Applications of Geospatial Data and Methods in Environmental Epidemiology

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MANCHESTER 1824

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Who Am I?

I am Labib.

From Bangladesh, travelled from Manchester.

My Academic Journey:

- ❑ BSc in Urban and Regional Planning (2014), Bangladesh University of Engineering and Technology.
- ❑ MSc in Geographical Information Science (2017), University of Manchester.
- ❑ PhD in Physical Geography (2017- 2020, submission), University of Manchester.

Bangladesh University of Engineering and Technology

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Research Interests:

Geographic Information Science,
Remote Sensing,
Green Infrastructure,
Transportation planning, and
Environmental Epidemiology.

Research Groups:

Mapping: Culture and Geographical Information Science (MCGIS); Environmental Processes (EPRG)

Content & Outline

- **Brief Overview of geospatial data and methods in epidemiology (5 min)**
  - Historic example and now
  - Geospatial approaches in practice
    Exposure assessment
- **Geospatial Data and methods case studies (10 min)**
  - Airborne imagery data,
  - OpenStreeMap data,
  - Volunteer GIS data
- **Examples of model coupling and their applications (10 min)**
  - Applying in transportation sustainability
  - Combining machine learning models with spatial data
- **Spatial dimensions in greenspace and health research- a systematic review (20 min)**
  - Scale
  - Exposure assessment (data, methods)
  - The buffering issue
  - MAUP and spatial autocorrelation
- **Q-A? (15 min)**
- **References**

