

Applied Cyber-GIS in the Age of Complex Spatial Health Data

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Complex Spatial Health Data

Big



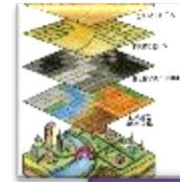
- Volume
- Person
- Group
- Multiple data streams
- Data org. and processing beyond traditional software

Deep



- Multiple levels of info that are **connected**
- Allows to extract meaning and explore causal links

Contextual



- XY coordinates
- Place, exposure, spatial relations, context
- Does environment play a role?

The Ideal Complex Spatial Health Data

- Health Outcomes
 - Electronic Medical Record
 - Self report
 - Sensor based
- Behavioral data
 - Survey based behaviors
 - Sensor based
 - App based
 - Life course data

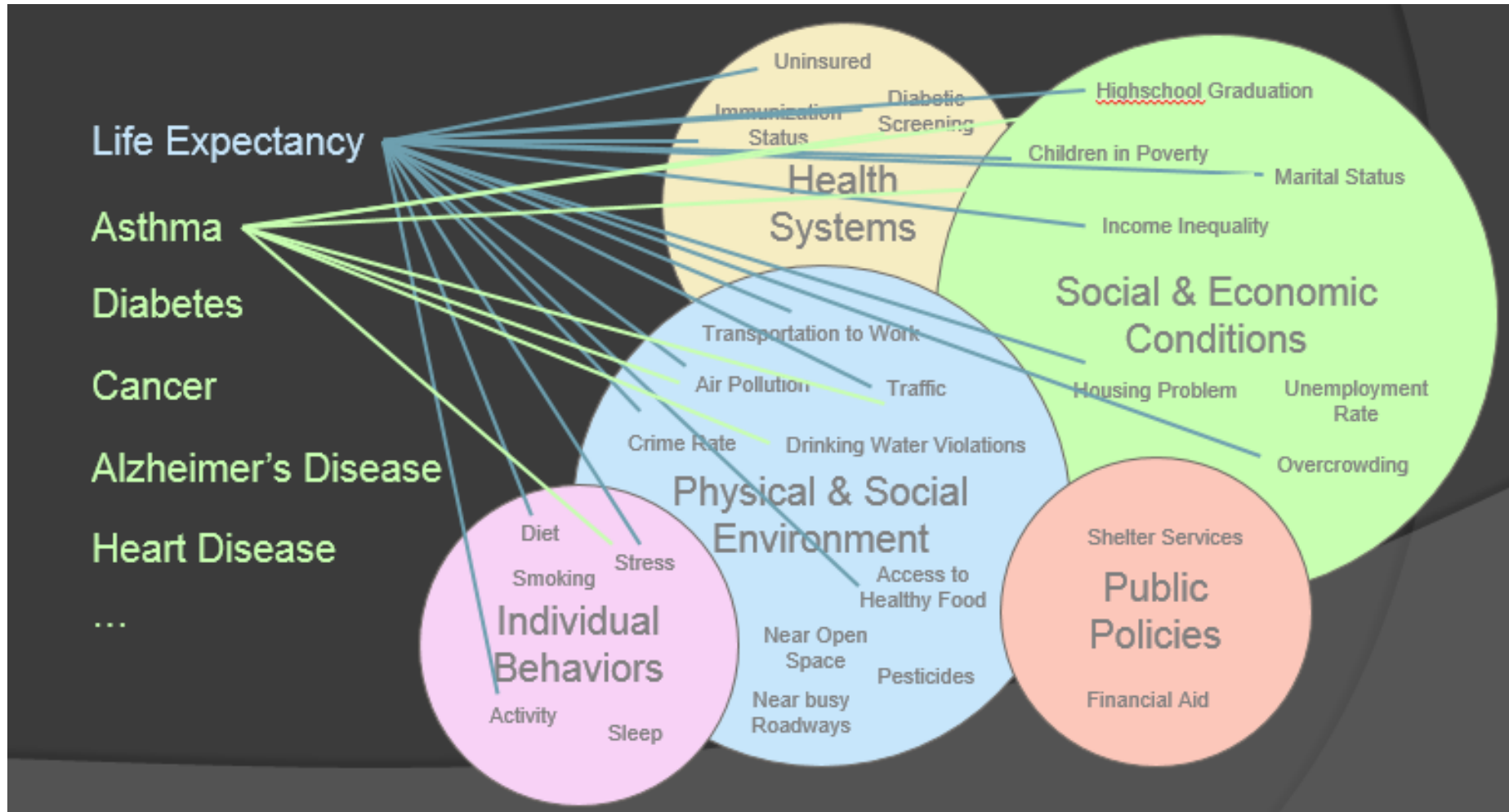


- Omics
 - Genetics
 - Microbiome
 - Etc.
- Context
 - Exposures
 - Access

Targeted Individual Intervention



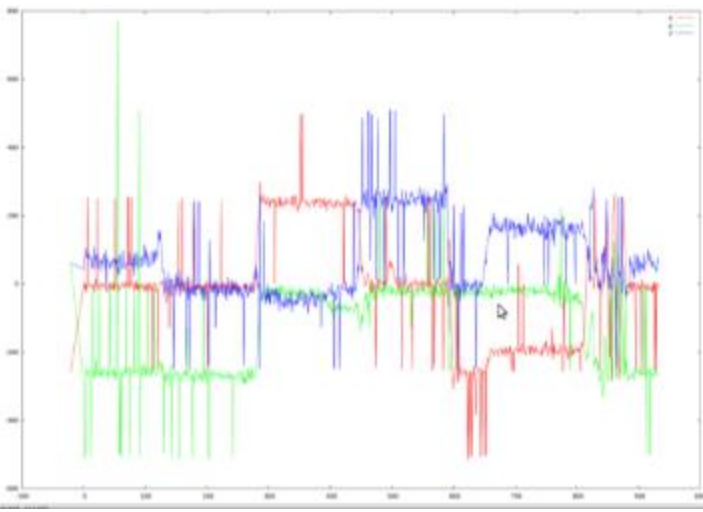
Population Level Health



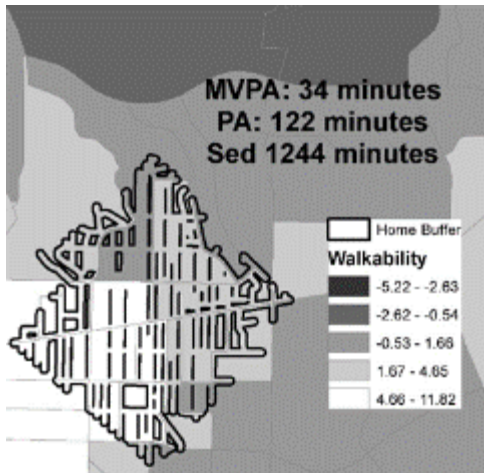
The reality of Complex Spatial Health Data



