At-Risk Identification Using AI and Social Determinants

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Welcome

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Conflict of Interest

Lisa M. Lines, PhD, MPH

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Have no real or apparent conflicts of interest to report.

Agenda

- Learning Objectives
- Context and Background
- Local Social Inequity Scores
- Applications

Learning Objectives

- Recognize how local area factors are independently associated with many health outcomes and may be informative either in conjunction with individual-level data or on their own

- Discover how artificial intelligence tools may improve incentives for providers to treat more difficult patients

- Discuss how commonly available area-level deprivation or vulnerability indices only partially explain the variation we see in healthcare outcomes

Determinants of Health

AIRA
ARTIFICIALLY INTELLIGENT RISK ADJUSTMENT

Defining Terms

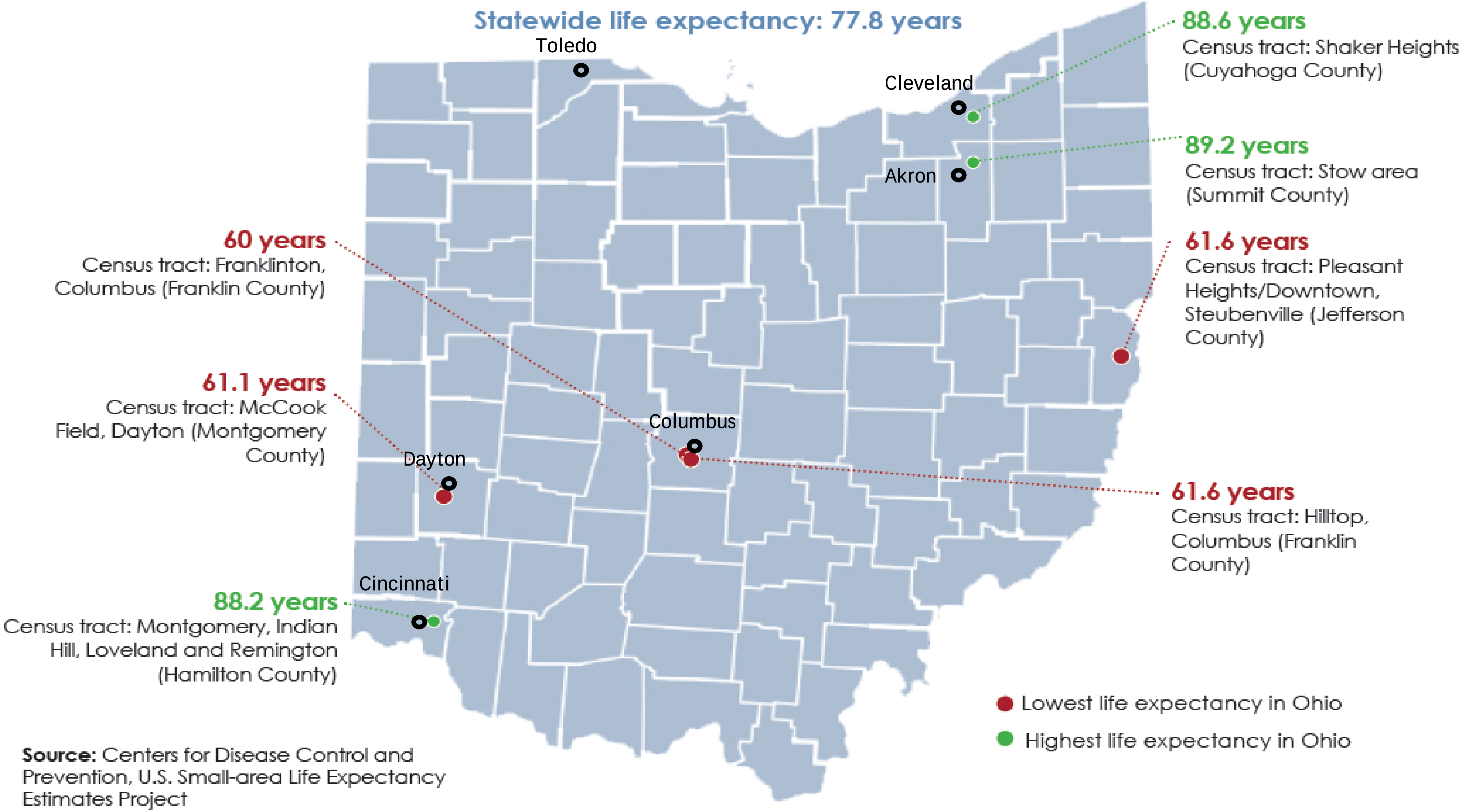
- Artificially Intelligent Risk Adjustment (AIRA): our approach to leveraging AI to inform risk adjustment for social factors
- Social determinants of health (SDoH): conditions in which people live, work, and grow
- Disparities: differences in outcomes that may be associated with social factors
- Inequities: another word for differences in outcomes that focuses on equity over parity
- Local social inequity (LSI): a measure explaining health outcome disparities (or inequities) in small geographic areas using predictors related to social factors

Context and Background

- Current risk-adjustment formulas and performance/quality measures don't take many, if any, social determinants of health (SDoH) into account
- This can lead to unintended consequences
  - Practices with lower-risk patients get rewards, those with worse-off patients lose out
  - Providers feel they are penalized for factors outside of their control
  - Payers & networks have incentives to enroll lower-risk members
  - Lack of good data on SDoH can bias interventions toward lower-risk populations, less benefit
- Current publicly available area-based indices are limited

We need better ways to measure, predict, and adjust for social factors in healthcare and population health