Part-1

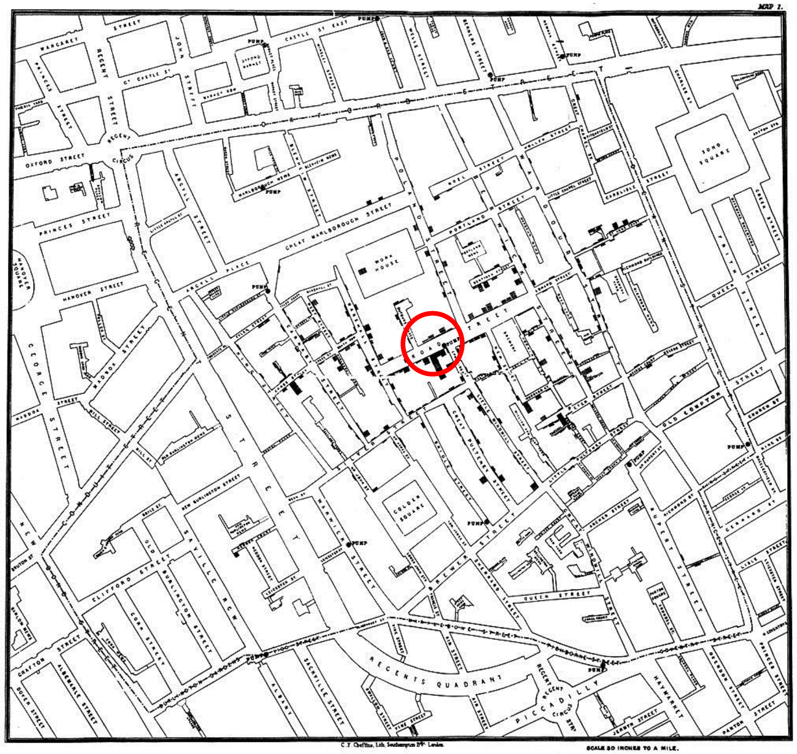
Part-2

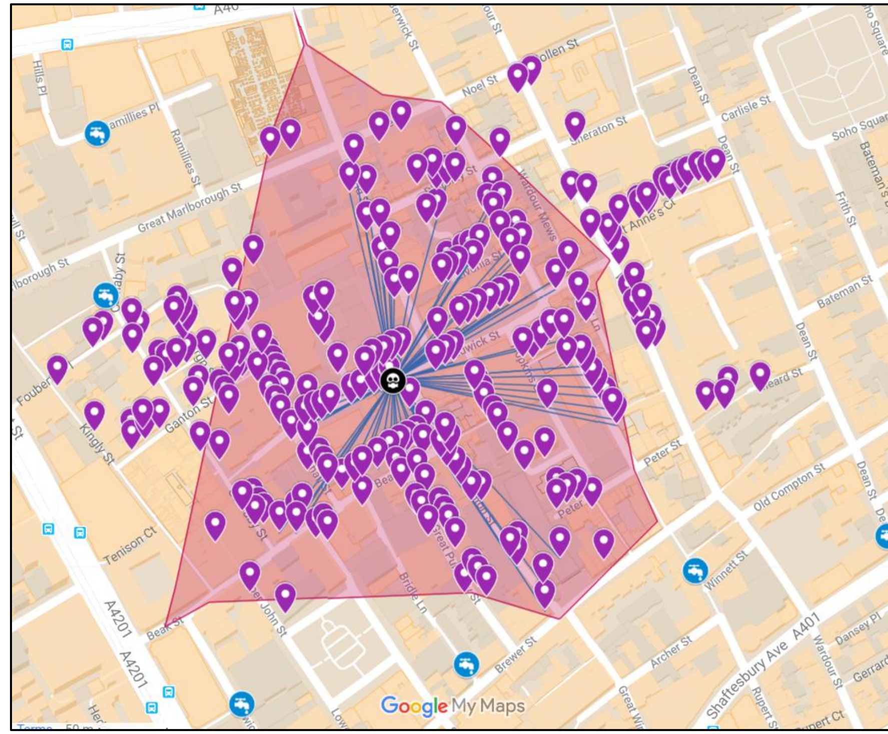
Part-3

Part-4

Part -1: Brief Overview of geospatial data and methods in epidemiology

Past and present…





Map 1854 **2020**

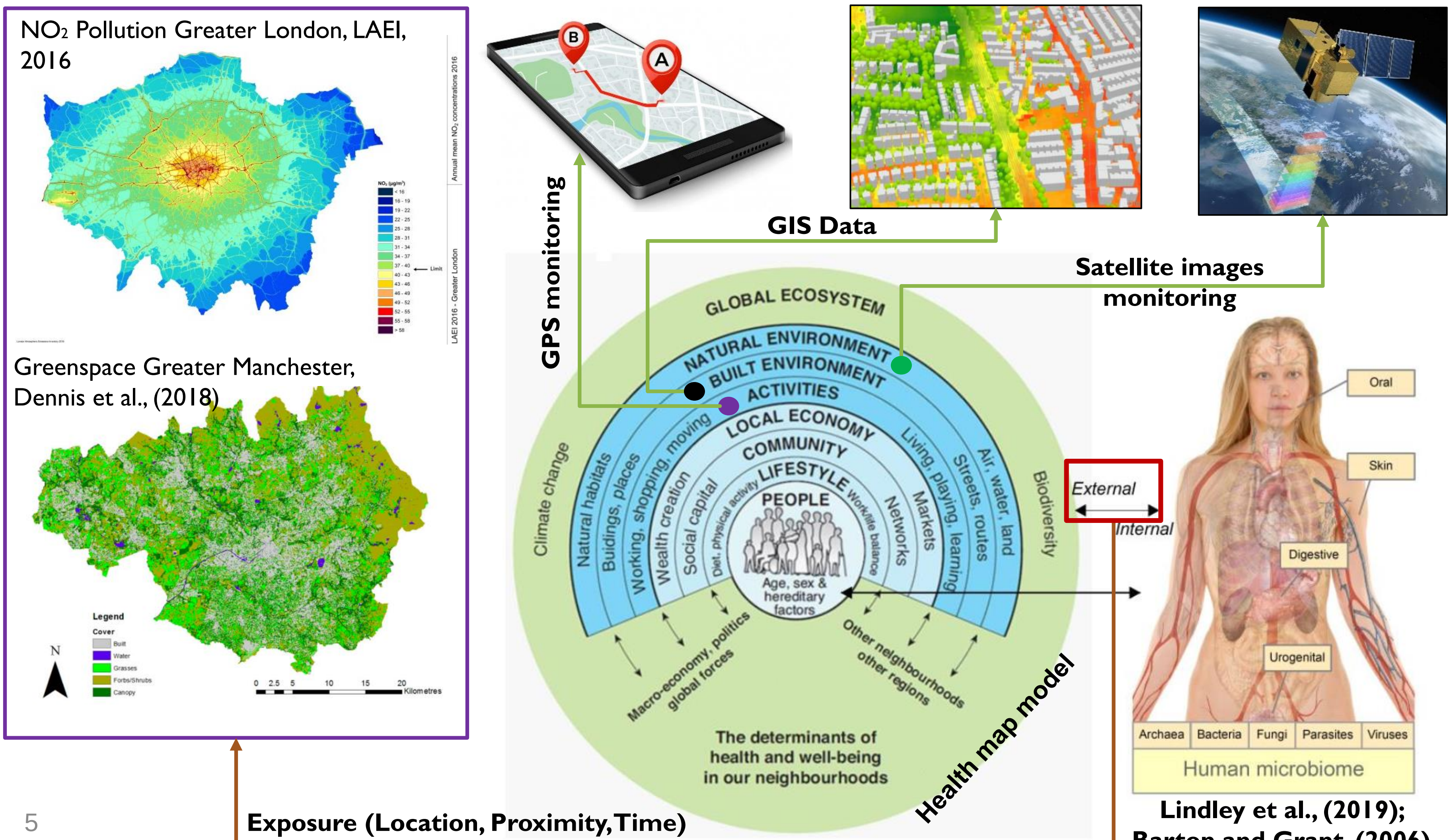
1854 Broad Street cholera outbreak

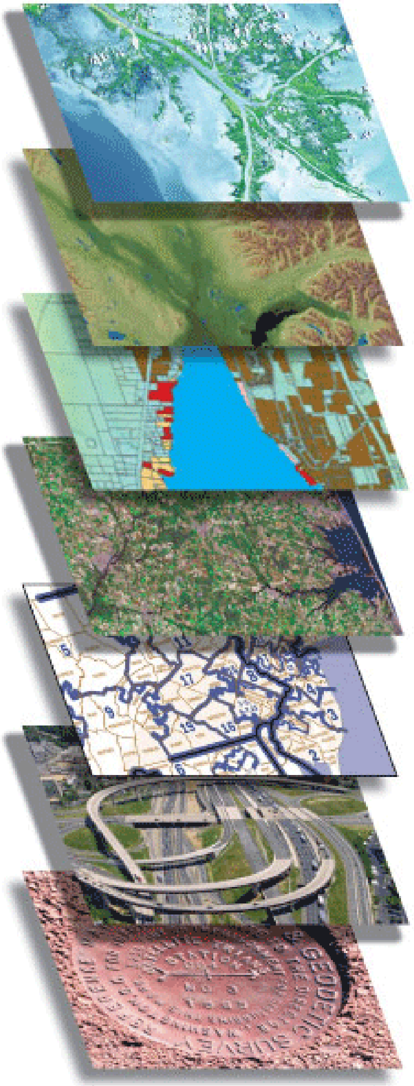
- What is the **average distance from the contaminated pump** to the surrounding locations?
- What is there now? http://tiny.cc/9j17jz

Data Source: [*http://blog.rtwilson.com/john-snows-cholera-data-in-more-formats/*](http://blog.rtwilson.com/john-snows-cholera-data-in-more-formats/)
Full Story: [*https://youtu.be/lNjrAXGRda4*](https://youtu.be/lNjrAXGRda4)

Geospatial approaches in practice

- **Environmental Factors:** Pollution sources (e.g., air, water pollution), natural environment, built environment. **Spatial Data dominance**!
- **External influence measurement: Exposure assessment-** a function of location (proximity) and time (Nieuwenhuijsen, 2009). **Spatial Methods dominance**!

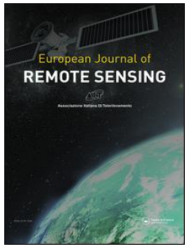




Part -2: Geospatial Data (case studies)

Geospatial Data (case studies)

Case study 1: Satellite imagery data



Taylor & Francis
Taylor & Francis Group

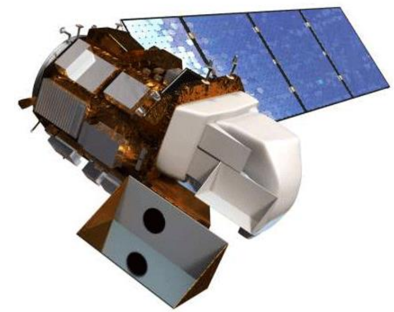
European Journal of Remote Sensing

ISSN: (Print) 2279-7254 (Online) Journal homepage: http://www.tandfonline.com/loi/tejr20

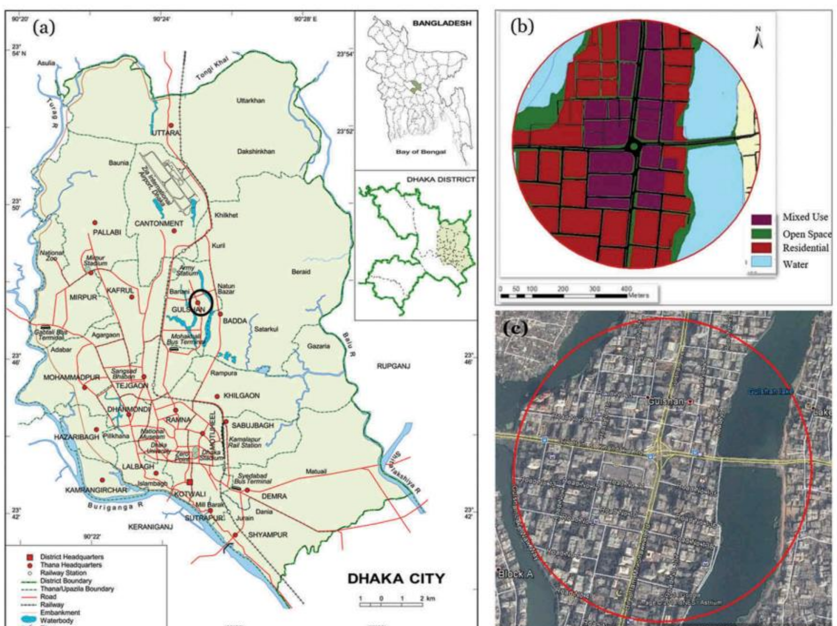
The potentials of Sentinel-2 and LandSat-8 data in green infrastructure extraction, using object based image analysis (OBIA) method

S M Labib & Angela Harris

Sentinel-2, 10m, 5 days revisit



Landsat-8, 30m, 15 days revisit



- **Low availability** of greenspace data in Dhaka, the existing data are usually outdated.
- New **free satellite data** from improved sensors are available (Sentinel-2, 10m), Landsat-8 (30m)
- Which **performs better** in extracting greenspace better, what are the issues?