- Big data processing challenges w/ added dimensions
- Cross disciplinary communication
- HIPAA and security
- Who sees/gets the data?
- Modeling challenges
- Data organization/infrastructure



x 7 days x 10 hours

[illegible]

MVPA: 34 minutes
PA: 122 minutes
Sed 1244 minutes

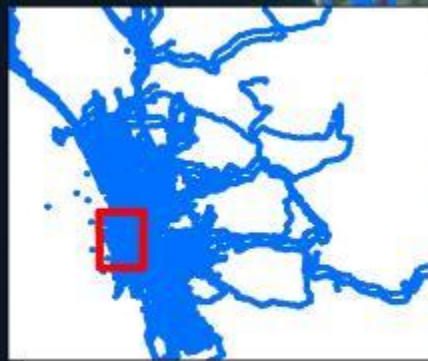
Walkability

5.22 - 2.63
2.62 - 0.54
0.53 - 1.66
1.67 - 4.05
4.06 - 11.82

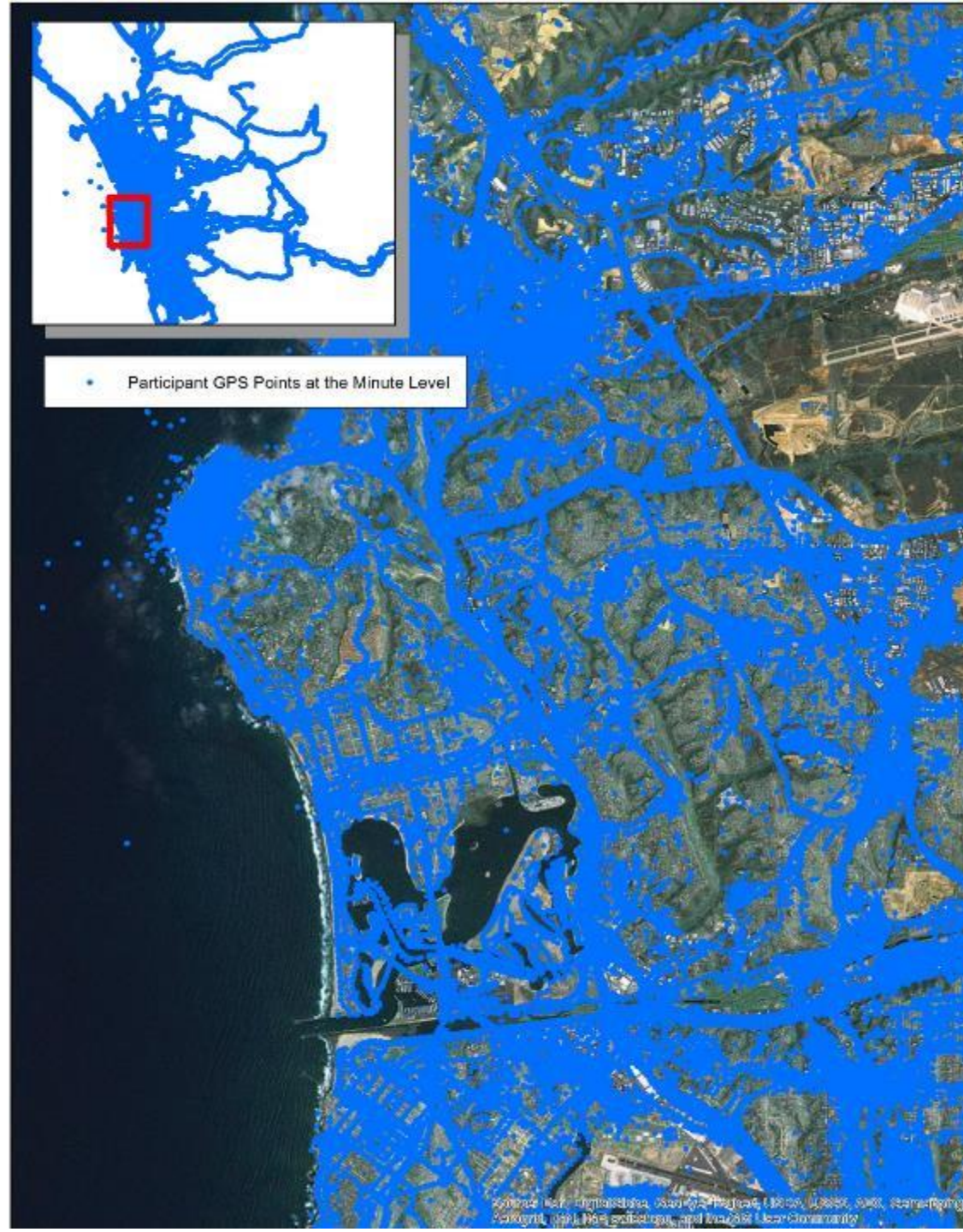
Photography (SenseCam)