Longest and Shortest Life Expectancy at Birth: 6 CTs in OH, 2010-15

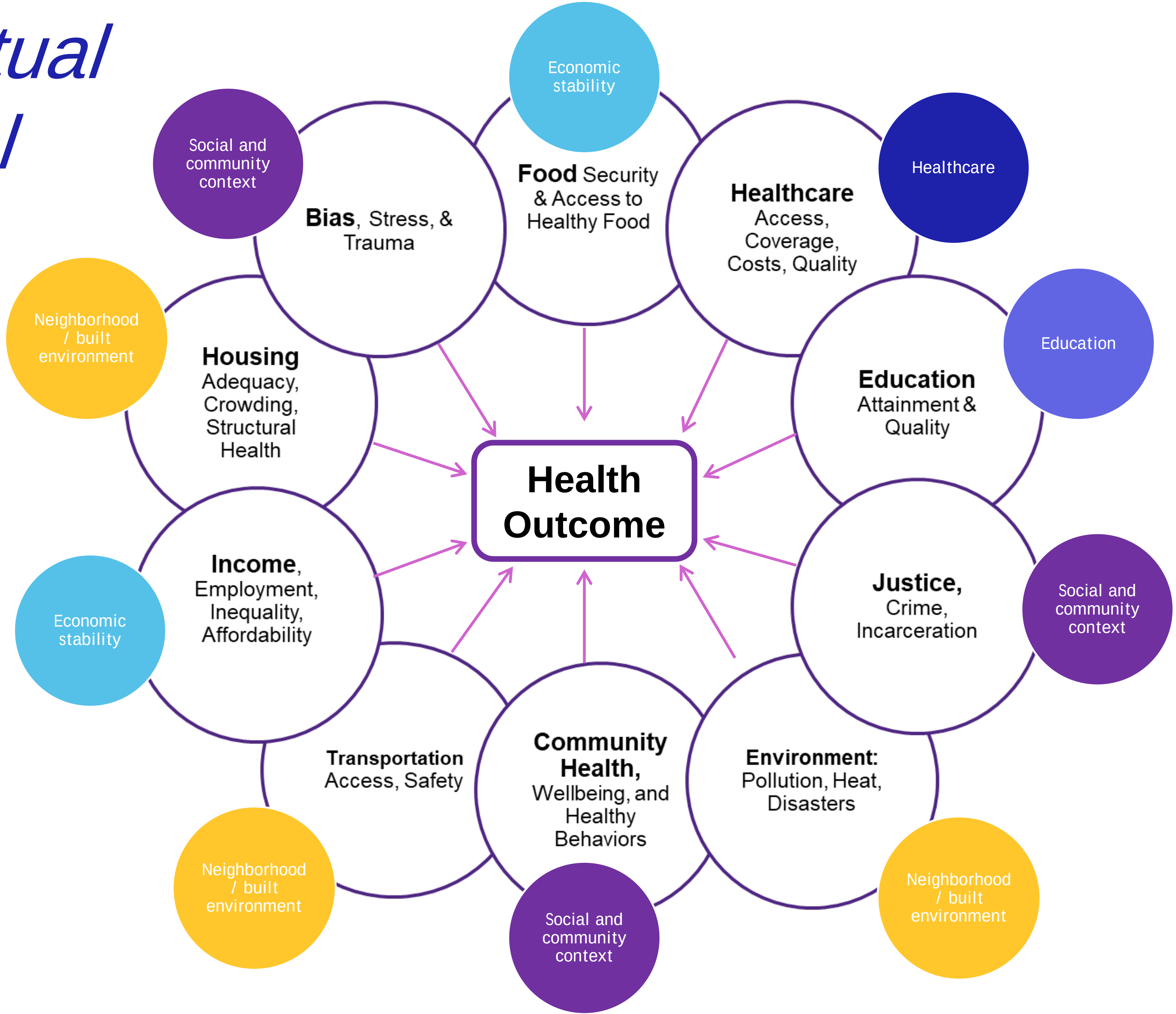


Source: Centers for Disease Control and Prevention, U.S. Small-area Life Expectancy Estimates Project

Conceptual Model

Infant Mortality

Life Expectancy



Drug Overdose Deaths

Excess Mortality: COVID-19

Selected Data Sources and Example Measures

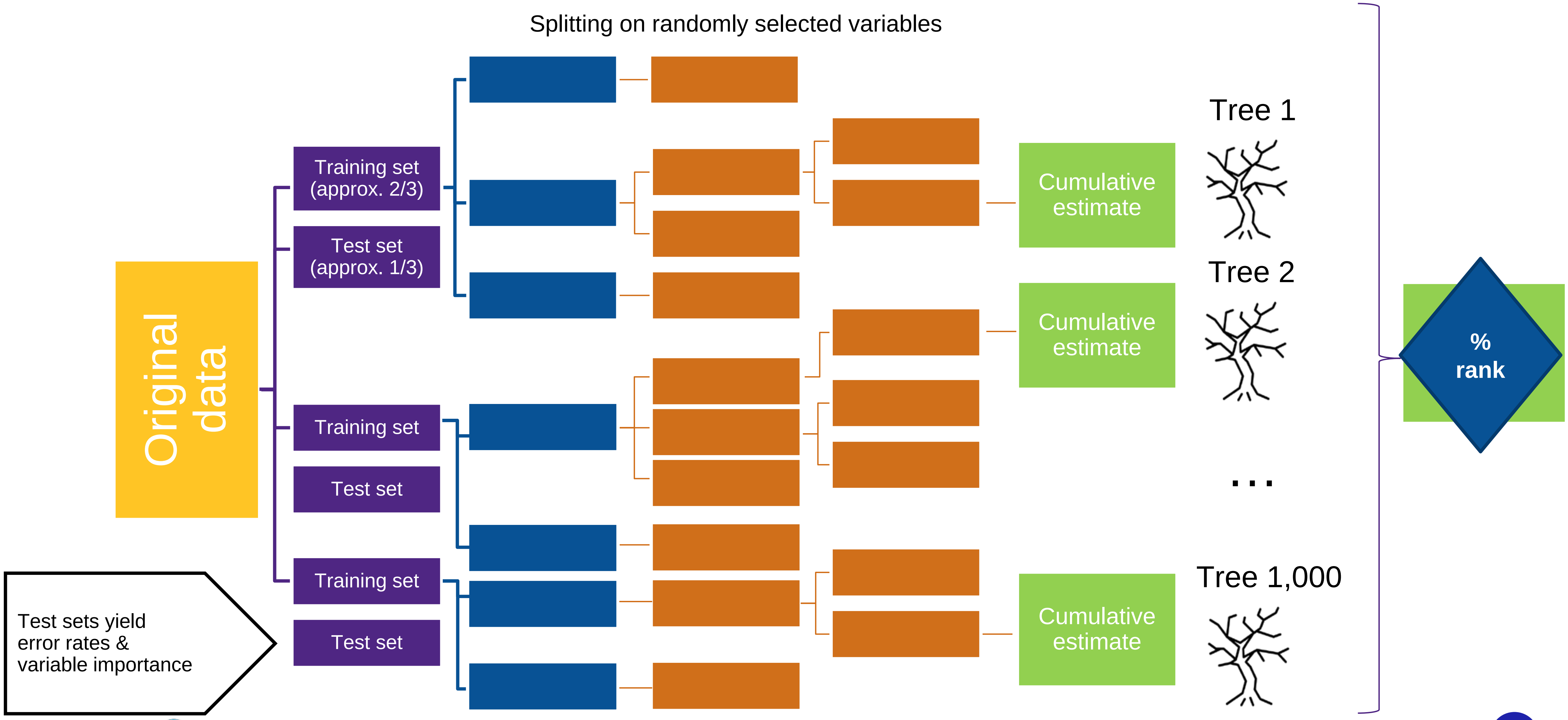
Integrated APIs

- PLACES – 21 BRFSS measures for chronic conditions and healthy behaviors
- TidyCensus – American Community Survey demographic data
- US DOT – transportation measures
- Diversity Data Kids – Childhood health measures
- USDA ERS – Food and nutrition data
- FBI's UCR – Crime data
- Homeland Infrastructure Foundation-Level Data – places of worship, sports venues, landfills
- RTI's Spark SDoH database – air pollution and Medicare data

