City of Hope

Is home where the heat is?

Comparing residence-based with time-weighted mobility-based measures of heat exposure in San Diego, California.

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Exposure to urban heat as a public-health risk

- Urban heat can cause increased mortality and morbidity from cardiopulmonary diseases, kidney disease, and mental illness.[1]
- The 2018 Japan heatwaves resulted in over 20,000 hospital admissions related to heat stroke, mostly in people aged 65 years or older.[2]
- 500,000 deaths annually have been attributed to excess heat.[3]

[1]Ebi KL et al. Hot weather and heat extremes: health risks. The Lancet. 2021;398(10301):698-708.
[2]The Lancet. Heatwaves and health. Lancet 2018;392:359.
[3]Zhao Q et al. Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: a three-stage modelling study. Lancet Planet Health. 2021;5(7):e415-e425.

Features of the urban environment can exacerbate heat

- Known as the urban heat island effect
- Impervious surfaces (asphalt, buildings) absorb heat.
- Green space and vegetation have cooling effects.
- The urban-heat island effect is most pronounced at night.

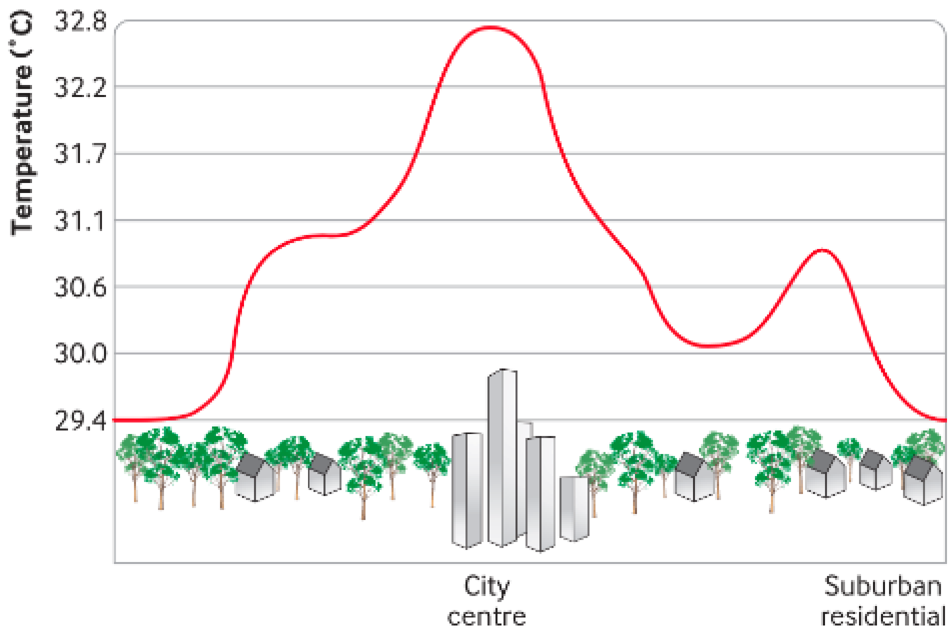
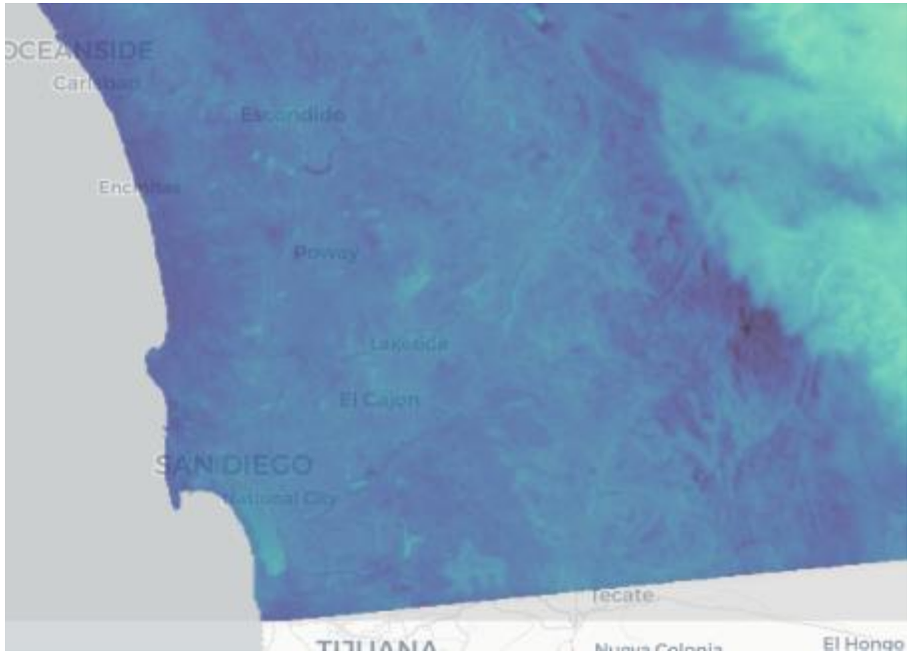


Fig 1 | Schematic profile of urban heat island effect

Tong S et al. Urban heat: an increasing threat to global health. BMJ. October 25, 2021:n2467.

Measurement of heat exposure



- Humans experience heat via ambient air temperature (and other factors like humidity), but **measurement of air temperature at a high spatial resolution** throughout the full extent of a city **is rarely feasible**.

- Research on the urban-heat island effect often uses satellite imagery to measure characteristics that represent or affect within-city variation in ambient temperature at a high spatial resolution.
    - Land surface temperature
    - The normalized difference vegetation index (NDVI)
    - Percent tree canopy
    - Percent impervious surfaces

How might activity space change measurement of exposure to urban heat?

- In epidemiologic studies, microclimate indicators obtained from satellite imagery are commonly linked to individuals based on residential location, either using a buffer around the home or an administrative areal unit.

- As the urban-heat-island effect varies spatially, exposure to microclimate indicators may depend not only on residential location but also on where a person travels away from their home.