- longitudinal data
- Microbiome
- Genetic data





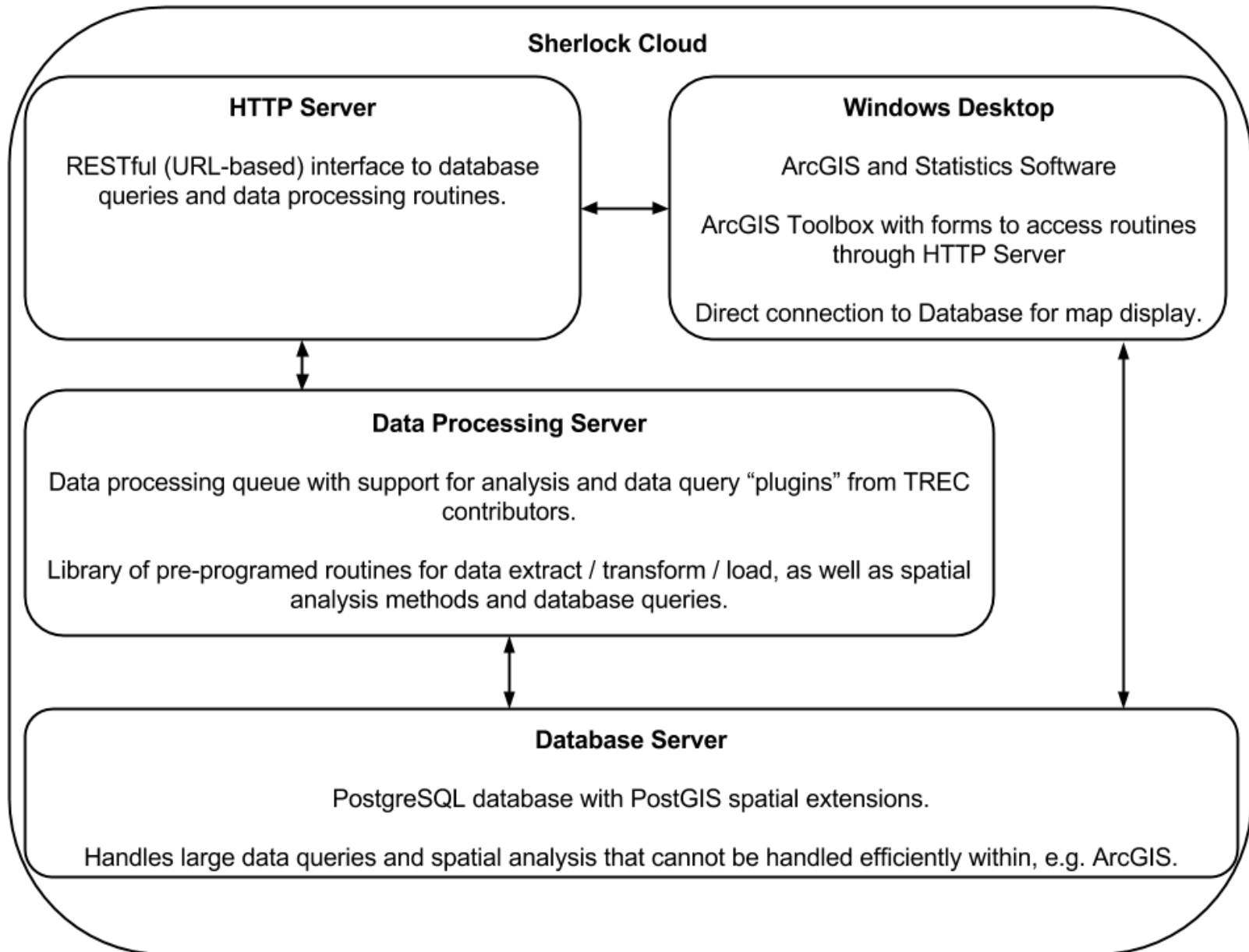
- Participant GPS Points at the Minute Level

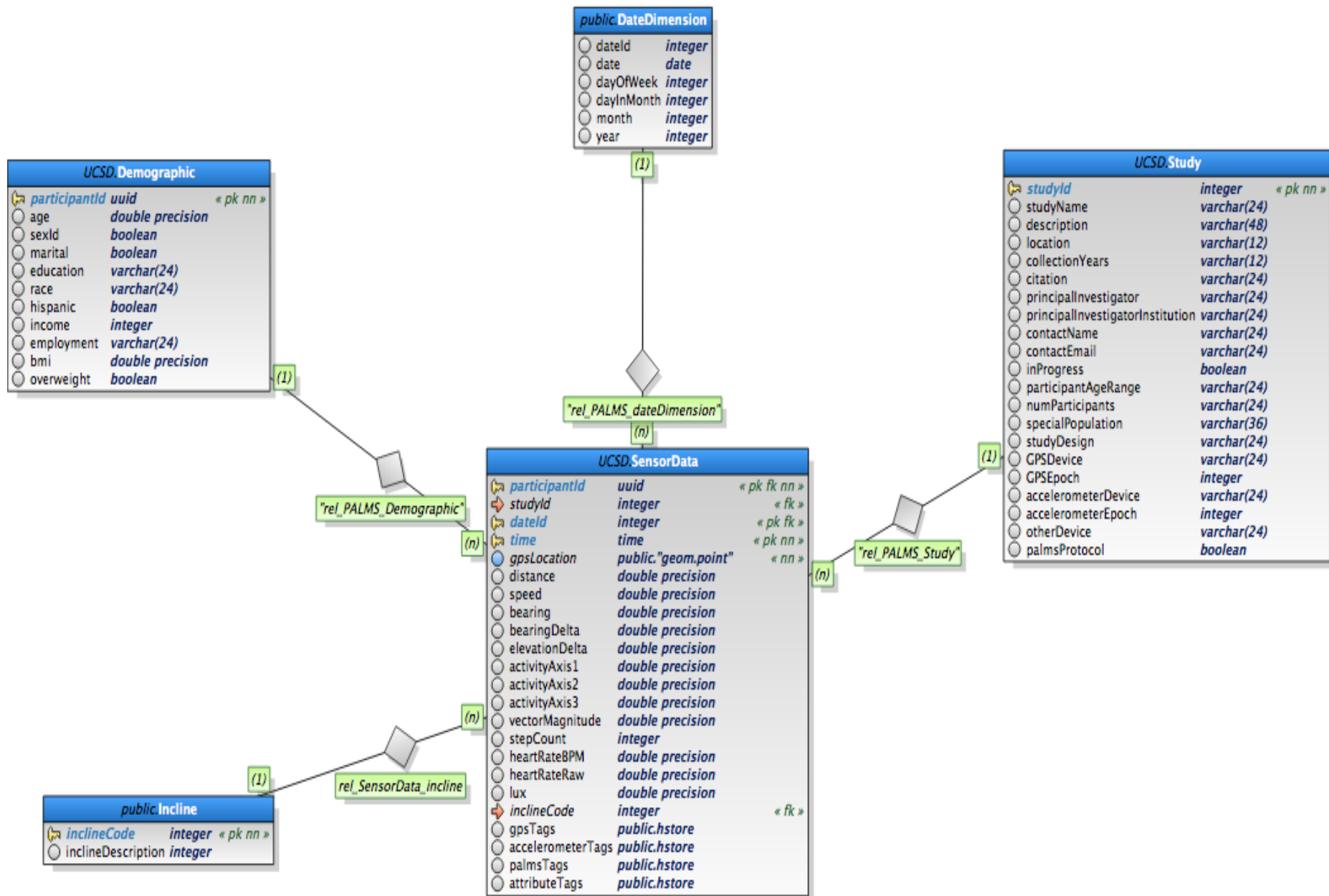
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How Can CyberGIS help?

