EXPANDING THE EXPOSURE ASSESSMENT LANDSCAPE USING NEW INFORMATION TOOLS

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The Places in Which We Live, Work, and Play Influence Our Health
Nurses’ Health Study Cohort

Began in 1976 with 121,701 female nurses aged 30-55

Originally from 11 States, have moved throughout the United States

Biennial questionnaires with disease and mortality follow-up

Residential mailing addresses geocoded from 1986-2018

Location of NHS residential addresses over follow-up
Nurses’ Health Study II Cohort

Began in 1989 with 116,000 female nurses aged 25-42

Originally from 14 States, have moved throughout the United States

Biennial questionnaires with disease and mortality follow-up

Biennial addresses geocoded from 1989-2017

Location of NHS II residential addresses over follow-up
Health Professionals Follow-Up Study

Began in 1986 with 51,529 male health professionals (e.g., dentists, optometrists)

Biennial questionnaires with disease and mortality follow-up

Biennial addresses geocoded from 1986-2018

Location of HPFS mailing addresses over follow-up
Growing Up Today Study

Children of NHSII participants

GUTS1 (N=16,882) enrolled in 1996, ages 9-14

GUTS2 (N=10,923) enrolled in 2004, ages 10-17

Complete follow-up questionnaires each year through age 18, every other year after age 18

Location of GUTS residential addresses over follow-up
Environmental Exposures

**PM$_{2.5}$**
- Spatiotemporal model to predict monthly PM$_{2.5}$ levels at any point (address) in the coterminous US
  - Generalized additive mixed models
  - EPA Air Quality Monitoring System data
  - Geospatial and meteorological predictors

Graphics by Cindy Hu
Environmental Exposures

Greenness
- Normalized Difference Vegetation Index (NDVI)
  - From Landsat satellite imagery
  - Satellite measure of vegetation based on the wavelengths absorbed by photosynthetically active plants
  - Available at 30m resolution every 16 days across the globe from 1984-present

Graphics by Cindy Hu
Environmental Exposures

Light at Night
- From the U.S Defense Meteorological Satellite Program’s Operational Linescan System
- Satellite imagery to detect light at night in nighttime radiance units
- Annual averages at 1 km² resolution starting in 1990s

Graphics by Cindy Hu
Environmental Exposures

Noise

• From the US National Park Service model of outdoor noise, using noise monitor data from 2000 – 2014 and land use regression
  • 270 m² grid
  • Anthropogenic nighttime noise median, Ldn, Leq, and other metrics available

Graphics by Cindy Hu
Mechanisms for Nature and Long-Term Health Outcomes

Environmental Factors
- Increase in ozone
- Increase in aerosol allergens

Physical activity
Examples:
- Increased walking for recreation
- Increased outdoor play

Social contacts
Examples:
- Increased interaction with neighbors
- Increased sense of community

Stress and Cognitive Function
- Acquisition of coping resources
- Affective, cognitive, physiological restoration

Health and well-being
Examples:
- Performance (e.g., academic, occupational)
- Subjective well-being (e.g., happiness)
- Persistent physiological changes (e.g., high cortisol levels)
- Morbidity (e.g., CHD, depression)
- Mortality (e.g., CVD, all cause)
- Longevity

Natural environment
Examples:
- Type (e.g., urban park)
- Quality (e.g., species diversity)
- Amount (e.g., tree canopy near home)

Contact with nature as such
Examples:
- Frequency of contact
- Duration of contact
- Activity affordance (e.g., for viewing, for walking)

Effect modifiers 1
Examples: Distance, other accessibility factors, weather, perceived safety, societal/cultural context

Effect modifiers 2
Examples: Gender, age, socioeconomic status, occupation, societal/cultural context

Hartig et al. 2014
Greenness and All-Cause Mortality in the Nurses’ Health Study (N=108,630 from 2000-2008)

<table>
<thead>
<tr>
<th>Cumulative Average Greenness in 250m</th>
<th>Fully Adjusted HR (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greenness Quintile 1</td>
<td>Ref</td>
</tr>
<tr>
<td>Greenness Quintile 2</td>
<td>0.92 (0.86, 0.98)</td>
</tr>
<tr>
<td>Greenness Quintile 3</td>
<td>0.90 (0.84, 0.96)</td>
</tr>
<tr>
<td>Greenness Quintile 4</td>
<td>0.94 (0.88, 1.00)</td>
</tr>
<tr>
<td>Greenness Quintile 5</td>
<td>0.88 (0.82, 0.94)</td>
</tr>
<tr>
<td>P for Trend</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Hazard ratios are adjusted for calendar time, age, race, smoking, individual SES, Census tract median home value and income
Growing Scientific Evidence for Health Benefits of Nature in an Exposomic Framework

Exposure to Nature

- Mental Health
- Cognitive Function
- Physical Activity / Sleep
- Birth Outcomes
- Cardiovascular Disease
- Cancer
- Mortality
Limitations of Epidemiologic Research on Nature and Health

Is “greenness” around the home the right measure?