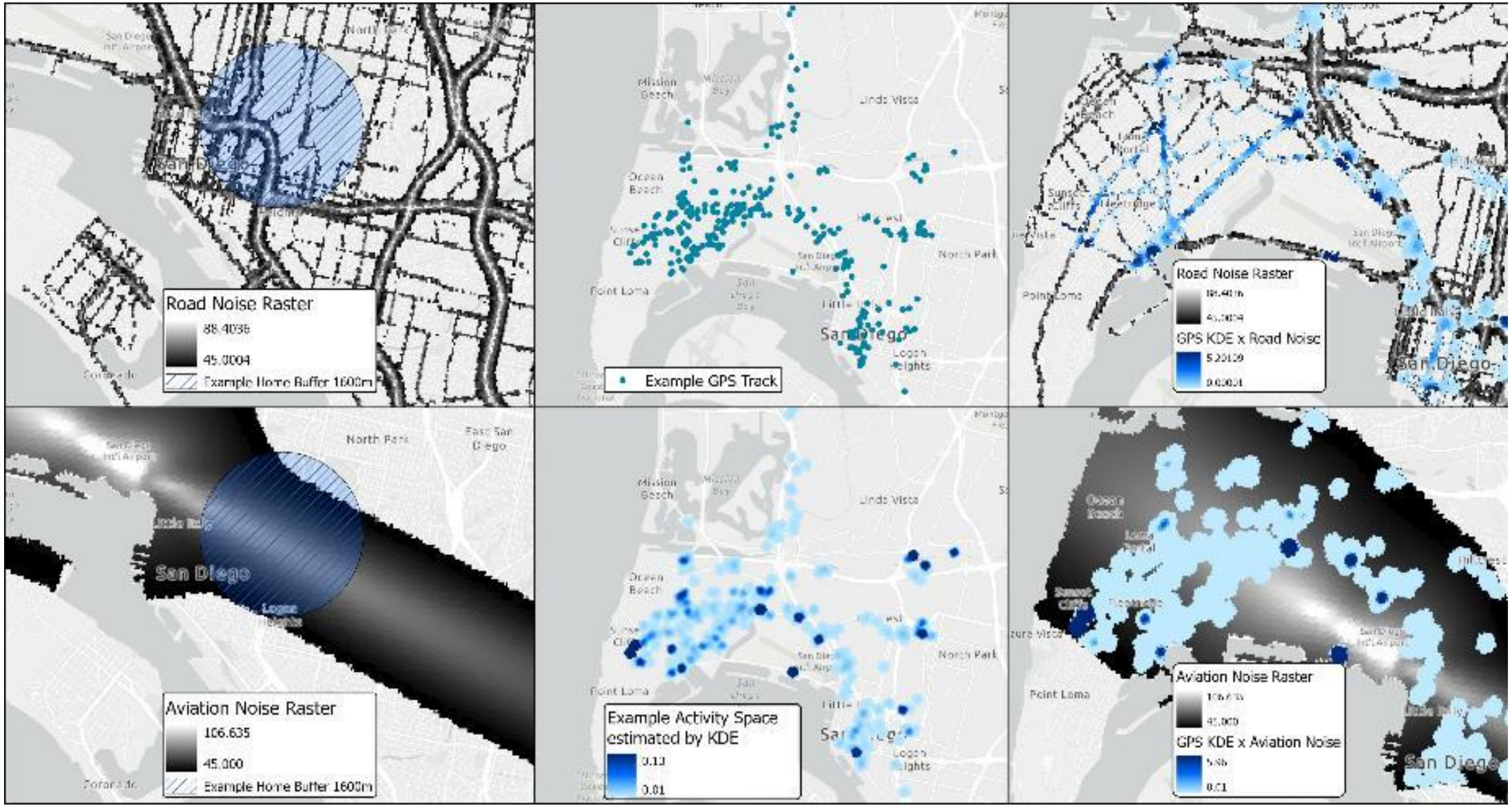
- I.e., their microclimate exposure may depend on their **activity space, the places a person visits throughout their routine day-to-day travel and the routes between those places.**

- Uncertain Geographic Context Problem "*arises because of the spatial uncertainty in the actual areas that exert contextual influences on the individuals being studied and the temporal uncertainty in the timing and duration in which individuals experienced these contextual influences".*[1]

Kwan, M. P. (2012). The Uncertain Geographic Context Problem. Annals of the Association of American Geographers, 102(5), 958–968. https://doi.org/10.1080/00045608.2012.687349

Advances in Estimating Environmental Exposure

home-based exposure (static) → estimating activity space from GPS trajectory → mobility-based exposure (dynamic)



Objective and Rationale

- Dynamic approaches are more costly and complex and may not be feasible for large-scale population studies.

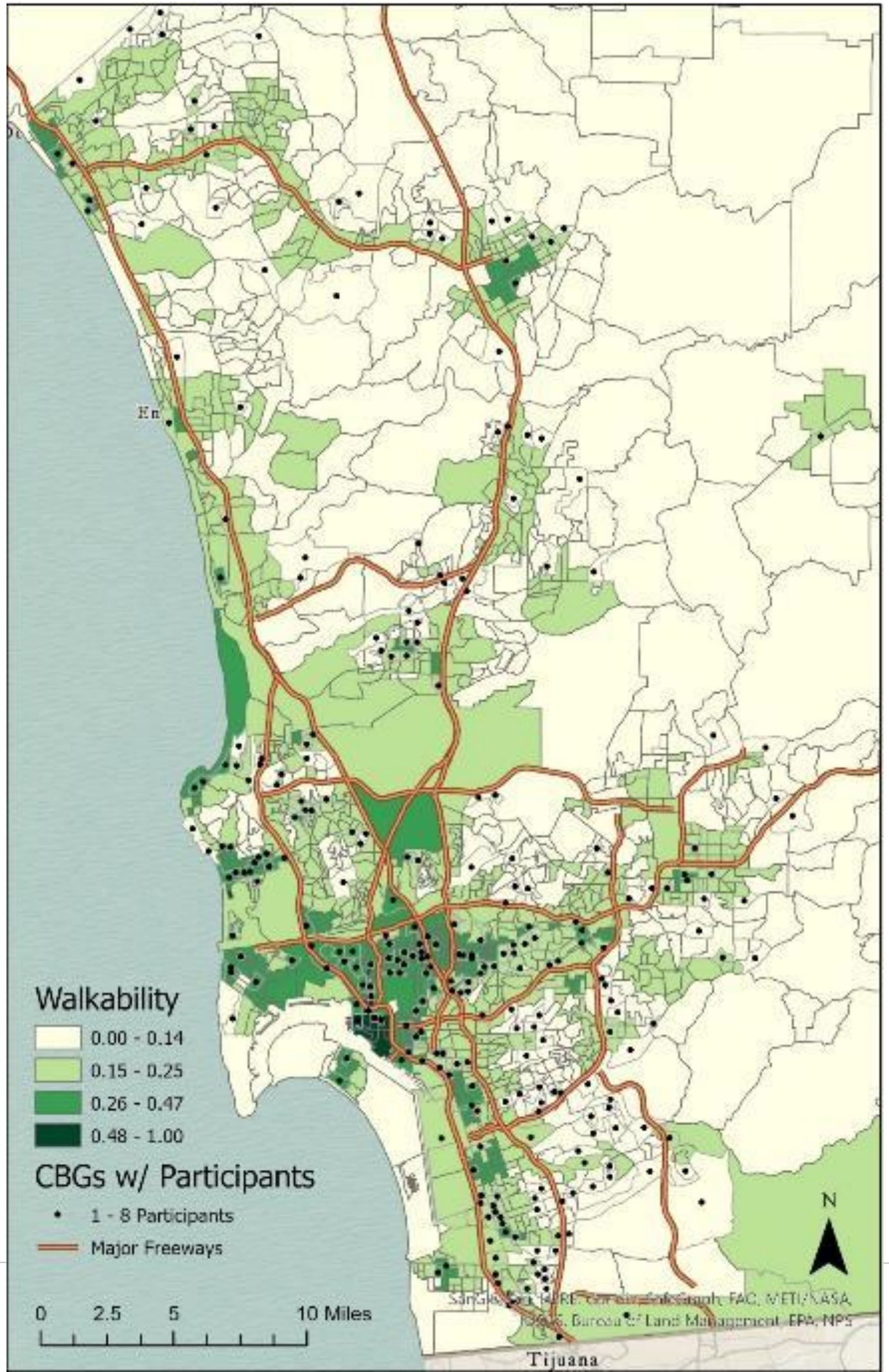
- Worth assessing how incorporating time-weighted activity spaces result in different measures of exposure compared to place of residence.