- CyberGIS as defined by ESRI: “GIS detached from the desktop and deployed on the web, with the associated issues of hardware software, data storage, digital networks, people, training and education.”
- Goldberg *et al.* Spatial-Health CyberGIS Marketplace
 - confidentiality and privacy protections
 - real-time analytic methods
 - data standardization
 - comprehensive end-to-end ecosystem architecture
- In addition:
 - need for shareable workflows to promote inter-field collaboration
 - diverse data type integration
 - replicability of analytic processes.

Step 1: Hosted HIPAA compliant Geodatabase



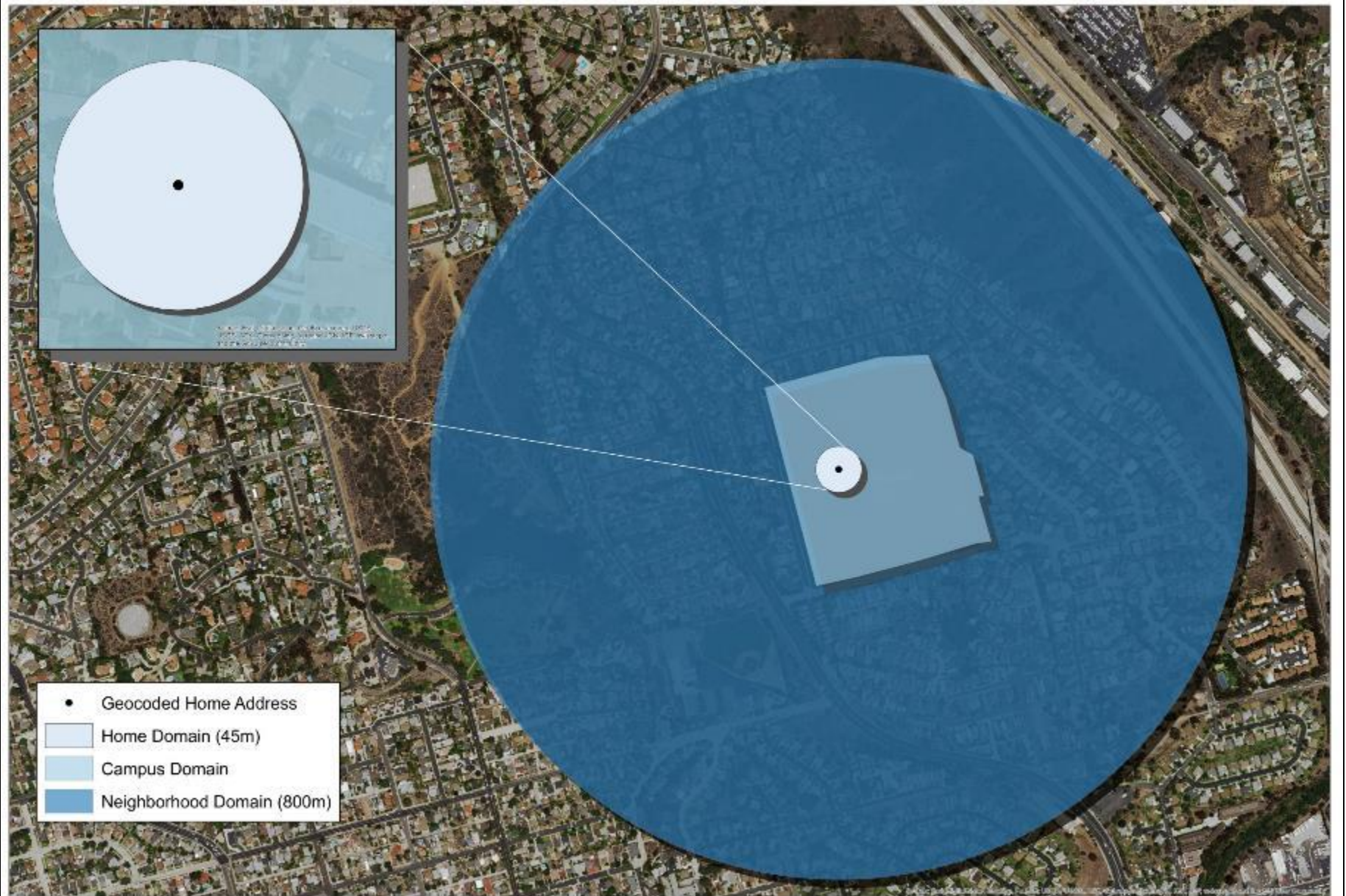


Study	Description/Population	n	F, M, (%F)	Age(SD)	%Hispanic	%Employed (full-time)	Mean BMI	Valid(Acc,GPS, Both)	Home Location Y,N
Context	Overweight and obese adults 21-60 years old	71	55, 16, (77.4%)	42(10)	26, 45, (37.0%)	40, 31, (56.3%)	33(3)	448, 576, 389	67, 4
DIAL	N=40 women who did not meet the strict eligibility criteria of the MENU or RfH studies	37	37, 0, (100%)	57(15)	3, 34, (8.1%)	20, 17, (54.1%)	33(4)	276, 325, 270	37, 0
MIPARC	351 residents over the age of 65 living in Continuing Care Retirement Communities (CCRC) in SD County n=307 participants, n=44 peer leaders	347	247, 100, (71%)	84(6)	5, 332, (1.4%)	0, 347, (0.0%)	NA	7924, 9207, 7073	334, 13
RfH	6-month randomized controlled trial of metformin, lifestyle intervention, or both, among a sample of 340 postmenopausal, overweight/obese breast cancer survivors.	126	126, 0, (100%)	61(7)	17, 108, (13.6%)	44, 82, (34.9%)	31(6)	946, 1117, 852	126, 0
RfH Memory	Postmenopausal, normal weight cancer survivors	40	40, 0, (100%)	63(7)	5, 35, (11.1%)	10, 30, (23.3%)	22(2)	294, 325, 254	39, 1
SDSU Cycling	SDSU students, faculty, and staff who were cyclists	33	8, 25, (24%)	NA	1, 32, (3%)	27, 6, (81.8%)	NA	105, 201, 105	32, 1
Sensecam Cycling	N=40, healthy, working adults or students from the UCSD Commuter Cycling Network	40	12, 28, (30%)	36(12)	0, 40, (0%)	31, 9, (77.5%)	23(3)	103, 154, 101	40, 0
PALMS007	Latino population	42	20, 22, (47.6%)	27(11)	42, 0, (100%)	3, 39, (7.1%)	26(6)	260, 204, 169	41, 1
SAGE	N = 40 participants from the Stein SAGE study, selected to vary in physical functioning based on the SF-36 measure, with 10 participants from each of four decades 60-100.	40	16, 24, (40%)	78(10)	3, 37, (7.5%)	4, 36, (11.1%)	25(3)	231, 282,228	40, 0
Community of Mine	Adults living in a geographically diverse set of neighborhoods throughout San Diego County	700			50%				