What area around the home? Are we capturing contact with or exposure to nature?

We focus on vegetation, but what are the specific “active ingredients” in nature?

Without specificity, we are limited in causal inference and in policy relevance

What tools can we use to address these limitations?
Open cohort of 49,000+ nurses and nursing students ages 19-46 across the entire US
Web-based questionnaires every six months
*Participants open emails using predominantly smartphones*
Nurses’ Health Study 3 Mobile Health Substudy

450 participants underwent seven-day sampling periods four times over a year

Fitbit device to measure steps, heart rate, and sleep at the minute-level

Custom smartphone app to measure location and administer questionnaires

Efficient, passive, objective, low-cost measurement of high spatial- and temporal-resolution data on health behaviors
Fore et al. 2020
Digital Phenotyping in Epidemiological Cohorts

The collection of **smartphone-based** GPS, accelerometer, sleep and social network data

Stored and processed by **cloud computing** infrastructure
Average follow-up of **195 days** per participant

Averaged 12.7 valid hours of accelerometer data and 14.3 valid hours of GPS data (**430,000+ participant-days**)

**23,000+ questionnaires** completed with response rates range between 40%~50%

Collected data are currently under processing in **cloud-based servers** to derive environmental exposures and physical activity

*Notes. Data summary as of November 1st, 2022. The data collection remains ongoing for ~50% of participants.*
Potential Applications

14 months of GPS trajectories by day based on data from a test subject.

How many days of global positioning system (GPS) monitoring do you need to measure activity space environments in health research?

Shannon N. Zenk, Stephen A. Matthews, Amber N. Kraft, Kelly K. Jones
Remote Assessment of Cognition through Smartphone Applications

Grants under review to incorporate the Ambulatory Research in Cognition (ARC) platform into Beiwe

Repeated testing in free-living environments
  - Reduces the impact of within-person variability
  - Improves measurement precision
  - Enhances assessment of ecologically valid cognitive function

Completed in 2 minutes or less

Timestamped and geotagged
Exposure Assessment through Deep Learning

Image-based Approaches to Spatial Factors and Health

1. Satellite-based data tell us little about the quality of natural and built environments.

2. Geocoded street-level images provide insight into specific environmental features from an on-the-ground perspective.

3. Machine learning approaches can segment specific components of an image for analysis.
Create Grids

Obtain Near-Grid GSV Images from 2007-2022

Deep Learning of Google Street View Images to Develop Novel Spatial Exposures
Deep Learning of Google Street View Images to Develop Novel Spatial Exposures
NHLBI-funded R01: Built Environment Assessment through Computer vision (BEACON): Applying Deep Learning to Street-Level and Satellite Images to Estimate Built Environment Effects on Cardiovascular Health

Aim 1: GPS-Based

**Built Environment**
- Physical Features
- Natural Features
- Perceptions
- Urban Form

**CVD Health Behaviors**
- Physical Activity
- Weight Change

**CVD Incidence**
- Stroke
- Myocardial Infarction

Aim 2: Annual Changes

Aim 3: Long-Term

Peter James (Harvard Medical School), Perry Hystad, Andrew Larkin, Lizhong Chen (Oregon State), Steve Hankey (VA Tech), Wenwen Zhang (Rutgers), Esra Suel (ETH Zurich), Jaime Hart (Brigham and Women’s Hospital), and Eric Rimm (Harvard TH Chan School of Public Health)
Disparities in Access to Green Space

- White neighborhoods have greater access to green space
- Exposure disparities persist over generations, possibly contributing to health disparities by race and socioeconomic status
- Greenspace may reduce health disparities

Casey et al. 2017
The Climate Crisis

Green space has massive co-benefits for human health and the health of natural systems

- Major carbon sink
  - Planting a half trillion trees could reduce atmospheric carbon by about 25 percent
  - Enough to negate about 20 years of human-produced carbon emissions at the current rate, or about half of all carbon emitted by humans since 1960
- Prevents soil erosion
- Provides substantial cooling in urban environments
- Counterpoint of wildfires

In the context of equity, low-income blocks have 15.2% less tree cover and are 1.5°C hotter than high-income blocks
Conclusions

Exposomic analyses account for multiple correlated exposures

Mobile health approaches add granularity on personalized exposures and health behaviors

Deep learning algorithms provide specific, time-varying, objective data on environmental exposures from unprecedented perspectives

These data combined may provide relevant, actionable information for planners, policy makers, and community members to design places that are optimal for health
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