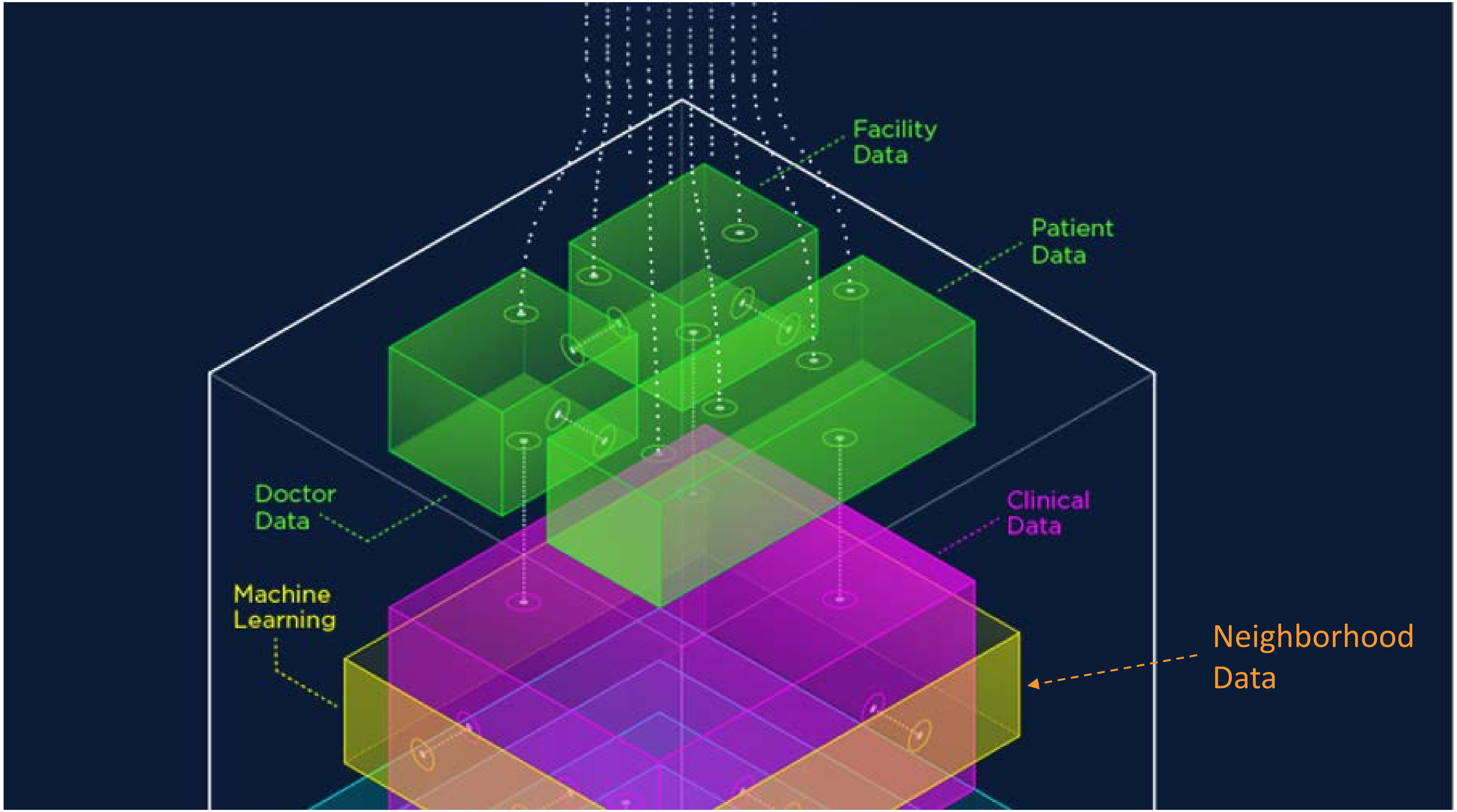
Selected Downloaded Datasets

- CDC's Environmental Public Health Tracking Network
- CDC's Compressed Mortality file
- CMS HCRIS Data: 2014-2017
- United States Drought Monitor
- Uniform Crime Reporting Program Data
- HUD data – subsidized housing
- Opportunity Atlas
- Child Opportunity Index
- Walkability Index

Simplified Illustration of Random Forest Algorithm



The Dream


Facility
Data
Patient
Data
Doctor
Data
Clinical
Data
Machine
Learning
Neighborhood
Data

Life expectancy, mean (range) – 5 states

- *Kansas*

  78.1 Years (62.5 to 89.7)

  Poverty rate: 20%

- *Kentucky*

  75.6 Years (62.4 to 88.9)

  Poverty rate: 22%

- *Ohio*

  76.6 Years (60.0 to 89.2)

  Poverty rate: 19%

- *South Carolina*

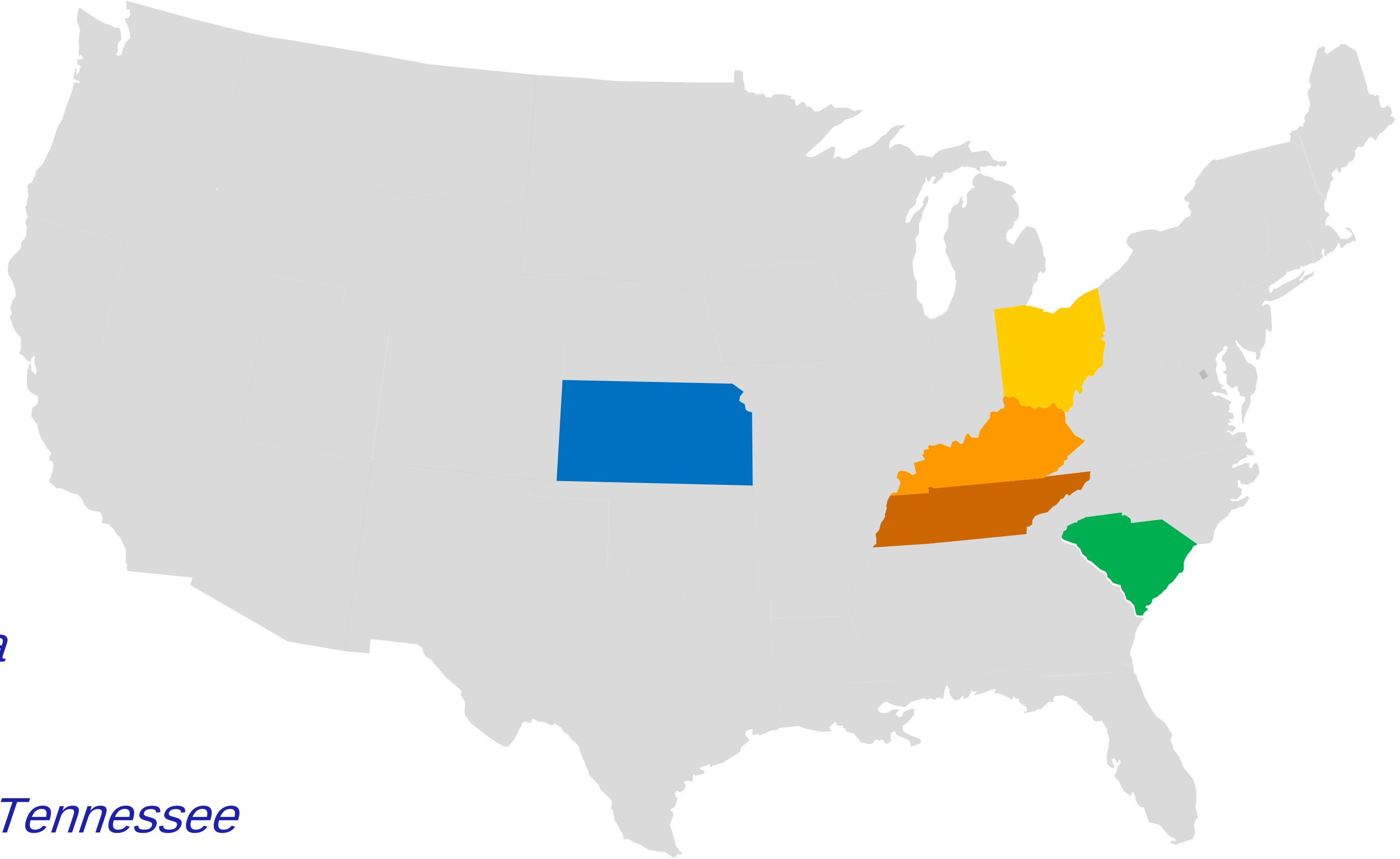
  76.6 Years (64.3 to 89.4)