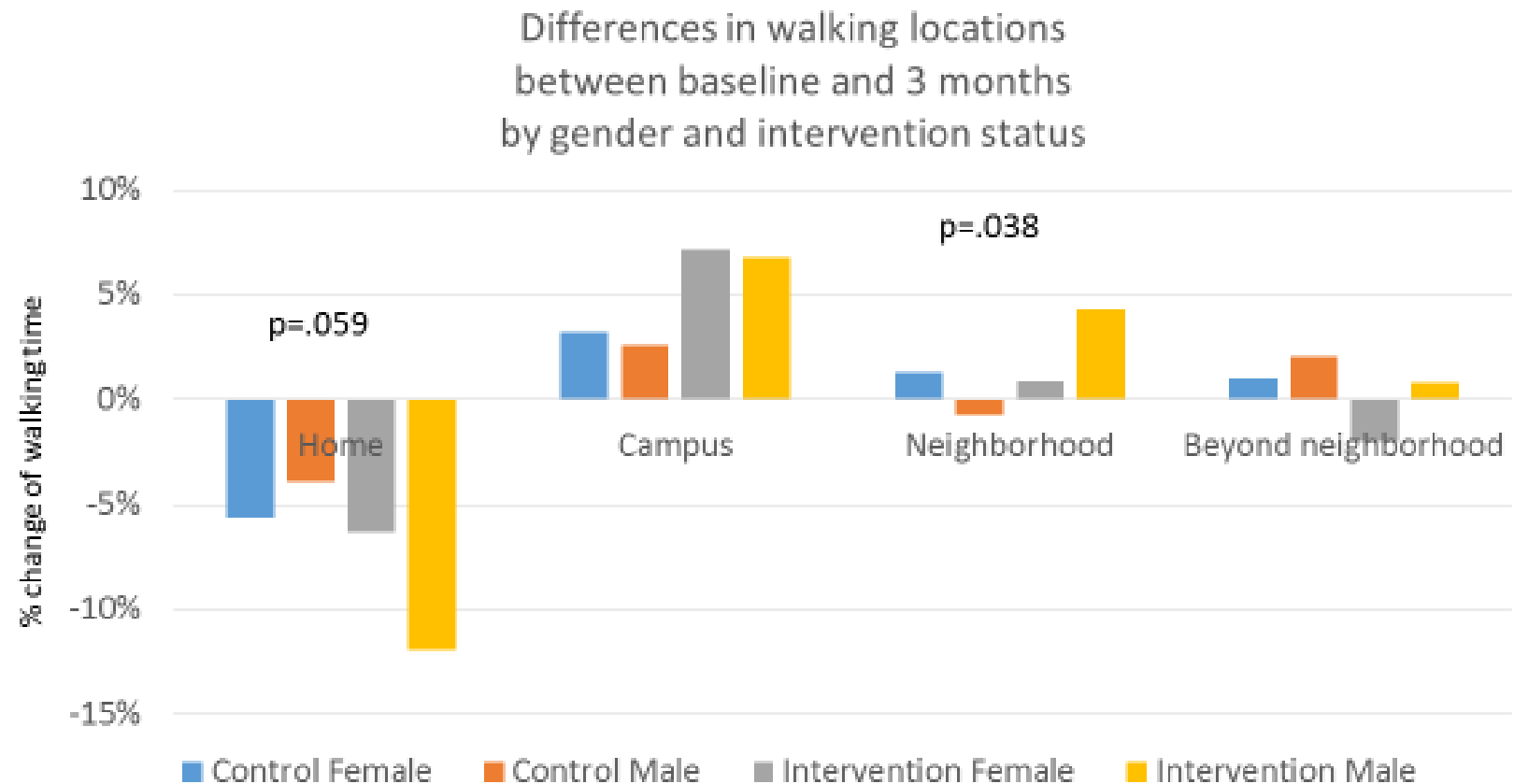
Change in Lifespace Over Time Within Retirement Communities: A Walking Intervention

Kristin Meseck, Marta Jankowska, Suneeta Godbole,
Jasper Schipperijn, Katie Crist, Michelle Black,
Loki Natarajan, Jacqueline Kerr

Methods: Lifespaces



Results





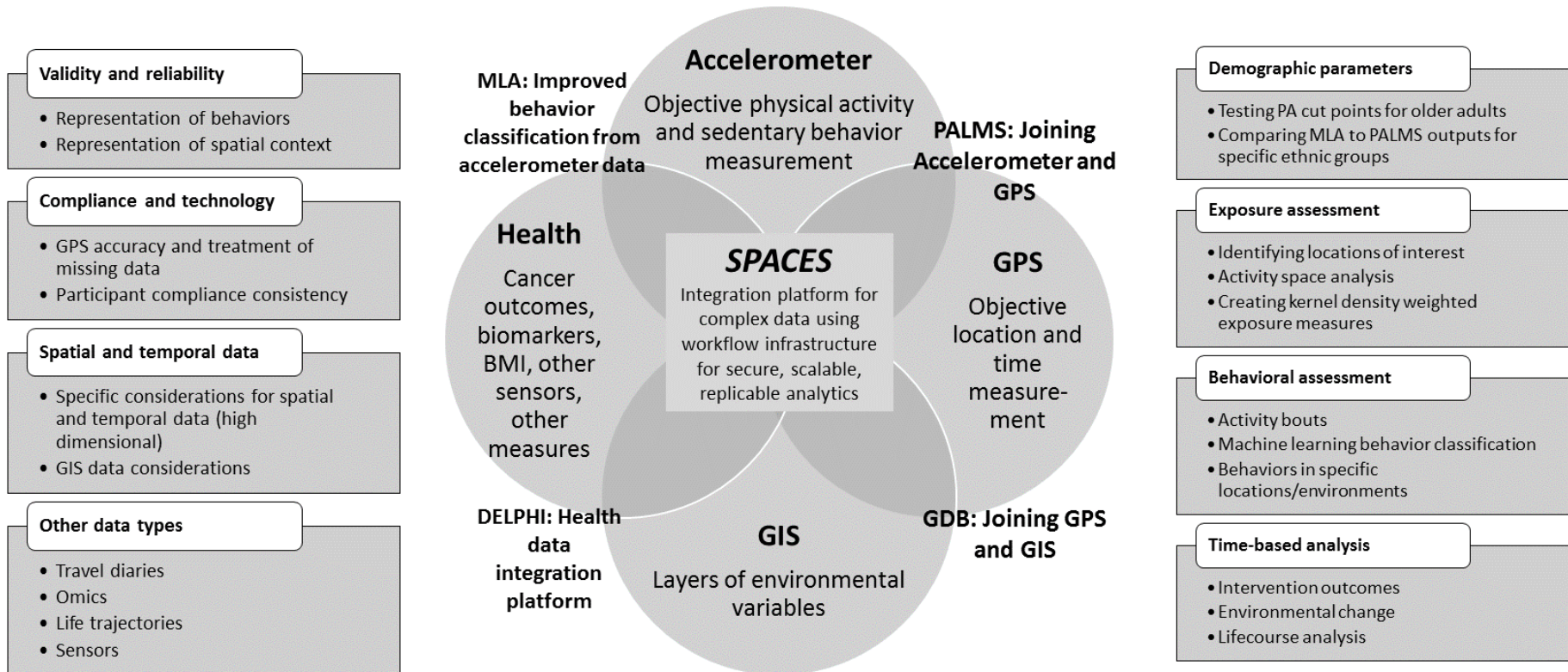
Activity hotspots, one school, ≥ 5
min of bout time per recess period