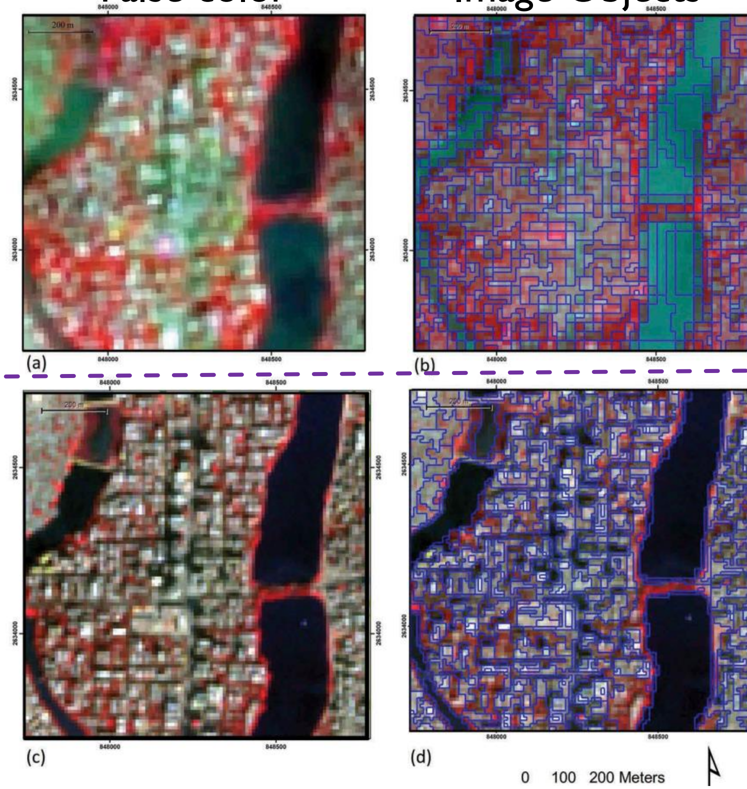
Geospatial Data (case studies)

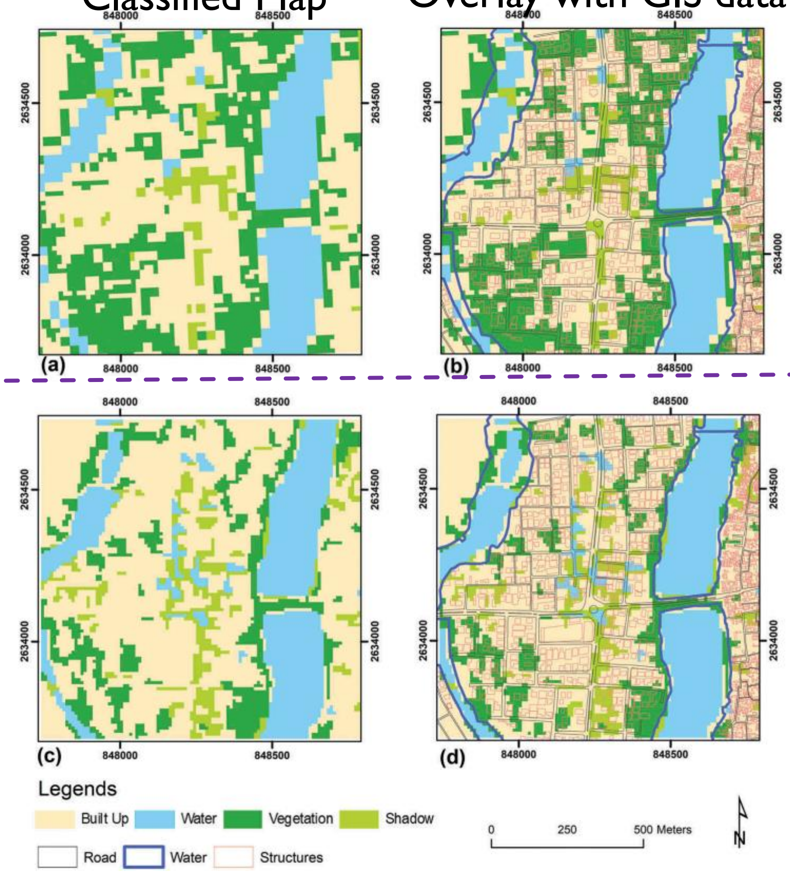
Case study 1: Satellite imagery data (cont…)

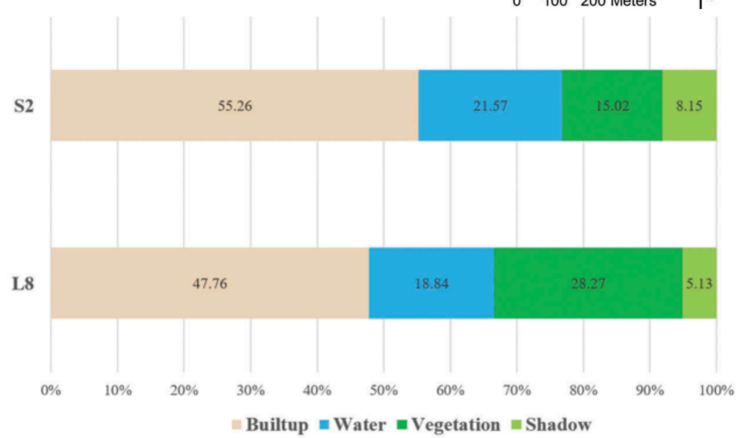
False color | Image Objects | Classified Map | Overlay with GIS data

Landsat-8

Sentinel-2





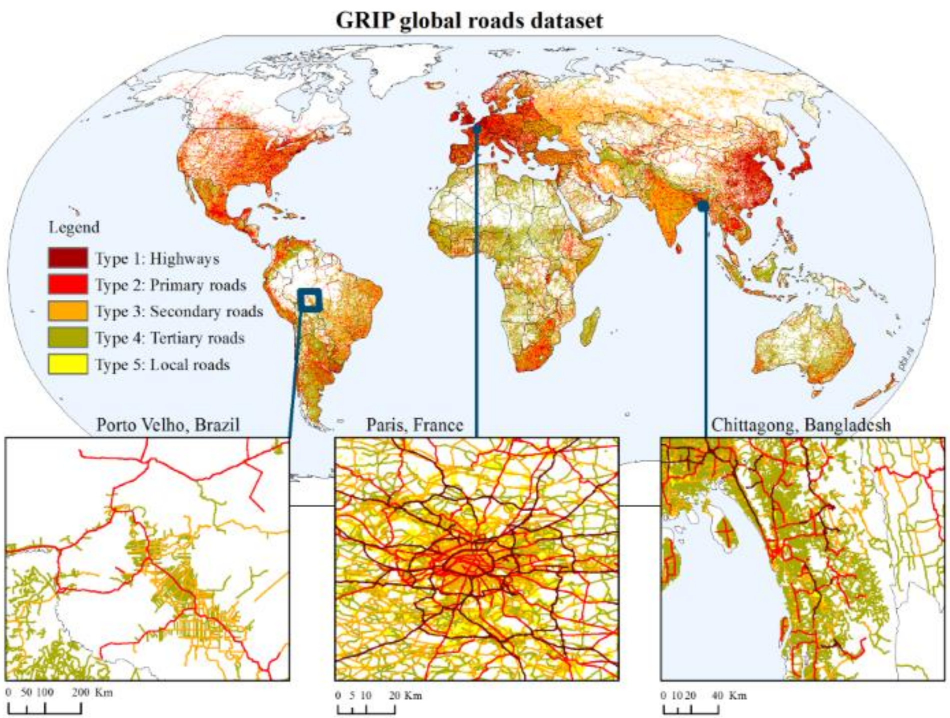


- Applied **Object based image analysis**. A semi-automation process
- **Sentinel-2 had greater accuracy** (71.24 %) in detecting greenspace, buildings; than Landsat-8 (67.85%)