- **Objective**: Compare dynamic and static measures of exposure to multiple microclimate indicators among a study population of Southern California residents.

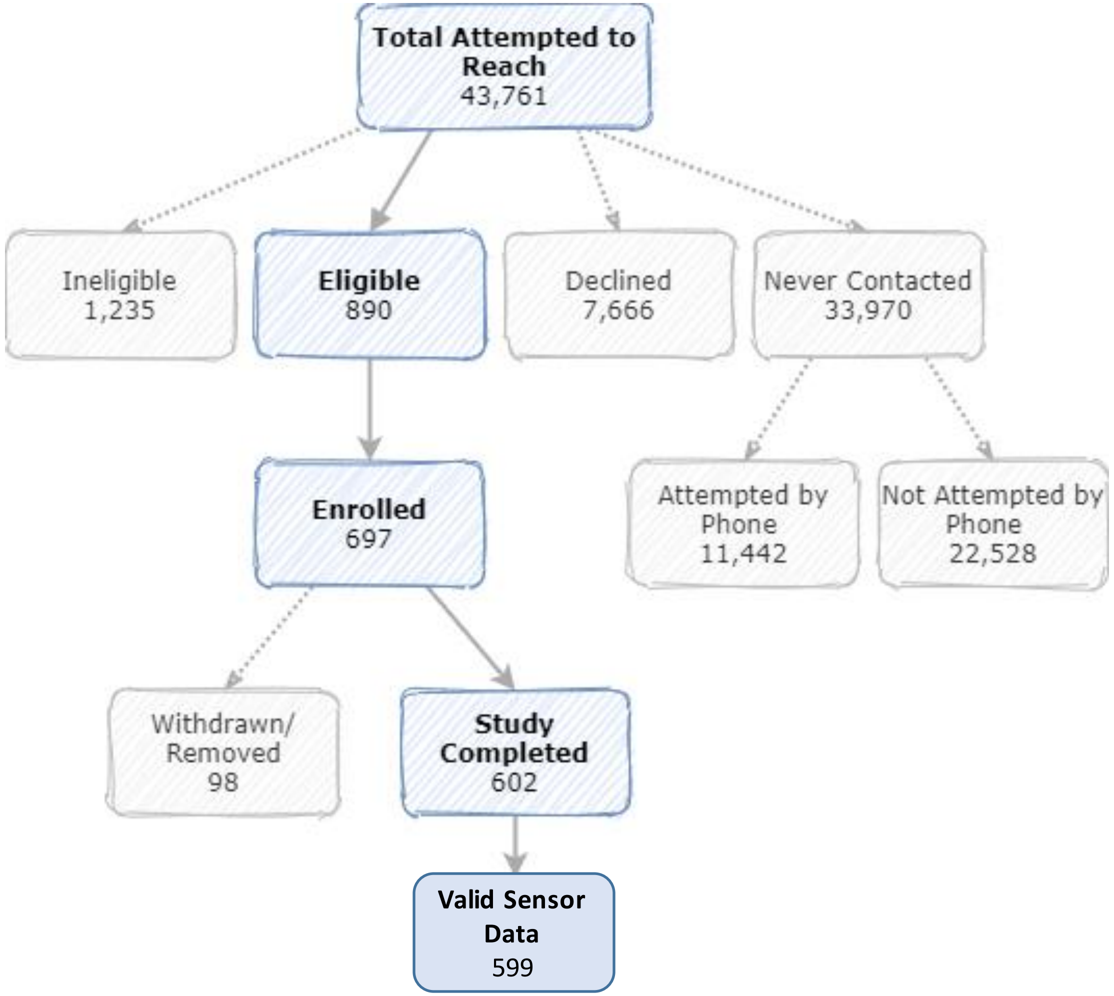
Methods

Participants and data collection

- Community of Mine
  - Cross sectional / observational study data collected from 2014-2017
  - Assessment of environmental exposures and their relation to cancer risk
- Selection of participants from a variety of walkable and food access environments
- Eligible adults 35-80 years old
- Attempted to recruit 50% Hispanic, 50% female, and 50% age 35-60 in each neighborhood type.



Participants and data collection



Asked to wear GPS (Qstarz BTQ1000XT) devices for 14 days with the goal of obtaining at least 7 days of sensor data

Participants who didn’t have 7 valid wear days were asked to re-wear devices.