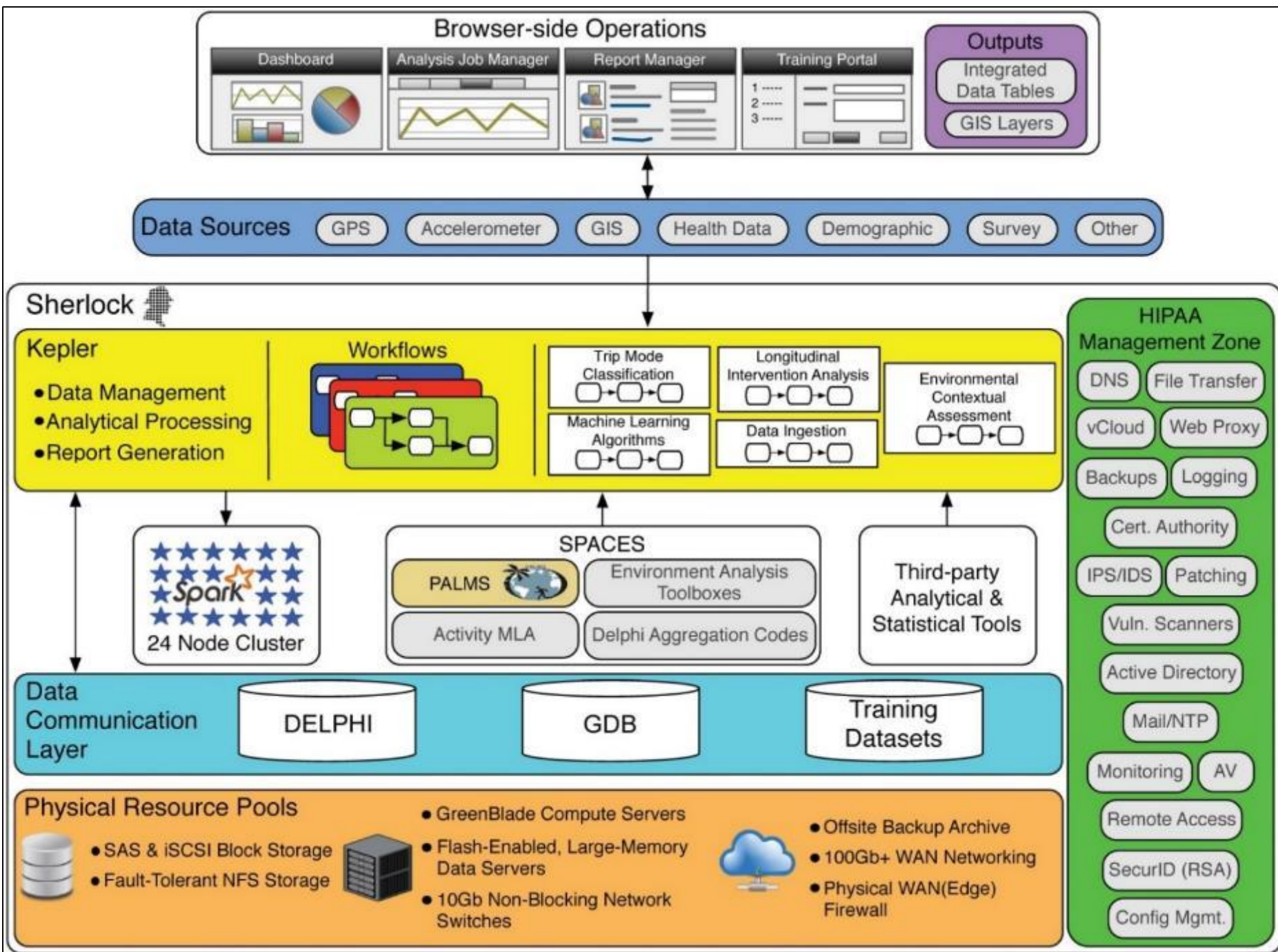
Step 2: SPACES

Data and Analytical Considerations

Data Integration and Output: SPACES

Analytic Workflow Examples: Kepler







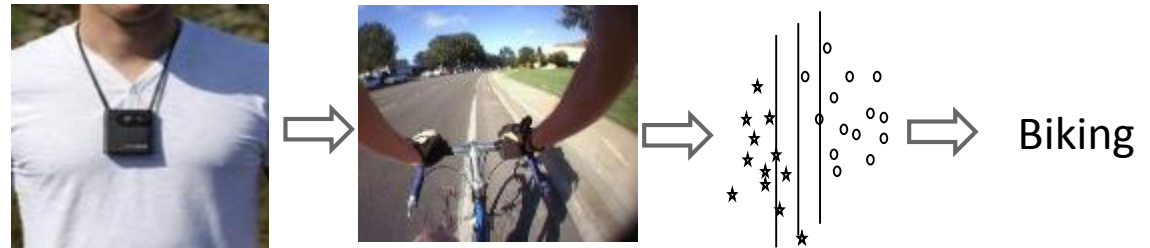
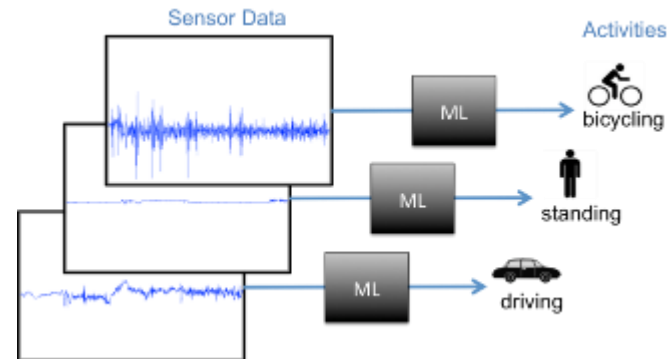
iWatch



Validating machine-learned classifiers of sedentary behavior & physical activity

Purpose:

1. Validate machine-learned algorithms to classify patterns of accelerometer data to better discriminate types of sedentary behaviors and physical activity.
2. To develop machine learned algorithms to classify behaviors using images collected by the SenseCam (Computer Vision).