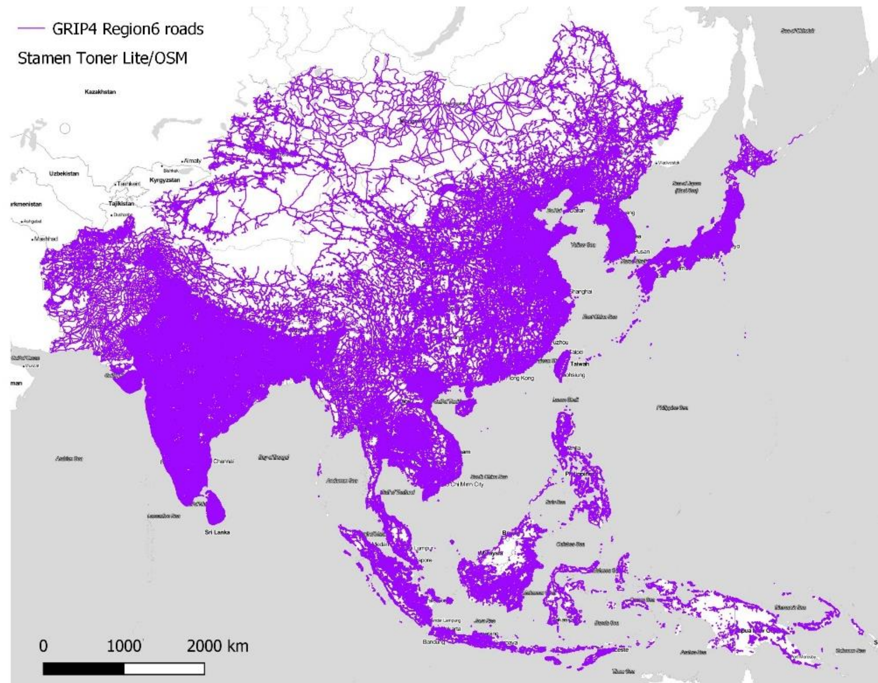
Geospatial Data (case studies)

Case study 2: OpenStreetMap data (a pilot test)

- **Largest open access crowdsourced Geo-data**
- Global coverage of street network, integrated in **Global Roads Inventory Project (GRIP)** dataset.
- Has **anonymized GPS tracks** up to 2013**,** global coverage (>21 GB of GPS points)
- Can such GPS data be useful for **understanding urban Park usage**?



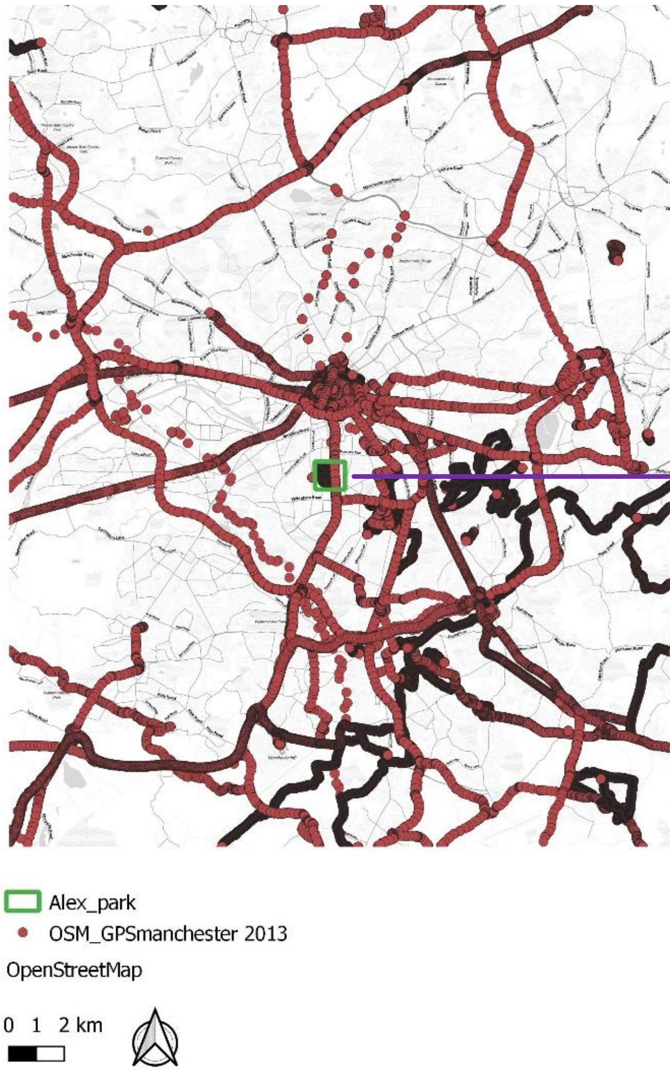
Source: Meijer et al., (2018)



Data Source: https://www.globio.info/download-grip-dataset

Geospatial Data (case studies)

Case study 2: OpenStreetMap data (a pilot test)



OSM GPS points Manchester

Alexandra Park Road network

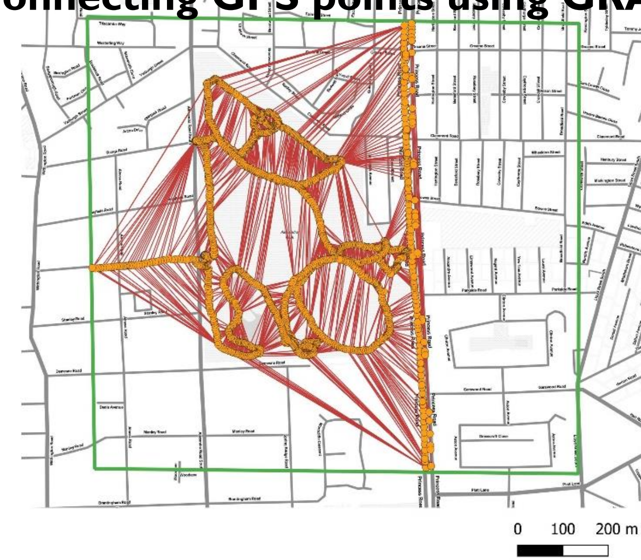
Alexandra Park GPS points

Data Source: thttps://planet.openstreetmap.org/gps/

Geospatial Data (case studies)

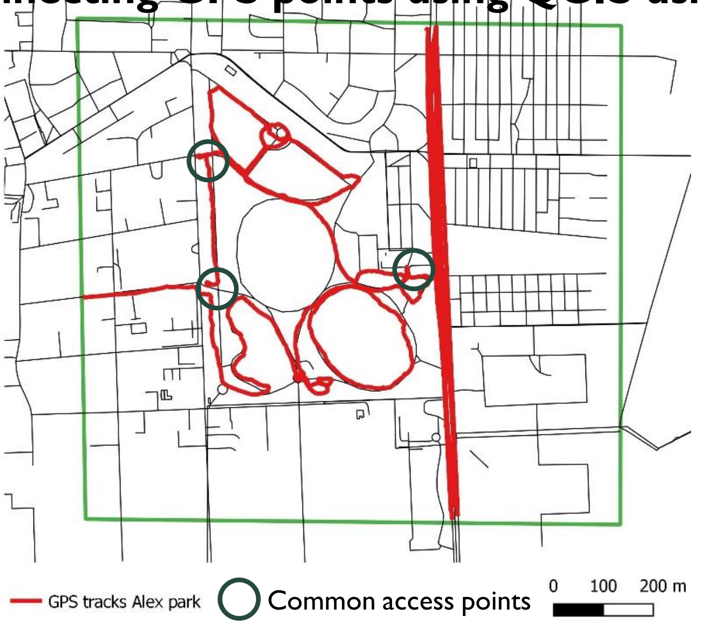
Case study 2: OpenStreetMap data (a pilot test)