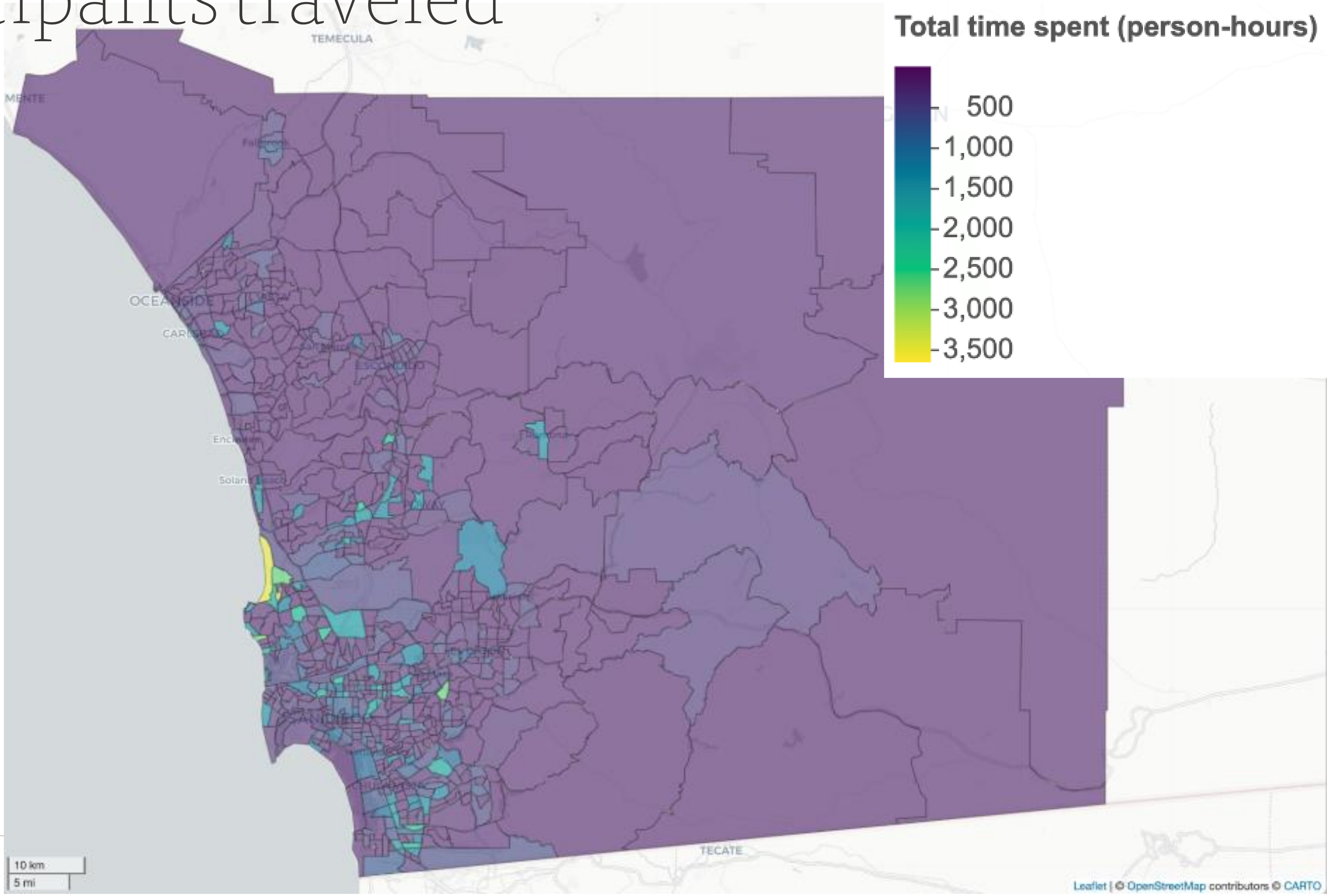
Sensor processing and data cleaning

GPS Data from Qstartz BT1000X
GPS worn for minimum of 7 days

Data aggregated at minute level using PALMS (noise cleaning)
Filtered to study area

Total sample of 599
7,320 days
Average of 12.2 days

Where participants traveled

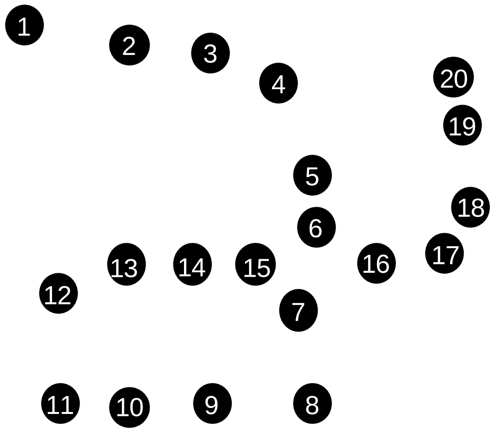


Microclimate indicators

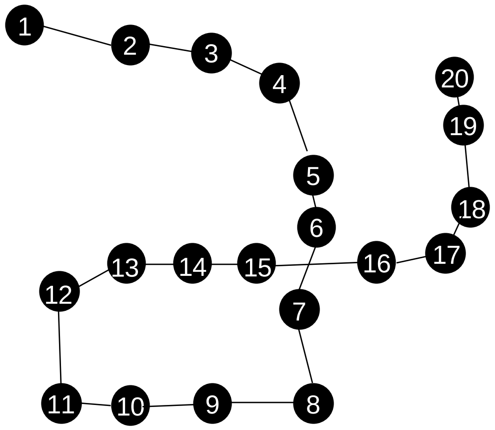
Name	**Definition**	**Spatial resolution**	**Year** (average over year)	**Data Source**
Land Surface Temperature (degrees Celsius)	**“Land surface temperature is how hot the “surface” of the Earth would feel to the touch in a particular location.** The “surface” is whatever the satellite sees when it looks through the atmosphere to the ground (e.g., grass on lawn, ice, roof of building, leaves in canopy of forest).”	70 m	2018	Earth Data AppEARS
Normalized Difference Vegetation Index	The normalized difference vegetation index (NDVI) is a **measure** ranging from -1 to 1 **indicating the greenness of vegetation**.	250 m	2018	MOD13Q1 V6 obtained via Google Earth Engine
Percent of the pixel covered by tree canopy	**Percent of the pixel that’s covered by tree canopy.**	30 m	2016	USGS National Land Cover Database obtained via Google Earth Engine
Percent of the pixel covered by developed impervious surface	**Percent of the pixel covered by impervious surfaces.** Impervious surfaces are covered by anthropogenic materials which prevent water from penetrating into the soil. Examples: asphalt, concrete, or buildings	30 m	2016	USGS National Land Cover Database obtained via Google Earth Engine

Dynamic exposure (1)

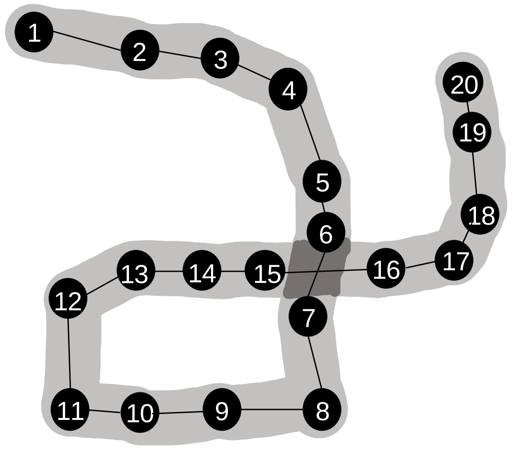
1: Begin with an **individual's sequence of GPS pings**, each containing latitude, longitude, date, and time.