  Poverty rate: 22%

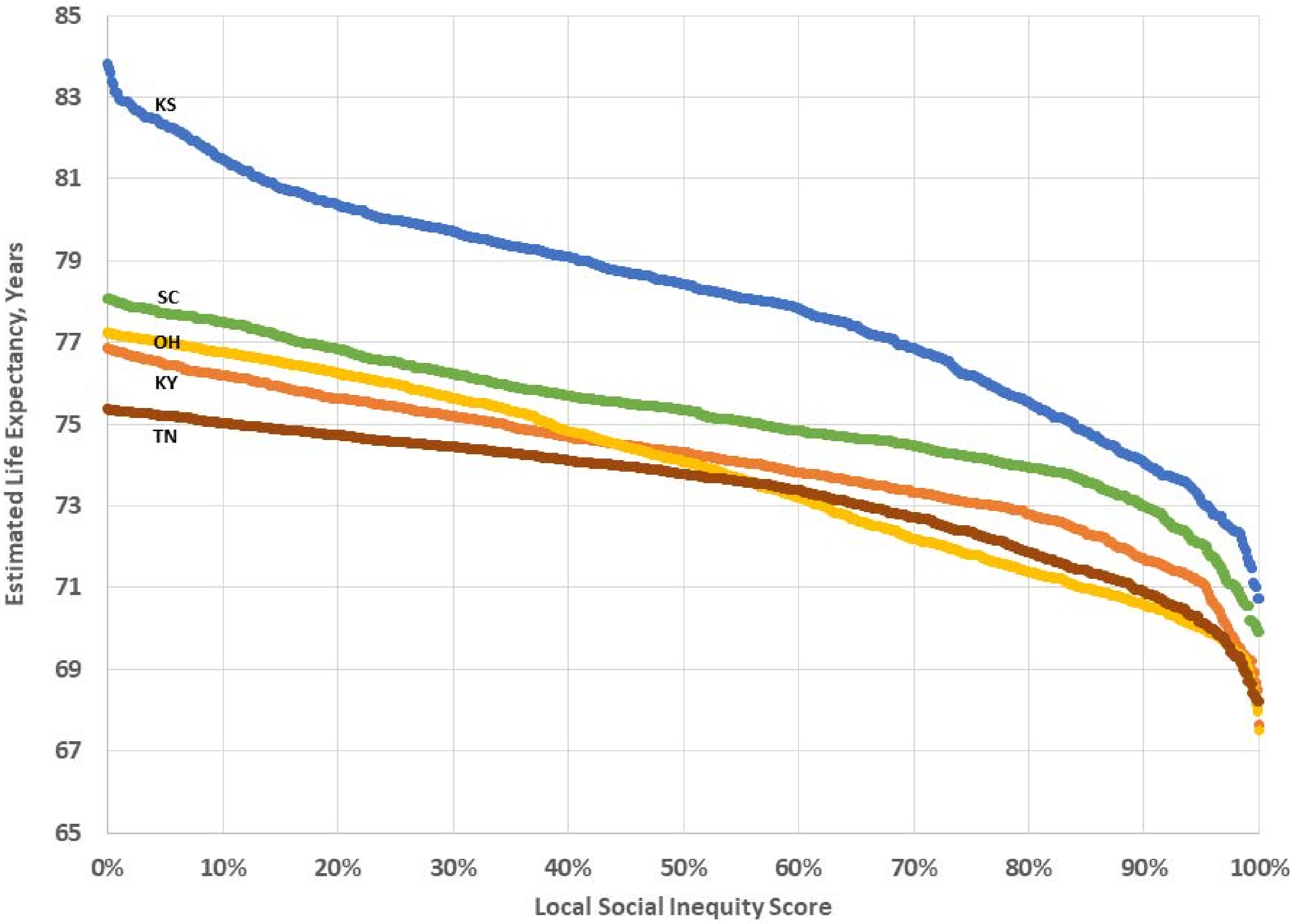
- *Tennessee*

  75.5 Years (64.3 to 88.0

  Poverty rate: 22%

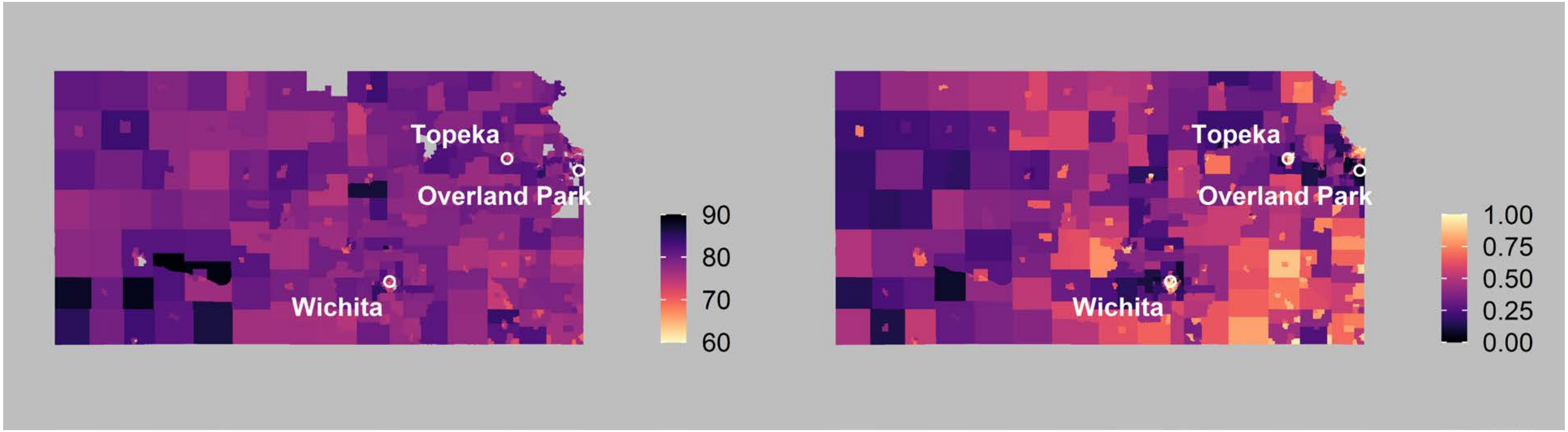


Life expectancy by local social inequity: 5 states



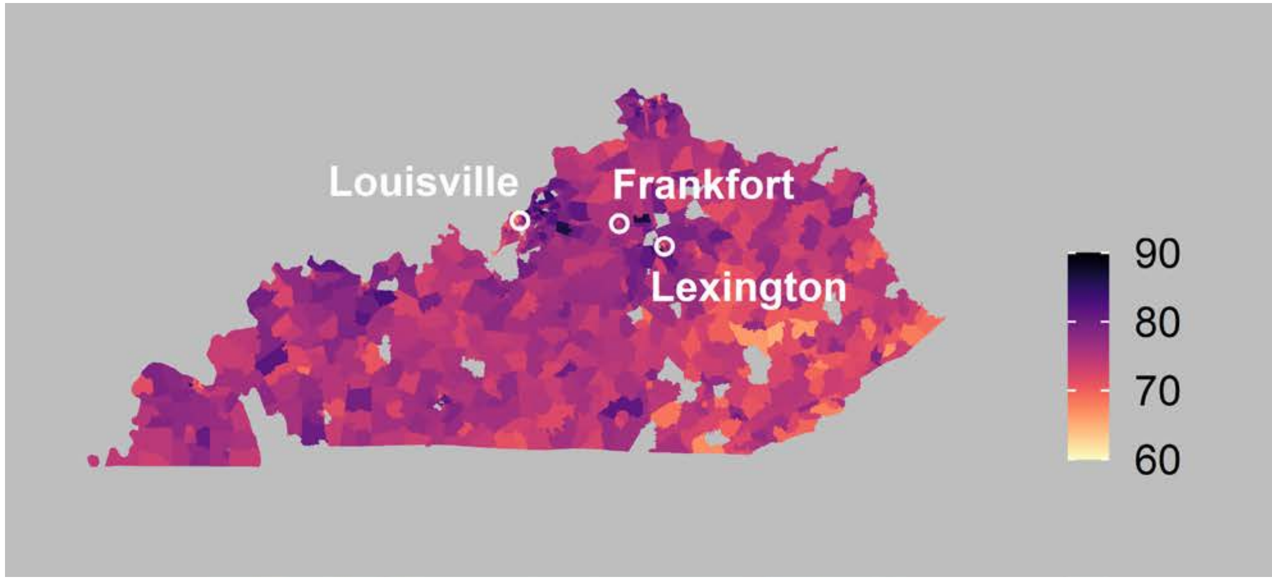
Maps of Life Expectancy and Social Inequity in Kansas