Connecting GPS points using GRASS GIS



Connecting GPS points using SAGA GIS

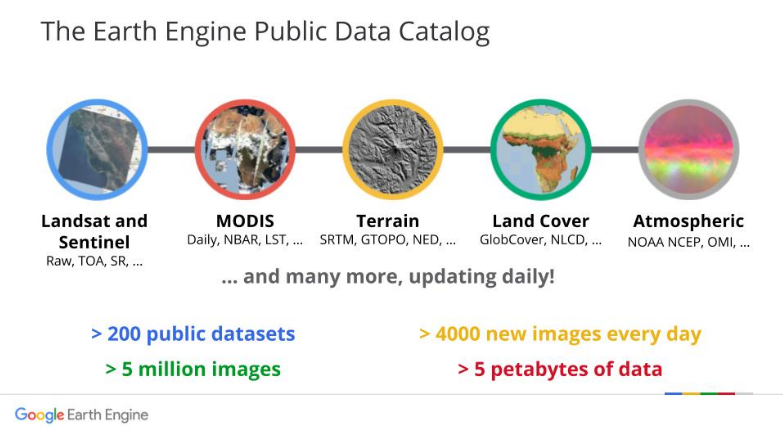
Connecting GPS points using QGIS using paths



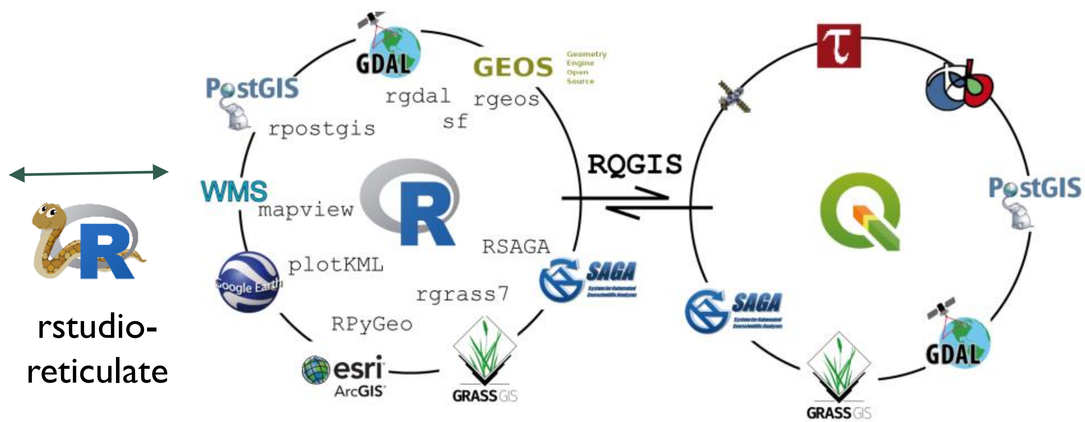
- Different analytical tools produced different track records.
- Some **paths and access points** are more used than others
- OSM GPS tracks can be used to **monitor activities in greenspace**
- **Issues:** (1) **No control over how many tracks available**, (2) cleaning and processing the data are challenging.

Geospatial Data (summary)

- **A lot of open, free, easily accessible data sources.**
- Platform such as **Google Earth Engine, OpenStreetMap** have wide verity of Big Geo-data. GEE for LST: https://code.earthengine.google.com/229c64e5d3ea6c34af203ea2b1aeaeb4?noload=true
- Analytical tools such as **QGIS, ArcGIS, R-packages, GDAL, GRASS** providing opportunities to analyse Geospatial data with ease.
- **Too much data!** Need to be careful about using **the appropriate data (e.g. resolution), scale and tools** based on purpose! (**will discuss more in Part-4**)



rstudio-reticulate



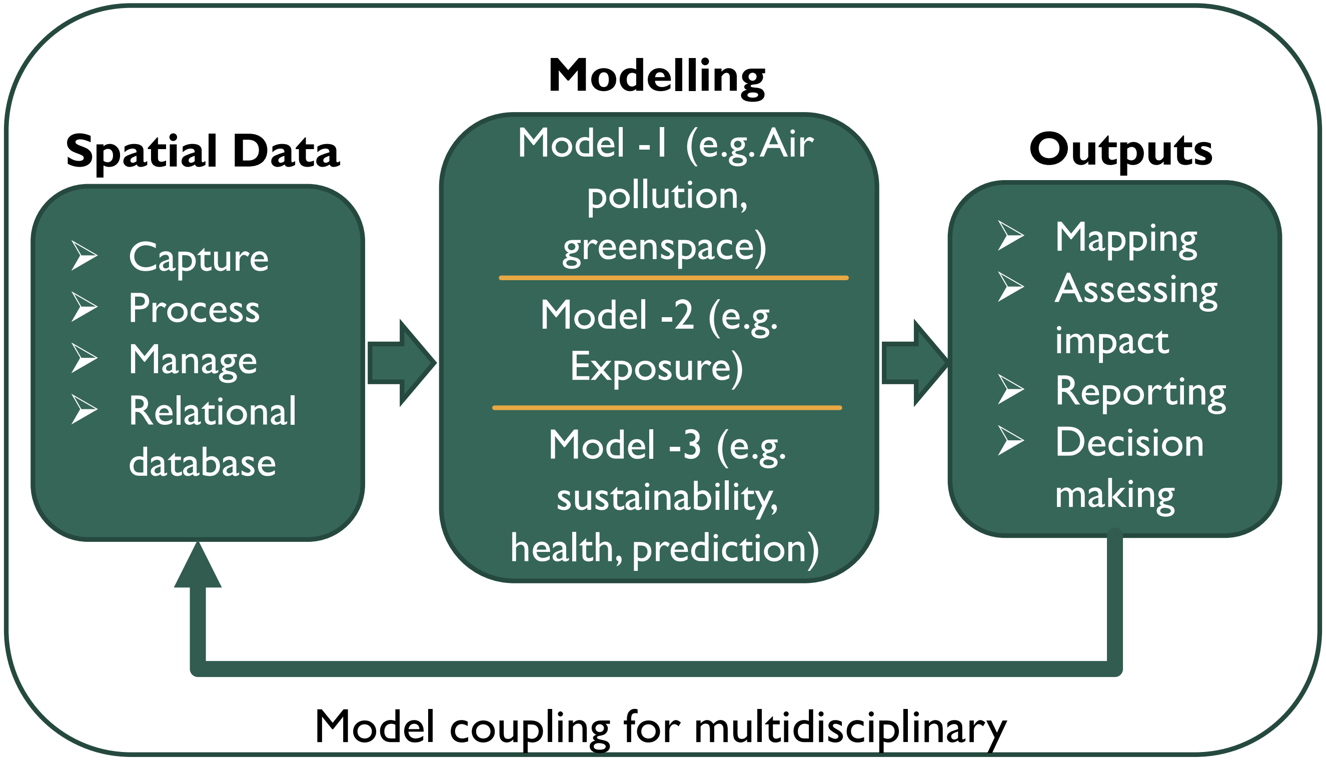
Sources:
- https://geohackweek.github.io/GoogleEarthEngine/01-introduction
- https://philippgaertner.github.io/2019/12/earth-engine-rstudio-reticulate/

Source: Muenchow et al., (2017)

Part -3: Examples of Geospatial model coupling

Geospatial Model coupling

- What all these **Geospatial data, and tools can do** in terms of decision making?
- Geospatial modelling provides the opportunity to **integrate multiple models** (e.g., earth system model, pollution) together.
- A **multidisciplinary modelling approach**.