2: **Create activity paths** with the individual's sequence of GPS pings, connecting each ping with its subsequent one in time as line segments ordered by date and time.

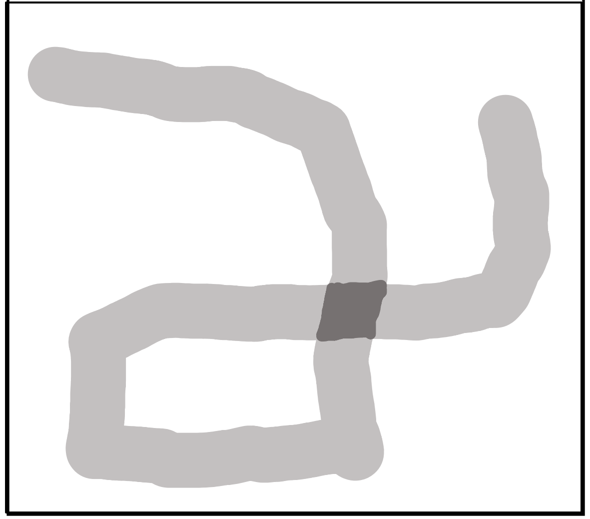


3: Draw a 200-meter buffer around the activity path, **creating activity-path buffers**, *keeping the time dimension*.



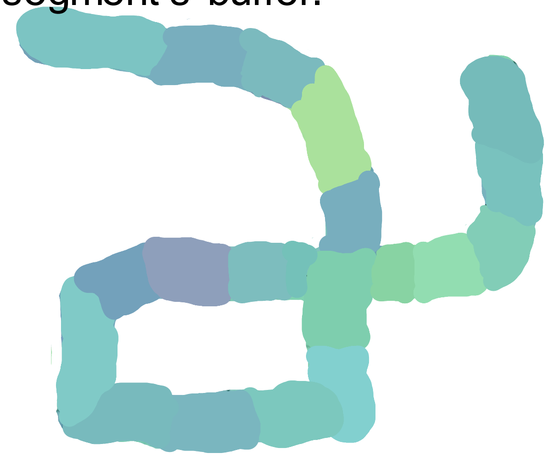
Dynamic exposure (2)

4: Overlay the activity-path buffer over the microclimate indicator.



5: Extract exposure values of pixels overlapped (at least in part) by the 200 m buffer.

6: Average values of pixels corresponding to each line segment of the buffer, weighting values by the amount the pixel is overlapped by that line segment's buffer.



Dynamic exposure (3)

Summary measures for each individual

Weighted mean, dynamic

Average values in the activity-path buffer, weighting each line segment's mean by its elapsed time, including overnight time.

Most extreme 10-minute increment

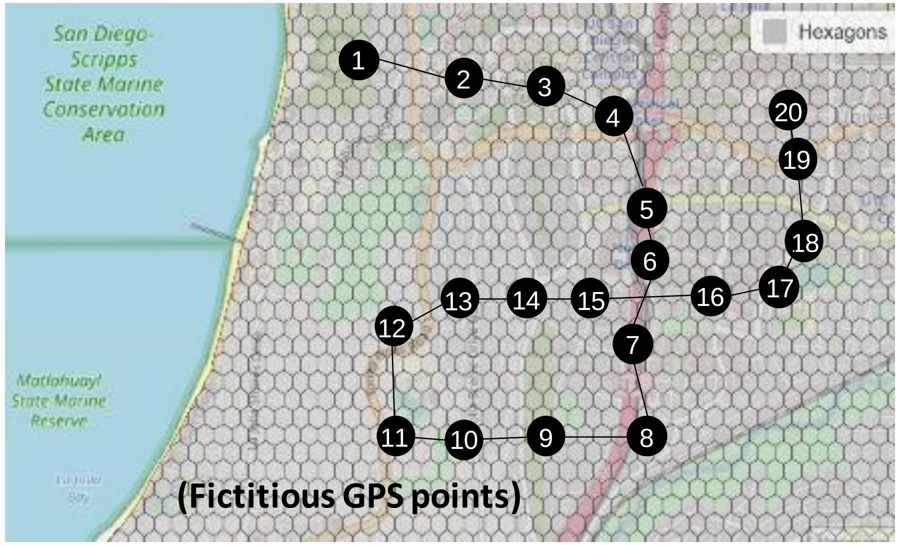
Group segments into ordered sequences of 10 minutes (usually 10 pings), take the average exposure value of each, and find the extreme associated with more heat

- LST (maximum)
- NDVI (minimum)
- Percent tree canopy (minimum)
- Percent impervious surface (maximum)

Static exposure (1)

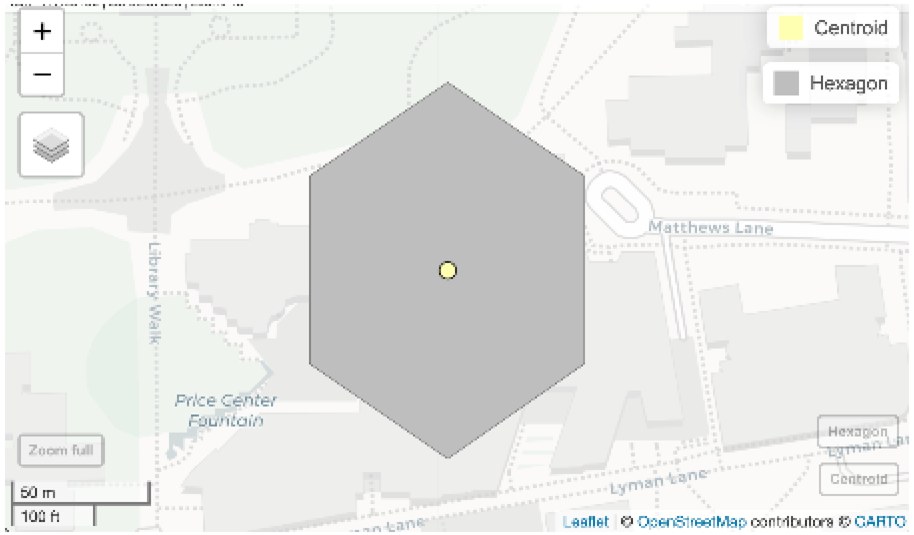
1. Create a hexagonal grid over San Diego County (each side of hex. ~ 62 m)

