texas school children (**Fig 2.1**) is related to their socioeconomic status (SES) (**Fig. 2.2**), and if such a relationship shows regional patterns.

Our examination shows that both Household Socioeconomic Status (SES) and Neighborhood SES (**Fig. 2.2**) affect childhood obesity. **Lower household SES is associated with higher rate of childhood obesity**. This relationship is especially strong in three regions as highlighted in **Figure 2.3**. Future study will examine how neighborhood SES affects childhood obesity.

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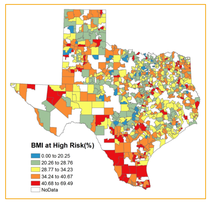

Fig. 2.1 Prevalence of obesity among school children across Texas school districts.

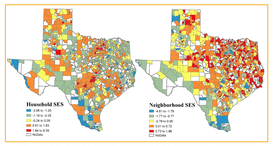

Fig. 2.2 Spatial distribution of two Socioeconomic Status (SES) factors across school districts in Texas.

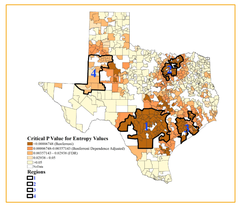

Fig. 2.3 Regional Patterns of the relationship between the prevalence of obesity among Texas school children and the two SES factors.

Tian N, Goovaerts P, Zhan FB, Chow TE, Wilson JG. Identifying risk factors for disparities in breast cancer mortality among African-American and Hispanic women. *Womens Health Issues*. 2012 May-Jun;22(3):e267-76. PubMed PMID: 22265181.

Tian N, Wilson JG, Zhan FB. Spatial association of racial/ethnic disparities between late-stage diagnosis and mortality for female breast cancer: where to intervene? *Int J Health Geogr*. 2011 Apr 4;10:24. PubMed PMID: 21463525.

Wan N, Zhan FB, Lu Y, Tiefenbacher JP. Access to healthcare and disparities in colorectal cancer survival in Texas. *Health Place*. 2012 Mar;18(2):321-9. PubMed PMID: 22118939.

Wu X, Lu Y, Zhou S, Chen L, Xu B. Impact of climate change on human infectious diseases: Empirical evidence and human adaptation. *Environ Int*. 2016 Jan;86:14-23. PMID: 2647983.

Yao Z, Tang J, Zhan FB. Detection of arbitrarily-shaped clusters using a neighbor-expanding approach: a case study on murine typhus in south Texas. *Int J Health Geogr*. 2011 Mar 31;10:23. PubMed PMID: 21453514.

Zhan FB, Brender JD, De Lima I, Suarez L, Langlois PH. Match rate and positional accuracy of two geocoding methods for epidemiologic research. *Ann Epidemiol*. 2006 Nov;16(11):842-9. Epub 2006 Oct 5. PubMed PMID: 17027286.

Zhan FB, Lin Y. Racial/Ethnic, socioeconomic, and geographic disparities of cervical cancer advanced-stage diagnosis in Texas. *Women's Health Issues*. 2014 Sep-Oct;24(5):519-27. PubMed PMID: 25128038.

Zou B, Wilson JG, Zhan FB, Zeng Y. An emission-weighted proximity model for air pollution exposure assessment. *Sci Total Environ*. 2009 Aug 15;407(17):4939-45. Epub 2009 Jun 6. PubMed PMID: 19501387.

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Project 4: Geospatial Data Science for Environmental Health Research

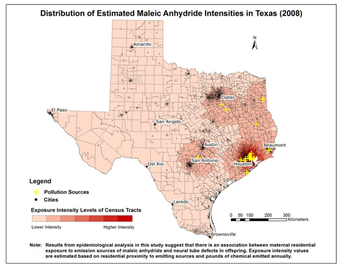

Fig. 4.1 Distribution of estimated maleic anhydride intensities in Texas in 2008.

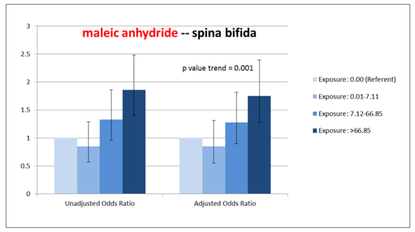

Fig. 4.2 Odds ratio showing maternal residential exposure to maleic anhydride as a potential risk factor for Spina Bifida in offspring.

The **identification of risk factors** associated with a specific illness is a challenging task. Geospatial data science combines the analytical power of visual geospatial analytics and the availability of rich geographically-referenced data to discover new knowledge about these risk factors.

Researchers in Texas State Geography developed new tools and used large datasets to examine risk factors associated with certain adverse health conditions. **Fig. 4.1** is an example map showing the geographic distribution of **estimated maleic anhydride intensities** in Texas in 2008. The odds ratio in **Fig. 4.2** suggests that **maternal residential exposure to maleic anhydride increases the risk of Spina Bifida in offspring**.

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