Life Expectancy Estimates **Local Social Inequity Scores**

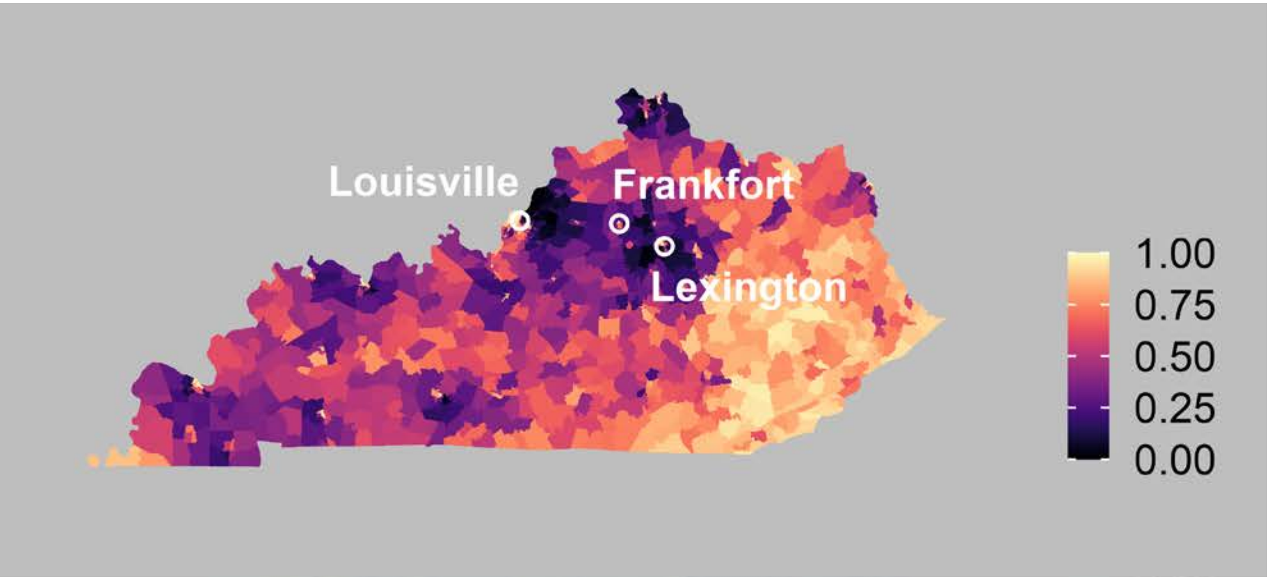


Maps of Life Expectancy and Social Inequity in Kentucky

Life Expectancy Estimates