Model coupling for multidisciplinary modelling within GIS framework

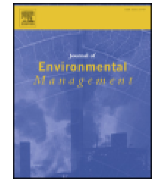
Geospatial Model coupling

Example study 1: Modelling transportation sustainability

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman



Research article

Carbon dioxide emission and bio-capacity indexing for transportation activities: A methodological development in determining the sustainability of vehicular transportation systems

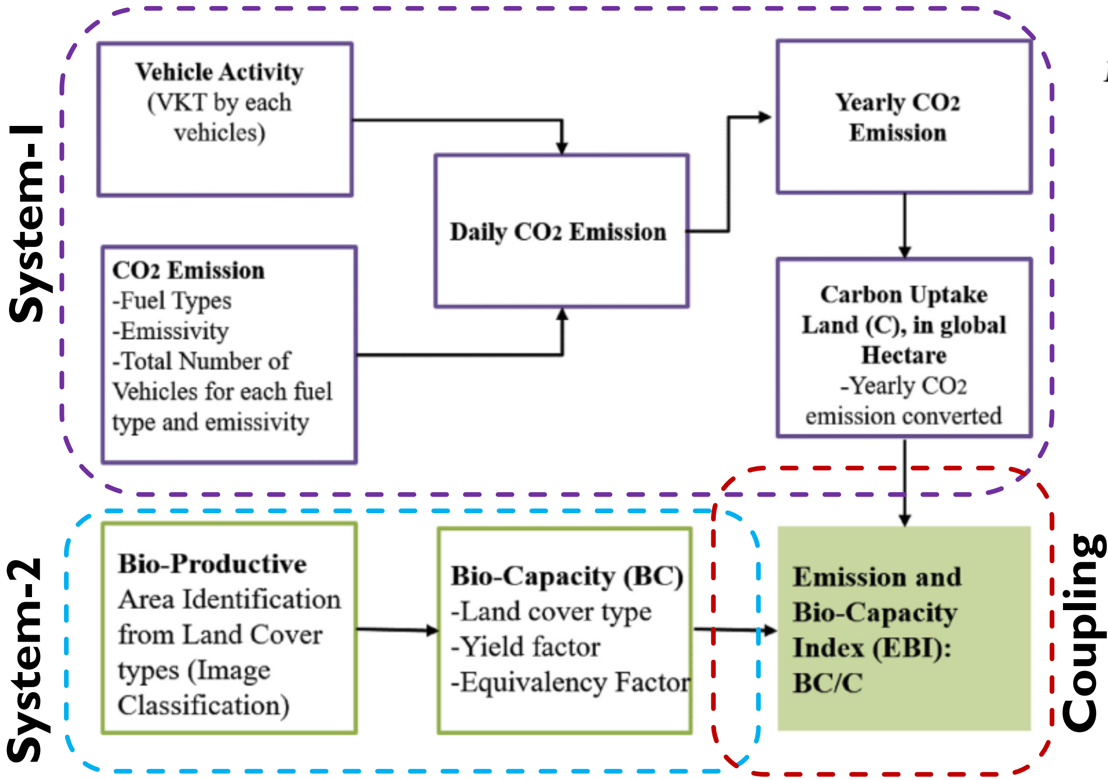
S.M. Labib[a,*], Meher Nigar Neema[b], Zahidur Rahaman[c], Shahadath Hossain Patwary[d], Shahadat Hossain Shakil[e]

[a] School of Environment, Education and Development (SEED), University of Manchester, Arthur Lewis Building (1st Floor), Oxford Road, Manchester, M13 9PL, UK
[b] Department of Urban and Regional Planning, Bangladesh University of Engineering and Technology (BUET), Bangladesh
[c] Ministry of Law, Justice and Parliamentary Affairs, Government of Bangladesh, Bangladesh
[d] Urban Planner, Sheltech (Pvt.) Ltd., Bangladesh
[e] Economic Growth Office, USAID. U.S. Agency for International Development, American Embassy, Madani Avenue, Dhaka, 1212, Bangladesh

- Transport is a major **determinant of global carbon emission**, and It is also a major source of air pollution and related health impact (Woodcock et al., 2009).
- Traffic related carbon emissions correlate with local available bio-capacity of carbon sequestration.
- Can we combine two components **(1) traffic carbon emission, and (2) local bio-productivity** to come up a sustainability rating tool?

Geospatial Model coupling

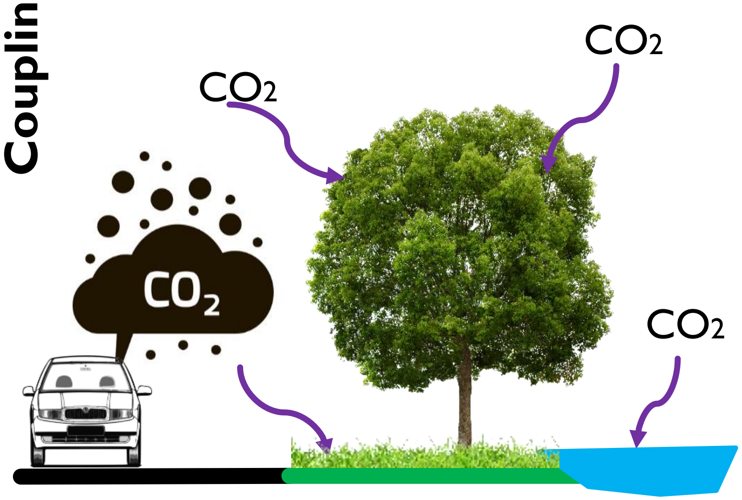
Example study1: Modelling transportation sustainability (Cont…)



$$E_i = \sum_{j=1}^{n} \sum_{k=1}^{n} EF_{ijk} A_{jk}$$

Where,

i = Type of a pollutant (in this case CO_2)
j = Fuels consumed (e.g. CNG, Gasoline)
k = Emitting Vehicular type (Volume survey)
E_i = Emissions from pollutant
EF_{ijk} = Emission Factor (g/km)
A_{jk} = Activity level for each pollutant source.



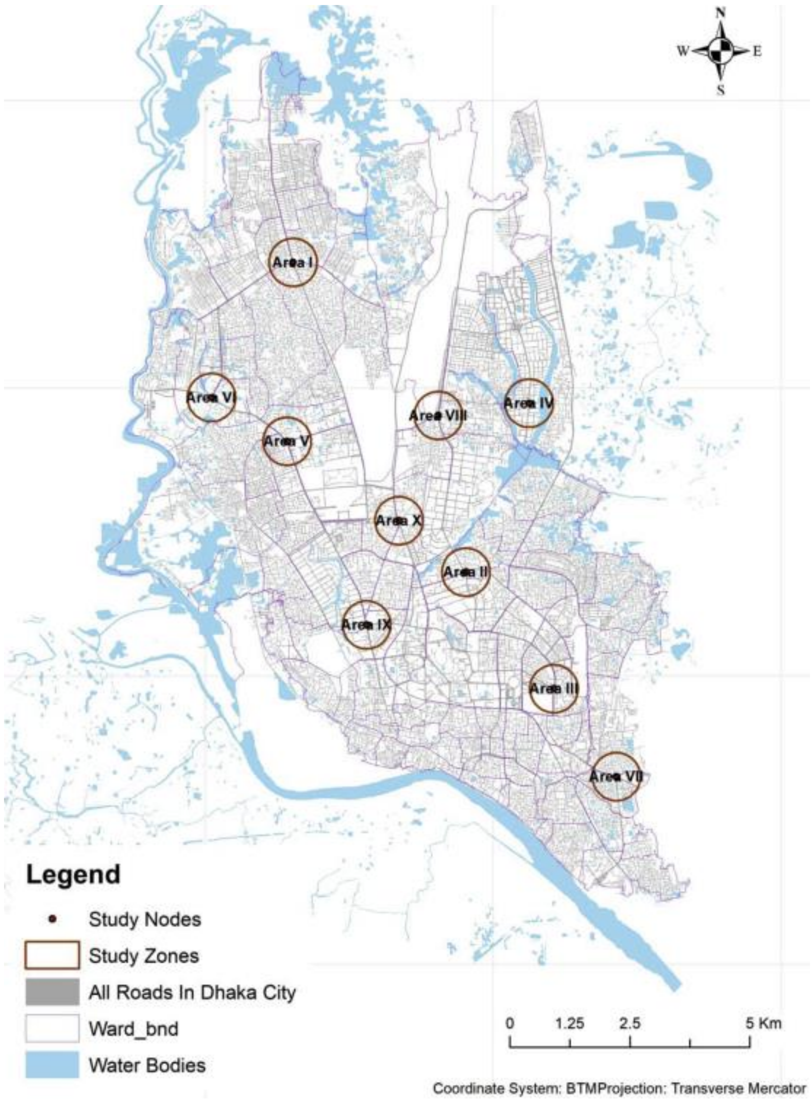
$$BC = \sum_{i=1}^{n} Ar_i * YF_i * EQF_i$$