2. Overlay each individual's activity path (sequence of GPS pings) over a hexagonal grid (each hex. Side ~ 62 m).

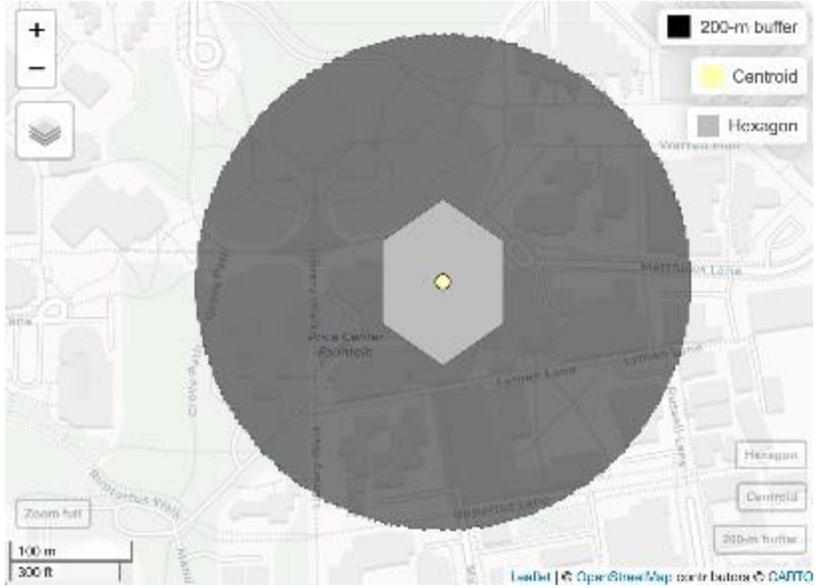


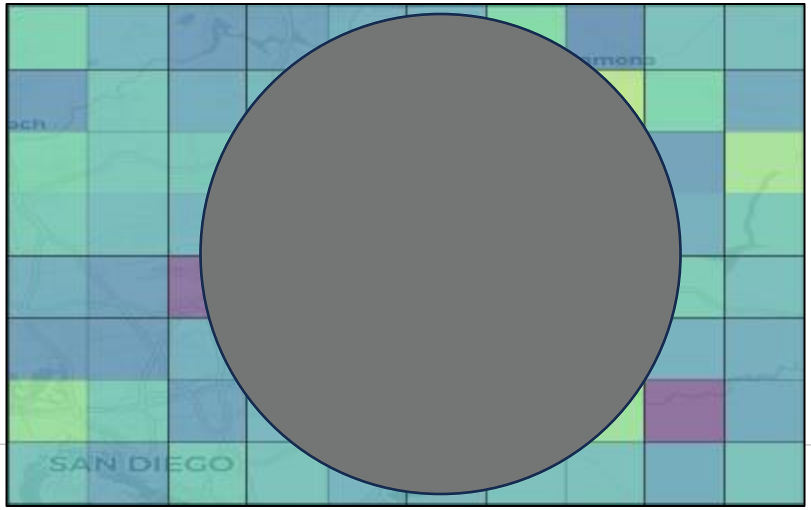
3. Select the hexagon in which the participant spent the most elapsed time.

4. Take the centroid

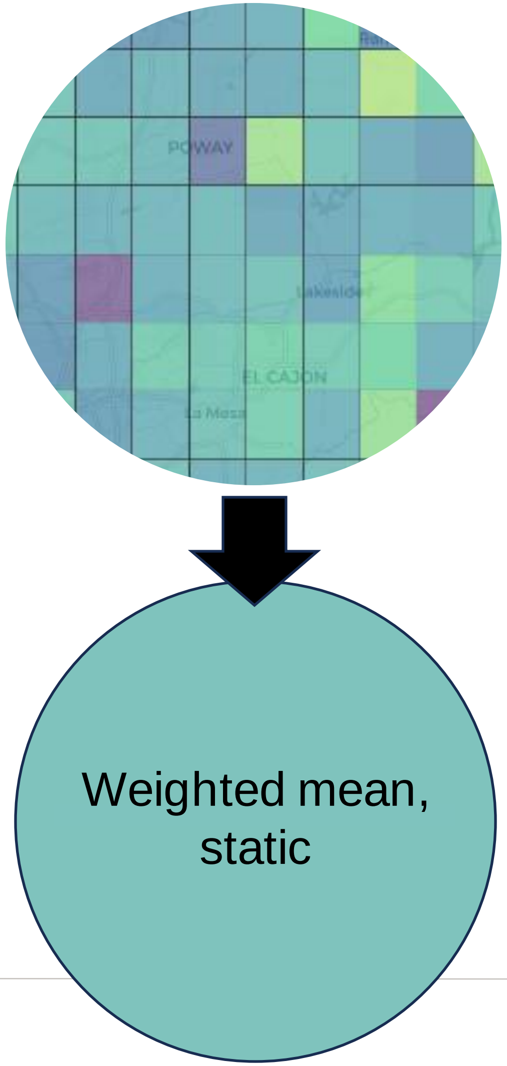


5. Draw a 200 m buffer around the centroid (assumed home); overlay over microclimate indicator.





6. Average the exposure within the 200 m buffer, weighting each pixel in the average by its areal overlap with the buffer.