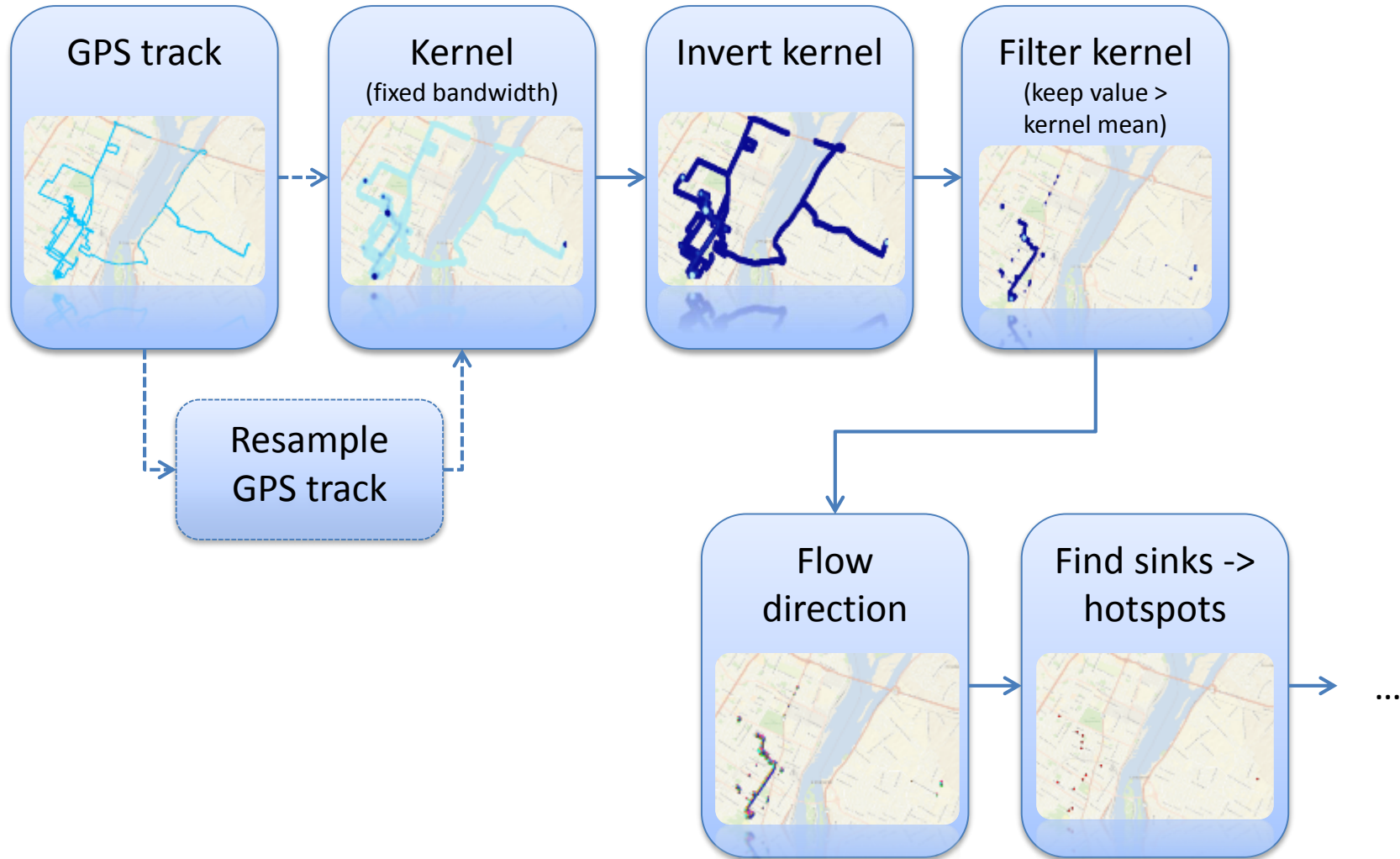


Jacqueline Kerr, Kevin Patrick, Jim Sallis, Simon Marshall, Loki Natarajan, Serge Belongie, Gert Lanckriet, Mohammad Moghimi, Katherine Ellis