where,

BC = Bio-capacity (in global hectare, gha)
Ar_i = Area of i land use type (hectare)
YF_i = Yield factor i type land use type (ratio of national yield world average yield)
EQF_i = Equivalency factor for i type land use type

Geospatial Model coupling

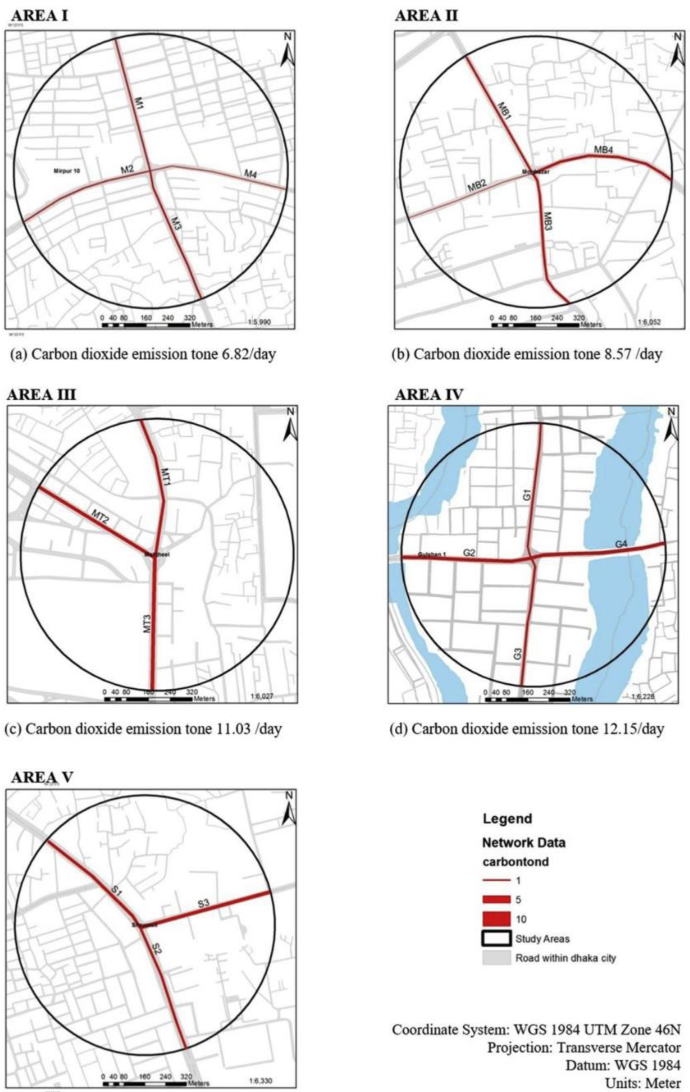
Example study1: Modelling transportation sustainability (Cont…)



- Ten studied nodes
- Critical locations on the transport network.

Geospatial Model coupling

Example study1: Modelling transportation sustainability (Cont…)



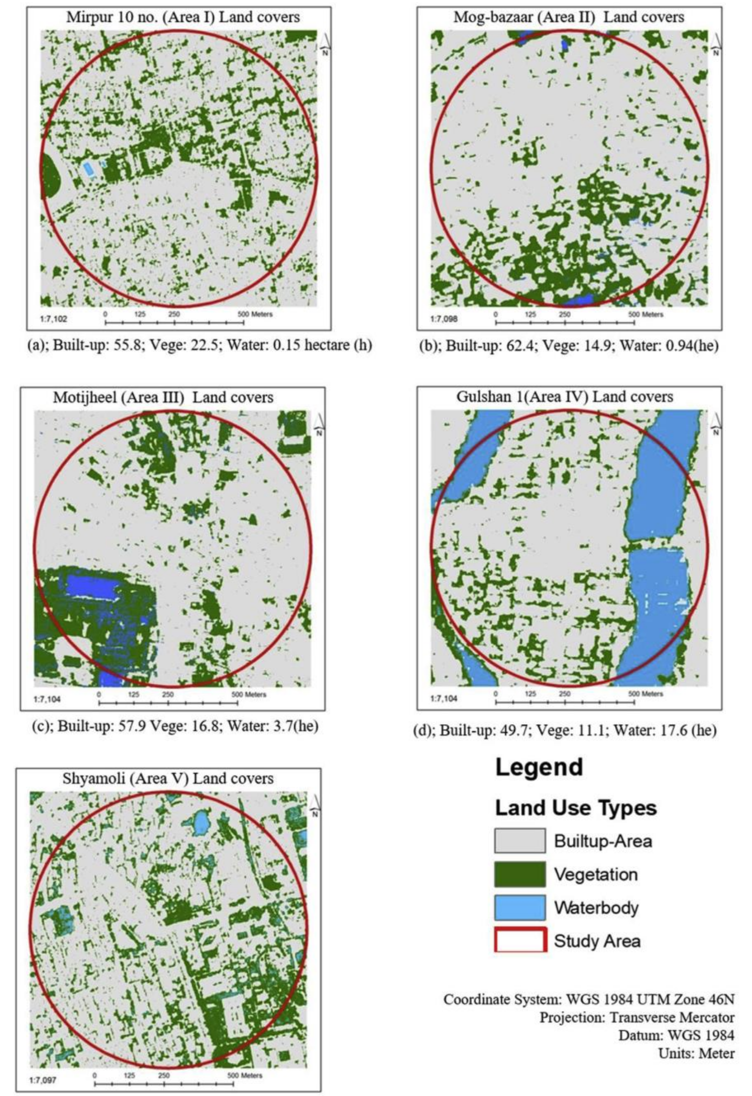
(a) Carbon dioxide emission tone 6.82/day

(b) Carbon dioxide emission tone 8.57 /day

(c) Carbon dioxide emission tone 11.03 /day

(d) Carbon dioxide emission tone 12.15/day

(e) Carbon dioxide emission tone 12.45/day



(a); Built-up: 55.8; Vege: 22.5; Water: 0.15 hectare (h)

(b); Built-up: 62.4; Vege: 14.9; Water: 0.94(he)

(c); Built-up: 57.9 Vege: 16.8; Water: 3.7(he)

(d); Built-up: 49.7; Vege: 11.1; Water: 17.6 (he)

(e); Built-up: 67.2; Vege: 11.1; Water: 0.2 (he)