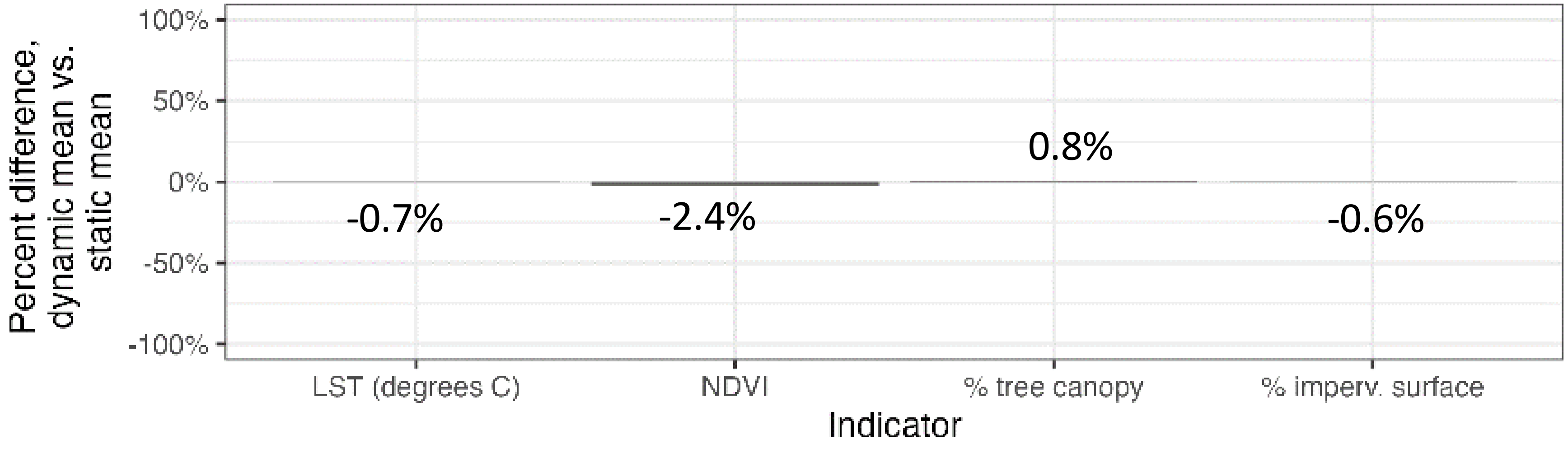
Results

Static versus dynamic exposures

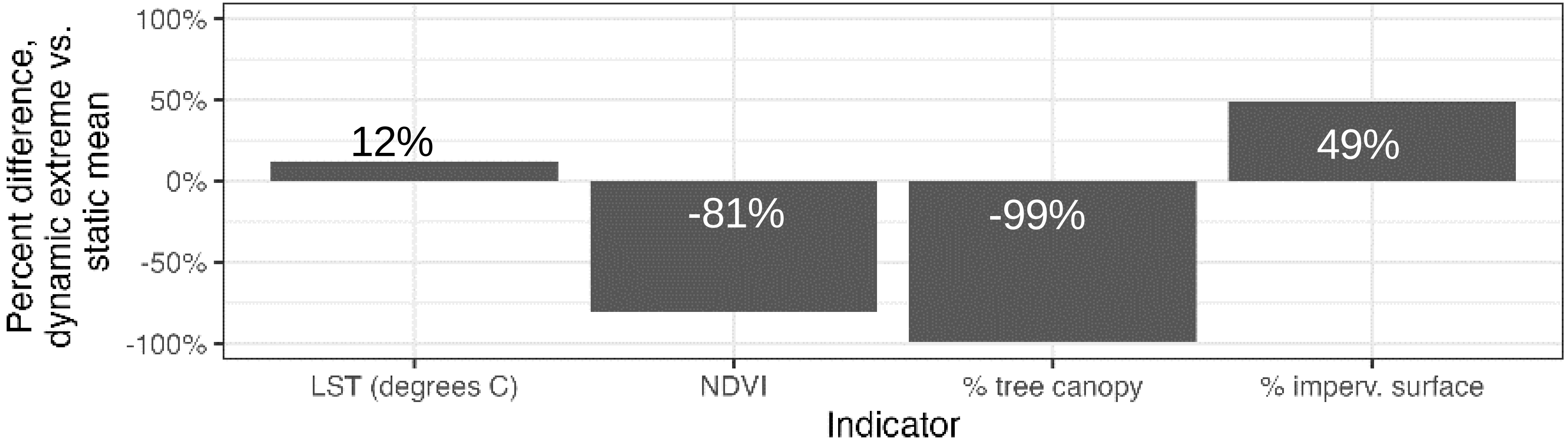
	Static measure		*Dynamic measure*		
Micro-climate indicator	**Mean**	**SD**	**Mean**	**SD**	**Mean of extreme** (over 10-minute intervals)
Land surface temperature (degrees C)	20.0	1.3	19.9	1.2	22.4
NDVI	0.27	0.08	0.26	0.06	0.05
% tree canopy	2.7%	3.3%	2.7%	2.5%	0.0%
% impervious surface	57.9%	15.5%	57.5%	12.4%	86.1%