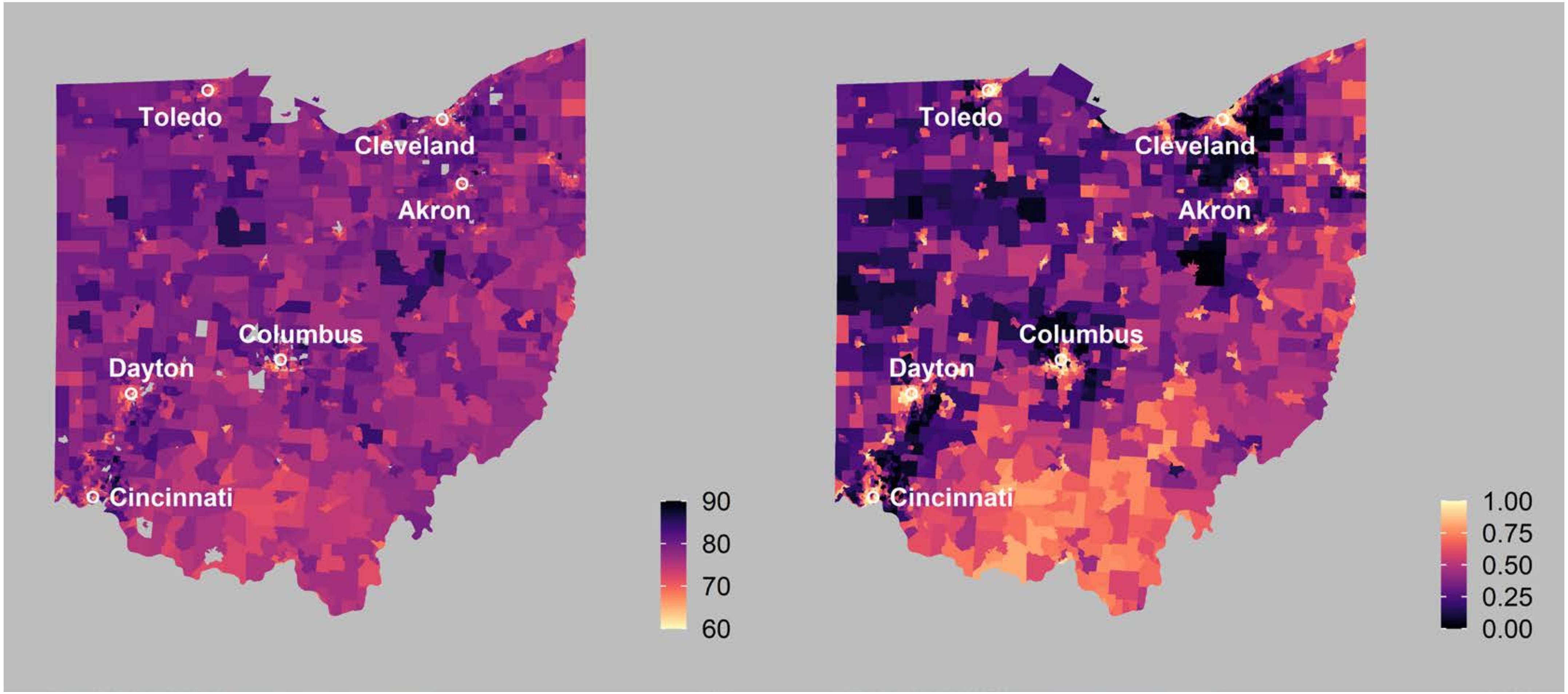


Local Social Inequity Scores



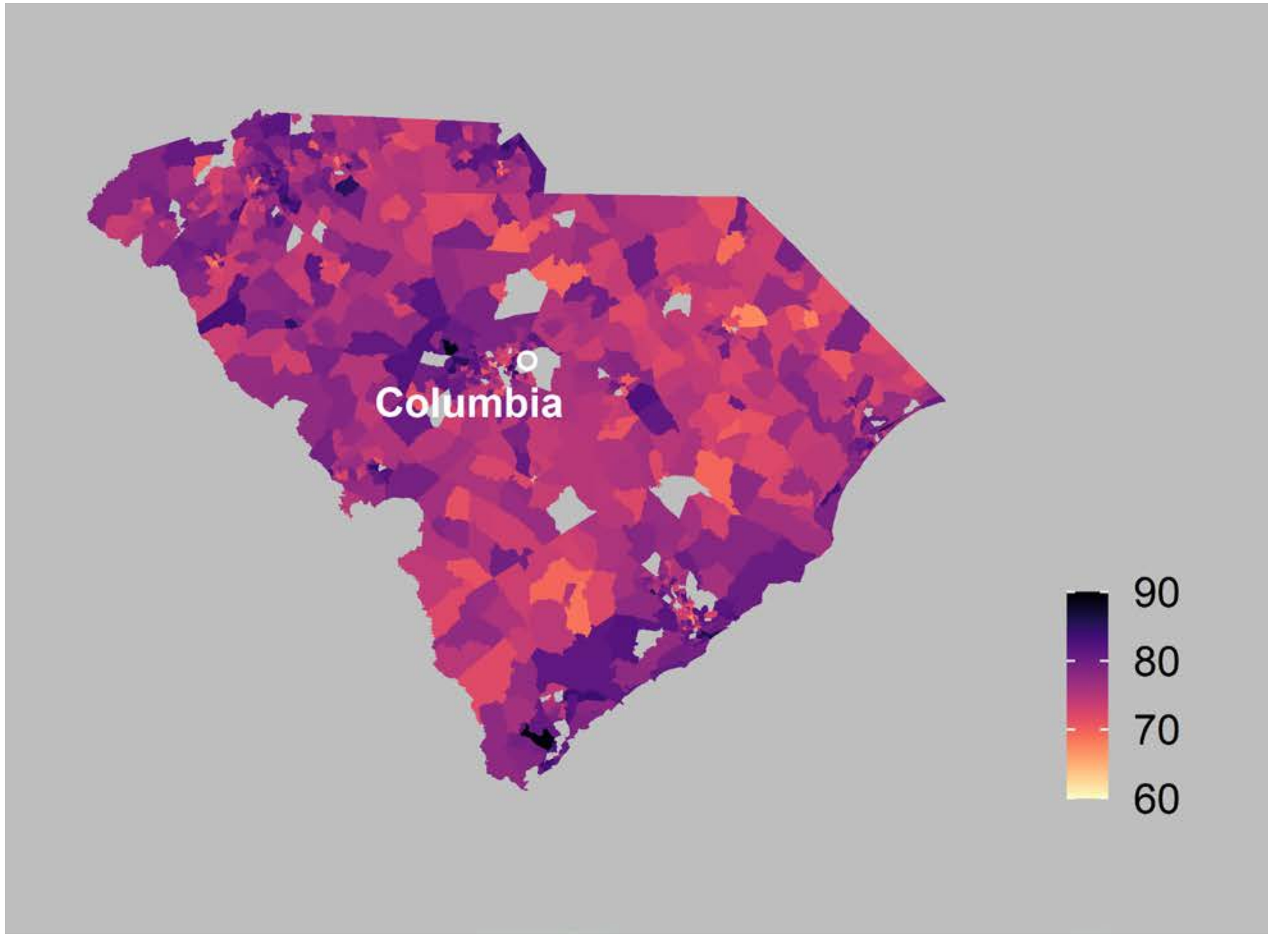
Maps of Life Expectancy and Social Inequity in Ohio