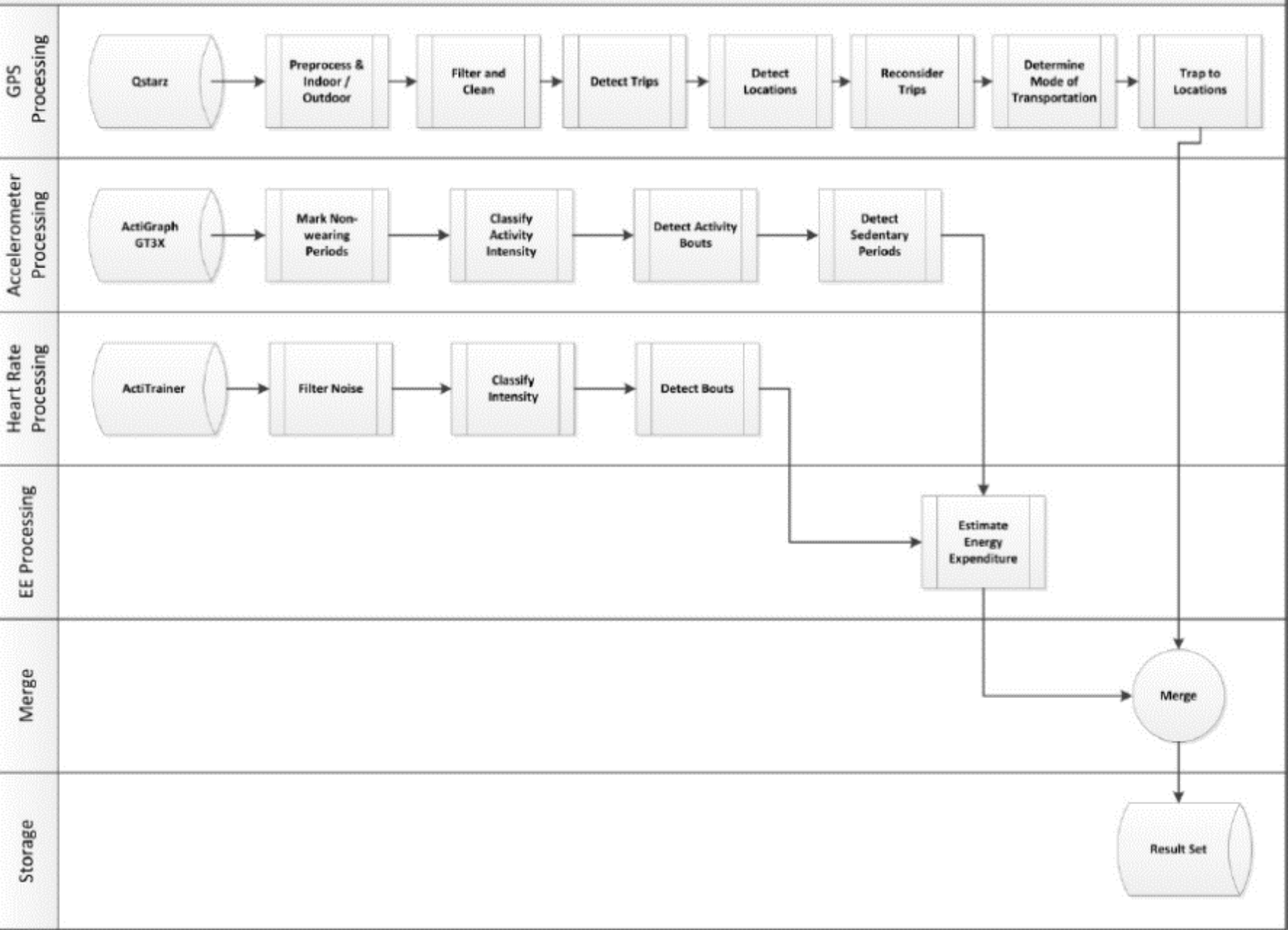
Funded by NIH/NCI Grant 1 R01 CA164993-01

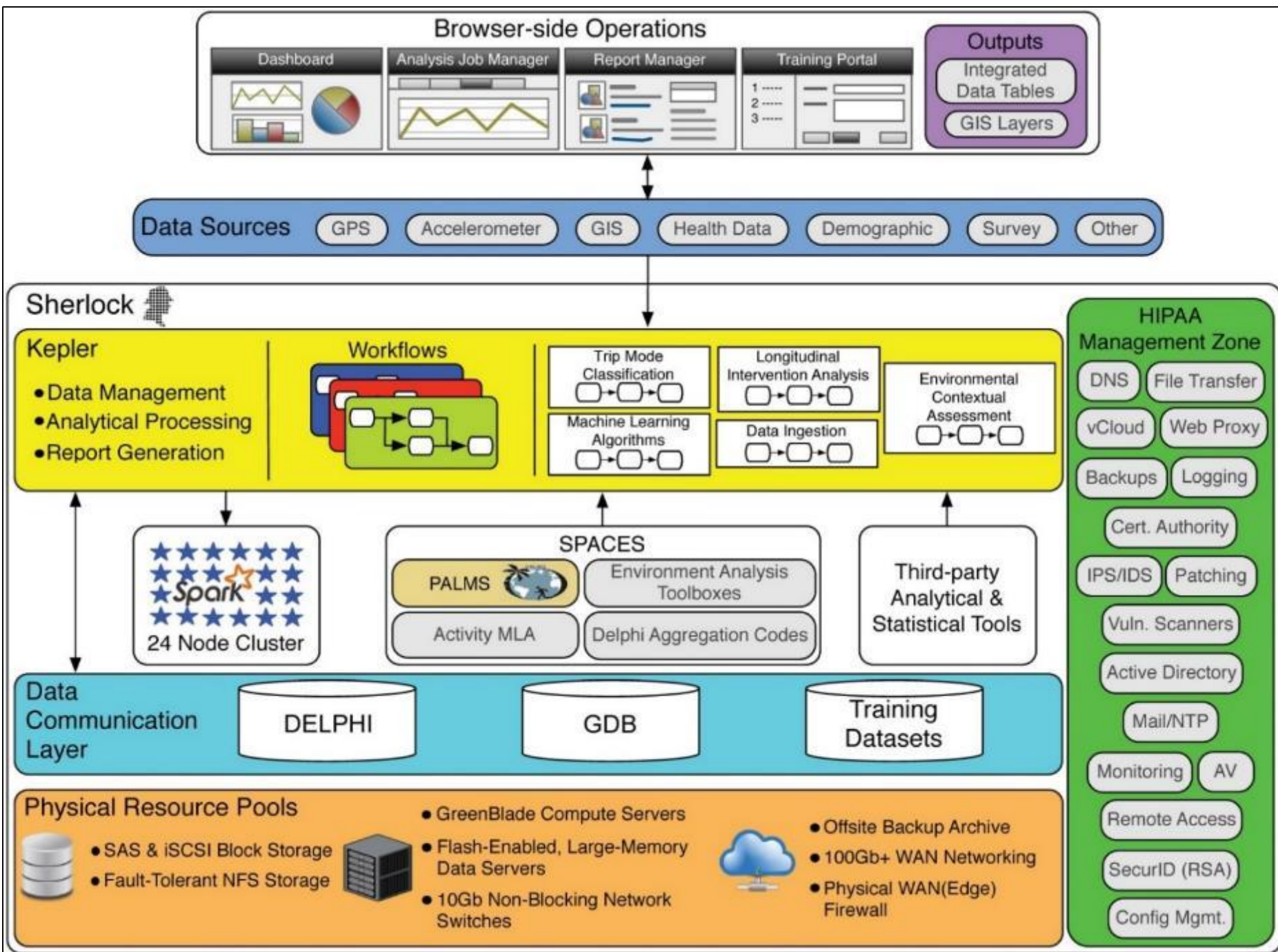
Hotspot detection algorithm (1)

Find hotspots



PALMS Calculation Workflow – GPS / Accelerometer / Heart Rate





SPACES goals

- Increase provenance in not only workflows and processing procedures, but also data formats and structures
- Provide a secure computing environment for sensitive data and studies
- Make CyberGIS and complex computer infrastructures more accessible to public health and behavioral researchers (not have to worry about 'big' data)
- Allow for collaboration between diverse disciplines to advance discovery and knowledge creation