Percent differences

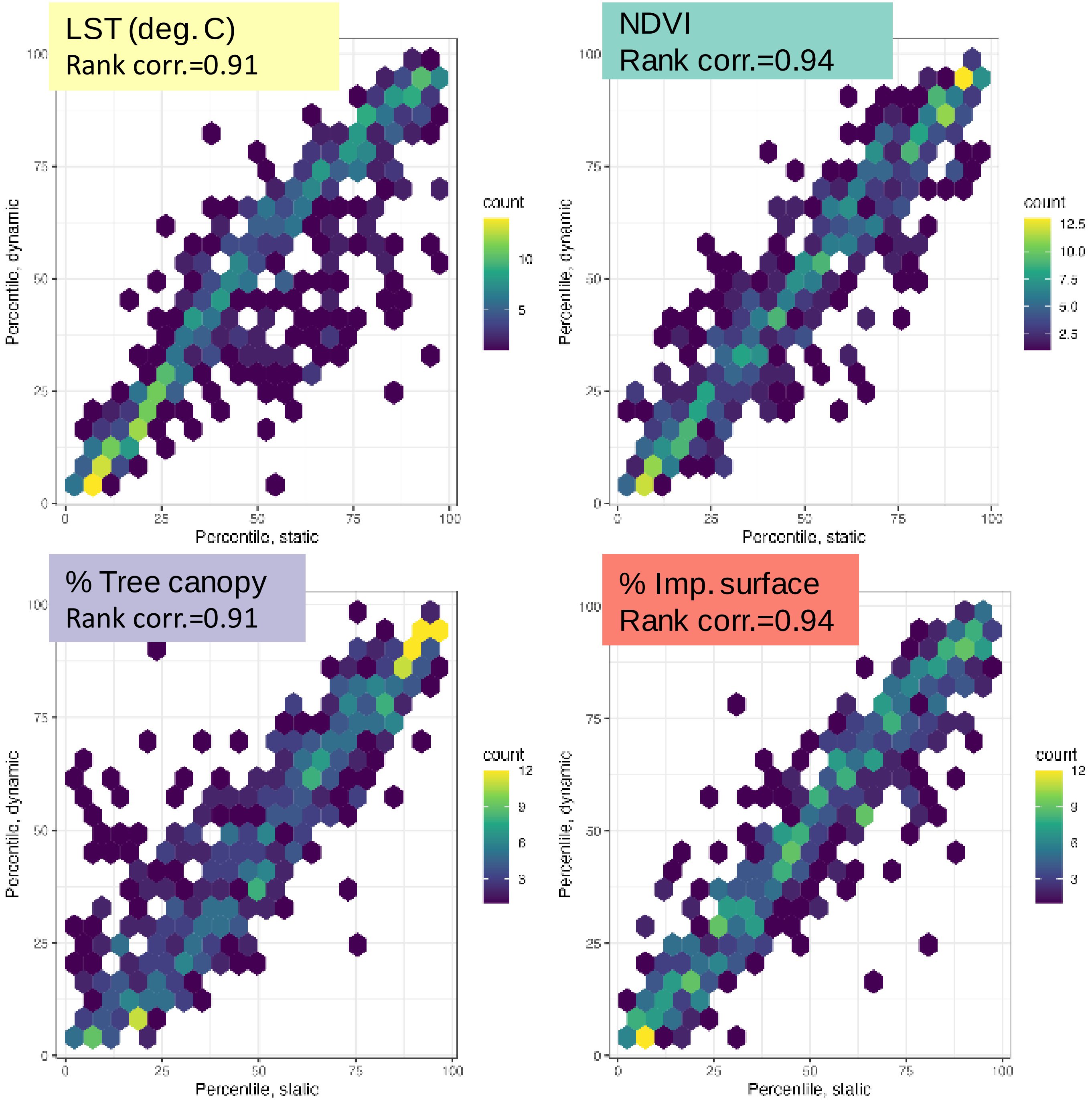
Dynamic mean vs. static mean



Most extreme 10-minute interval vs. static mean



Rank correlations between means



Rank correlation excluding overnight time

Micro-climate indicator	Rank correlation, including overnight time (main analysis)	Rank correlation, excluding overnight time
Land surface temperature (degrees C)	0.91	0.86
NDVI	0.94	0.89
% tree canopy	0.91	0.86
% impervious surface	0.94	0.90

Conclusions

- When weighted by time elapsed, means are very similar.
- Compared with the most extreme 10-minute interval experienced, the residence-based mean differs by quite a bit.
- If the health outcome of interest is acute and is affected by short bouts of exposure, then dynamic measurement may be important.
    - Heat stroke can develop in 10 minutes.
- If health outcome is chronic and is affected by cumulative exposure, residence-based exposure measures may suffice.
    - Chronic dehydration due to extreme-heat exposure can exacerbate chronic diseases of the cardiovascular or renal systems.

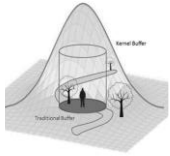
Tool development

Fulbright work with Dr hab. Jakub Nowosad UAM

- Development of R package for automated processing of GPS collected data (post cleaning)

- Igor Graczykowski (UAM student)
  - TWIGPS to be published soon!

R package for time-weighted exposures



Method

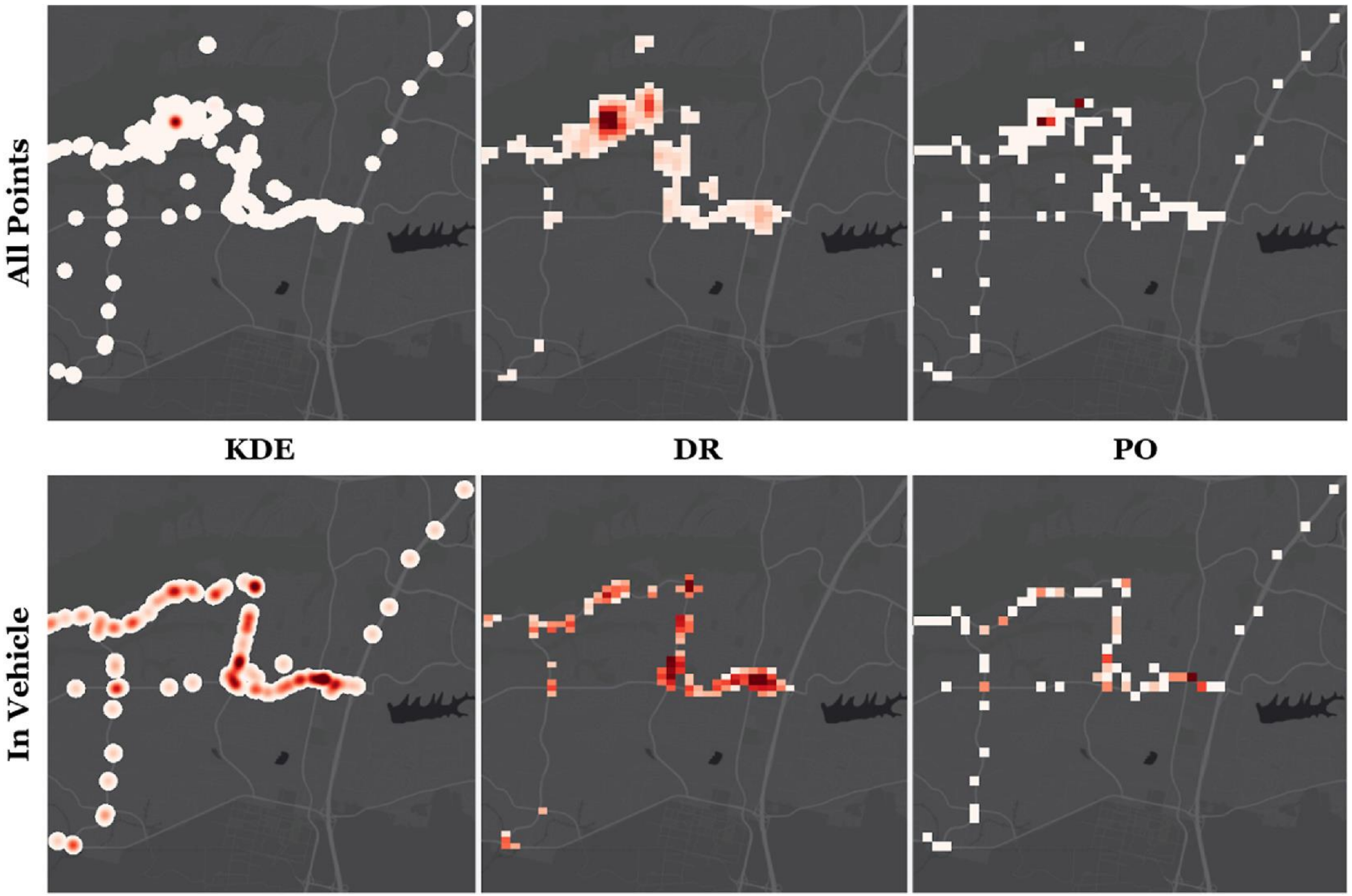
- KDE
- Point overlay
- DR
- Weighted line segment

Behavior

- Driving
- Walking
- Running
- Stationary

Context

- Time of day/week
- Location
- Activity bias



TWSA Methods

Jankowska, M. M., J. Yang, N. Luo, C. Spoon, T. Benmarhnia. 2021. “Accounting for space, time, and behavior using GPS derived dynamic measures of environmental exposure." Health and Place

Thank you!

City of Hope

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