Life Expectancy Estimates | **Local Social Inequity Scores**

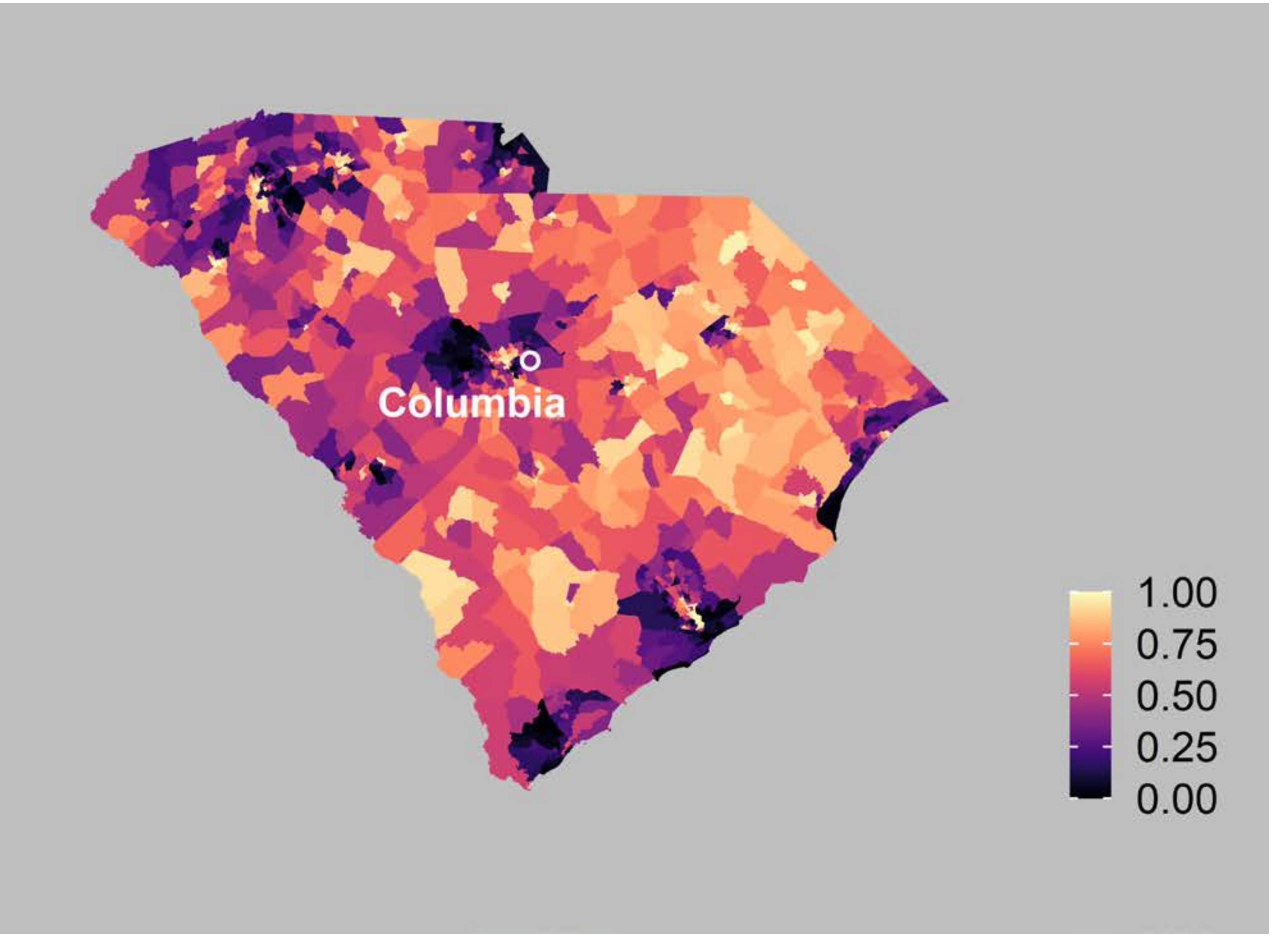


Maps of Life Expectancy and Social Inequity in South Carolina

Life Expectancy Estimates



Local Social Inequity Scores

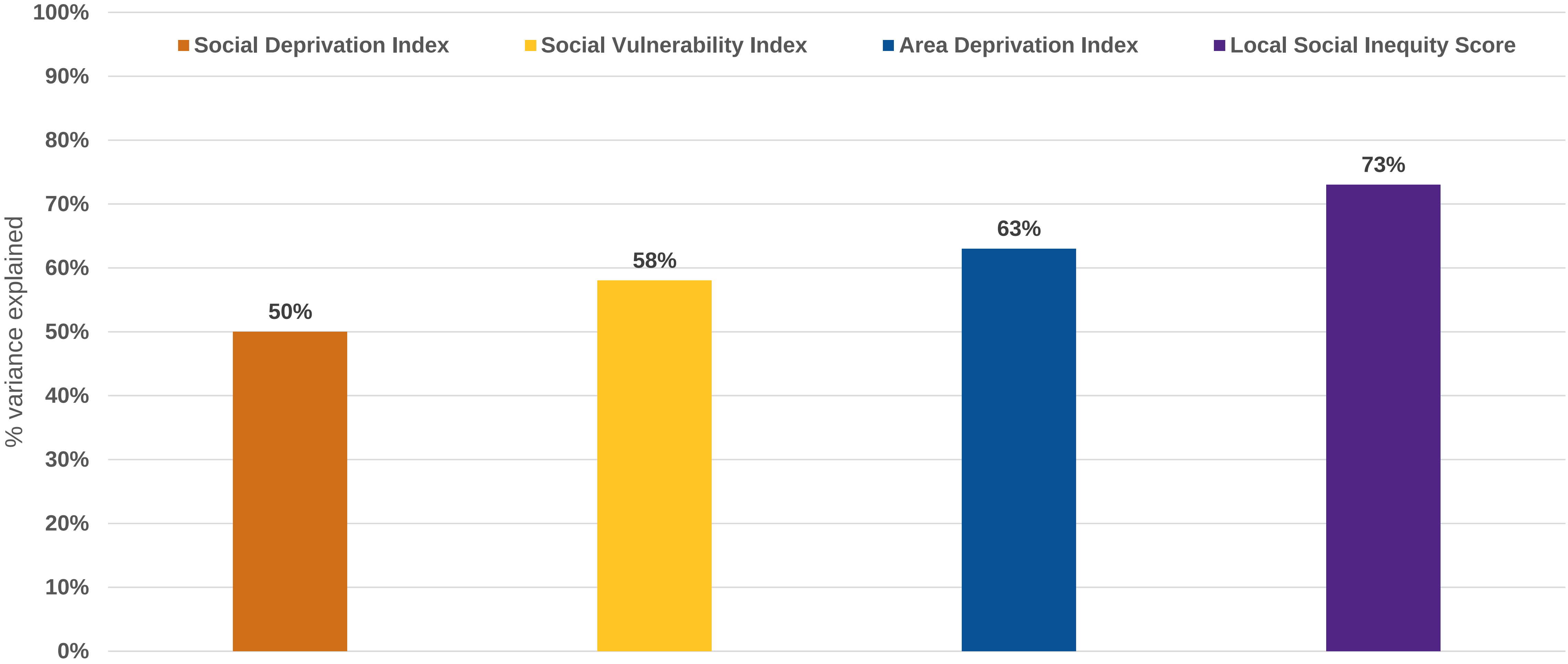


Maps of Life Expectancy and Social Inequity in Tennessee

Life Expectancy Estimates

Local Social Inequity Scores

Explaining the variance in life expectancy in Ohio with publicly available tract -level measures



Comparative Statistics for Ohio – Overall, Highest Decile of LSI, and Lowest Decile of LSI

	Statewide		Highest LSI Score Decile		Lowest LSI Score Decile	
	Mean	SD	Mean	SD	Mean	SD
Life expectancy, CT, 2010-15 (years)	76.6	4.1	70.3	3.0	81.6	2.1
Social Risk Score	0.50	0.29	0.95	0.03	0.05	0.03
Top 10 Predictors of Life Expectancy						
Child Opportunity Index, 2010-15*	44	28	5	4	87	12
Food assistance rate, %, 2010-14	18	15	46	11	3	2
Raised in two-parent family, %**	71	18	41	16	87	7
Owner-occupied home value, median $, 2010-14	127,013	65,688	57,968	28,444	251,790	80,366
Probability of earnings in the top 20% among children who grew up in tract**	18	10	4	3	36	8
Medicaid enrollment, %, 2010-14	20	14	45	11	5	3
Asthma prevalence, %, 2017	10	2	13	1	8	1
Physical inactivity prevalence, %, 2015	28	7	40	5	19	3
Mentally unhealthy days, mean, 2015	16	4	22	3	11	2
Smoking prevalence, %, 2015	23	6	33	4	14	4

*Child Opportunity Index includes 29 indicators in 2010 and 2015. **Opportunity Atlas measures drawn from 1978-2015 data.

Applications

	Providers	Payers	Policy Makers
Understand drivers of health in order to identify most important issues to address	X	X	X
Use LSI scores to identify individuals or neighborhoods for SDoH interventions	X	X	X
Use LSI scores to risk adjust value-based payment models		X	X
Incorporate LSI scores in evaluations of healthcare innovations, payment models, and interventions on SDoH on higher-risk communities	X	X	X

Example: Merged with Medicaid Population Data in OH

Figure 1. Any inpatient admission by quartile and year

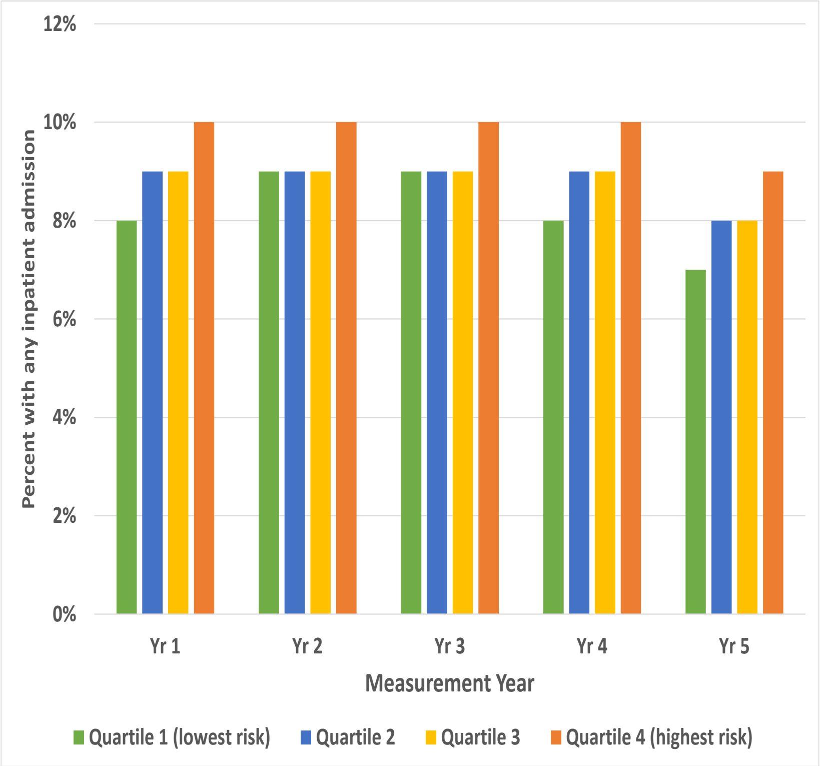


Figure 2. Number of PCP visits by quartile and year

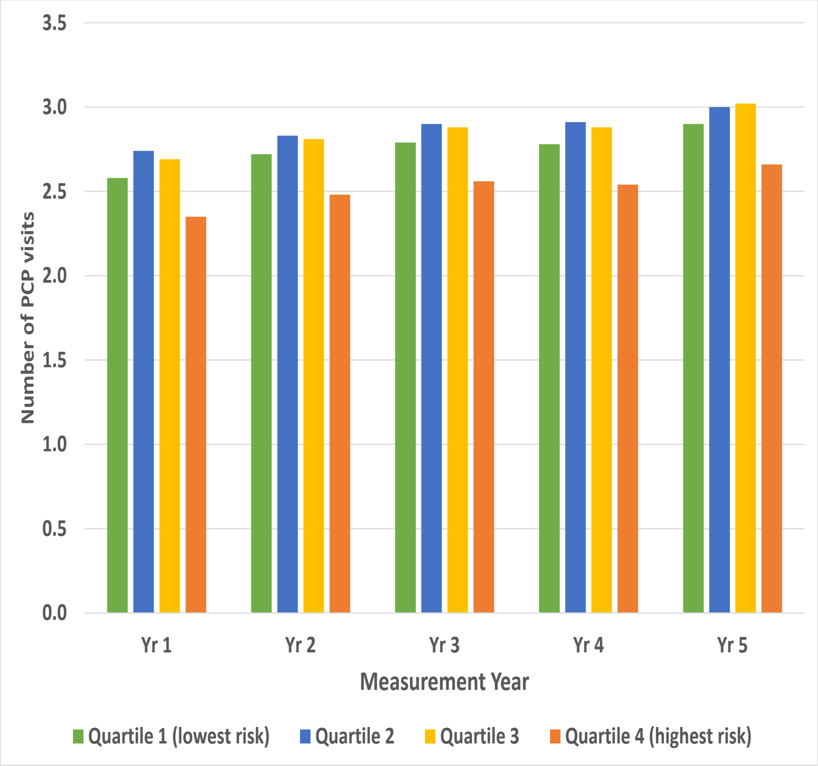
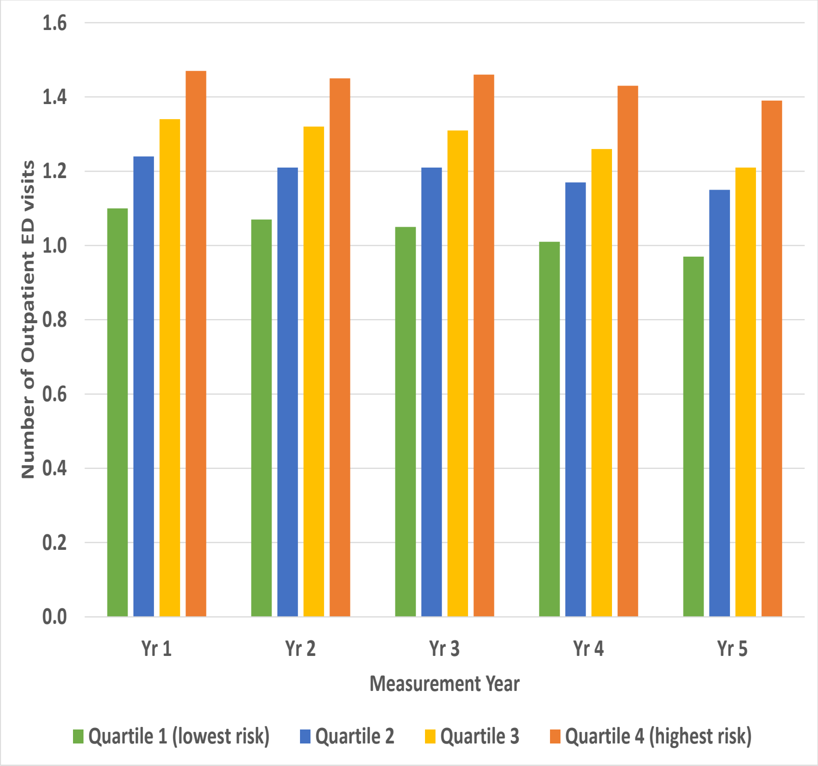


Figure 3. Number of ED visits by quartile and year



n=12.1 million person-years

Conclusions

- Our LSI scores explain 73% of the variation in life expectancy in Ohio – an improvement over existing indices that explain 50-63%
- Top individual important factors include child opportunities, receiving food assistance, being raised in 2-parent family, property values, probability of earnings in the top 20% (among children born in the same year)
  - These measures are complex and multidimensional, covering far more nuance than just “poverty rate”
  - We are limited to what data are available, and there may be bias in terms of who is included in the samples used for the underlying measures
  - While some of the top predictors may track with prior research, others may not be as obvious or amenable to interventions
- Using information on social risk to explain variation in population health status and outcomes can go beyond just maps

Questions

AIRA

ARTIFICIALLY
INTELLIGENT
RISK
ADJUSTMENT

Thank you!

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