Spatially explicit estimated CO_2 emission

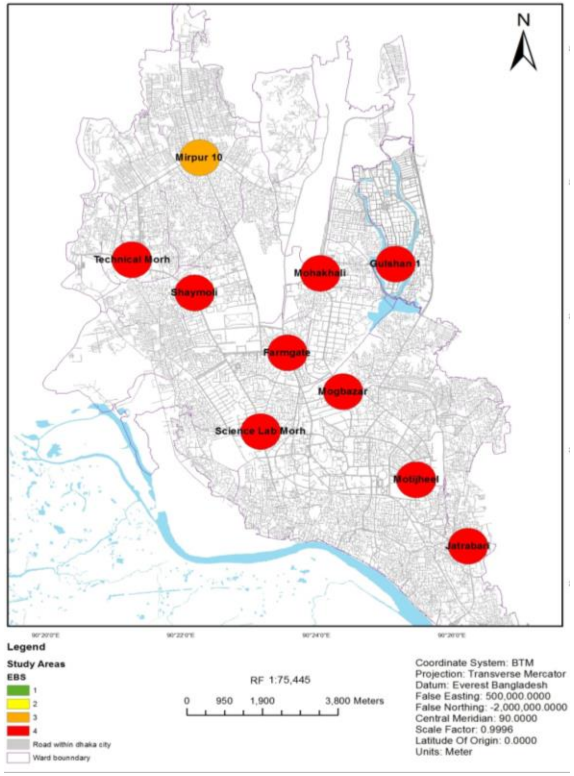
Remote sensing based land use classification

Geospatial Model coupling

Example study1: Modelling transportation sustainability (Cont…)

Table 5
Emission and bio-capacity Index and Score values for each AOI.

Area	Carbon Uptake Land (gha)	Bio-capacity Area (gha)	EBI	EBS	Color Code
Area I (Mirpur 10)	785.20	269.43	0.343	3	Orange
Area II (Mog bazaar)	987.08	298.06	0.302	4	Red
Area III (Motijheel)	1269.36	278.20	0.219	4	Red
Area IV (Gulshan 1)	1398.43	242.60	0.173	4	Red
Area V (Shymoli)	1432.89	233.91	0.163	4	Red
Area VI (Technical Morh)	1477.91	217.92	0.147	4	Red
Area VII (Jatrabari)	1779.99	335.08	0.188	4	Red
Area VIII (Mohakhali)	1868.61	317.41	0.170	4	Red
Area IX (Science lab)	2363.18	285.57	0.121	4	Red
Area X (Farm gate)	2440.20	289.00	0.118	4	Red



- Emission Bio-capacity Index (EBI) = Carbon Uptake land / Bio-capacity
- Values over One (1) indicate full sequestration of CO_2 with the local bio-capacity. Expressed in four color rating; **Red, Orange, Yellow, Green**.
- 9 nodes indicated rating: **"Red"**, implying the CO_2 emission is beyond the capacity to local bio-productive areas to offset the impact.
- **Main reasons**: Increased motorized traffic volume, poor signal system, low facilitation for non-motorized vehicles, and overall low availability of greenspace.

Geospatial Model coupling

Example study 2: Modelling Green infrastructure using ML

ELSEVIER

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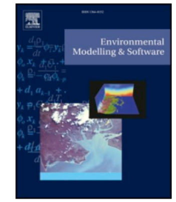
Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft



Investigation of the likelihood of green infrastructure (GI) enhancement along linear waterways or on derelict sites (DS) using machine learning

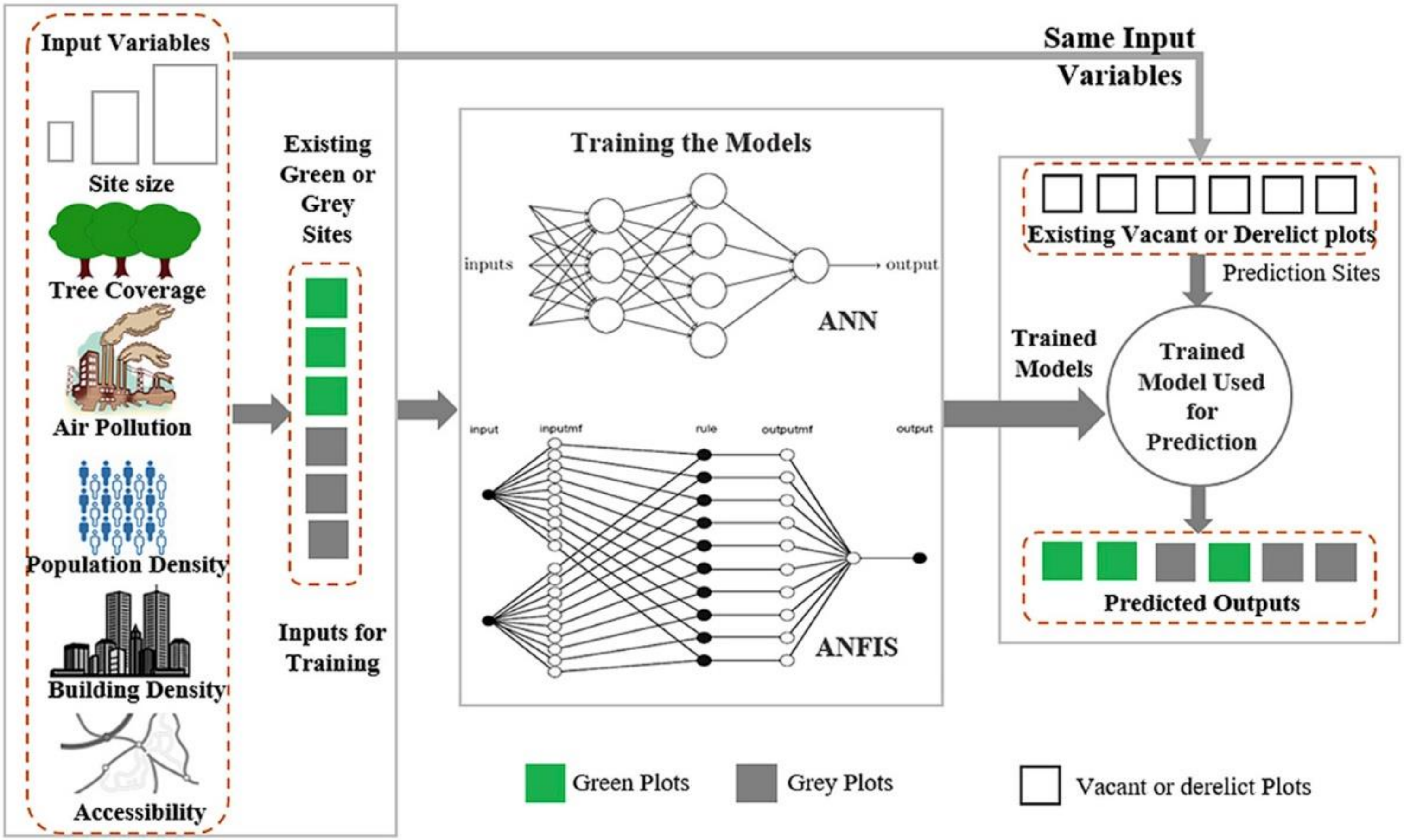
S.M. Labib

School of Environment, Education and Development (SEED), University of Manchester, Arthur Lewis Building (1st Floor); Oxford Road; Manchester; M13 9PL, UK

- **Green Infrastructure** (e.g., greenspace, blue space) is associated with ecosystem services and health in urban areas (Tzoulas et al., 2007).
- Increased presser on urban land use resulted in loss of GI in cities.
- Can we model what would be **future scenarios of GI** (along waterways or existing derelict sites) based on previous trends, applying machine learning models?
- Can we **compare ML models with traditional regression** based models (i.e., logistic regression)?

Geospatial Model coupling

Example study 2: Modelling Green infrastructure using ML (Cont…)



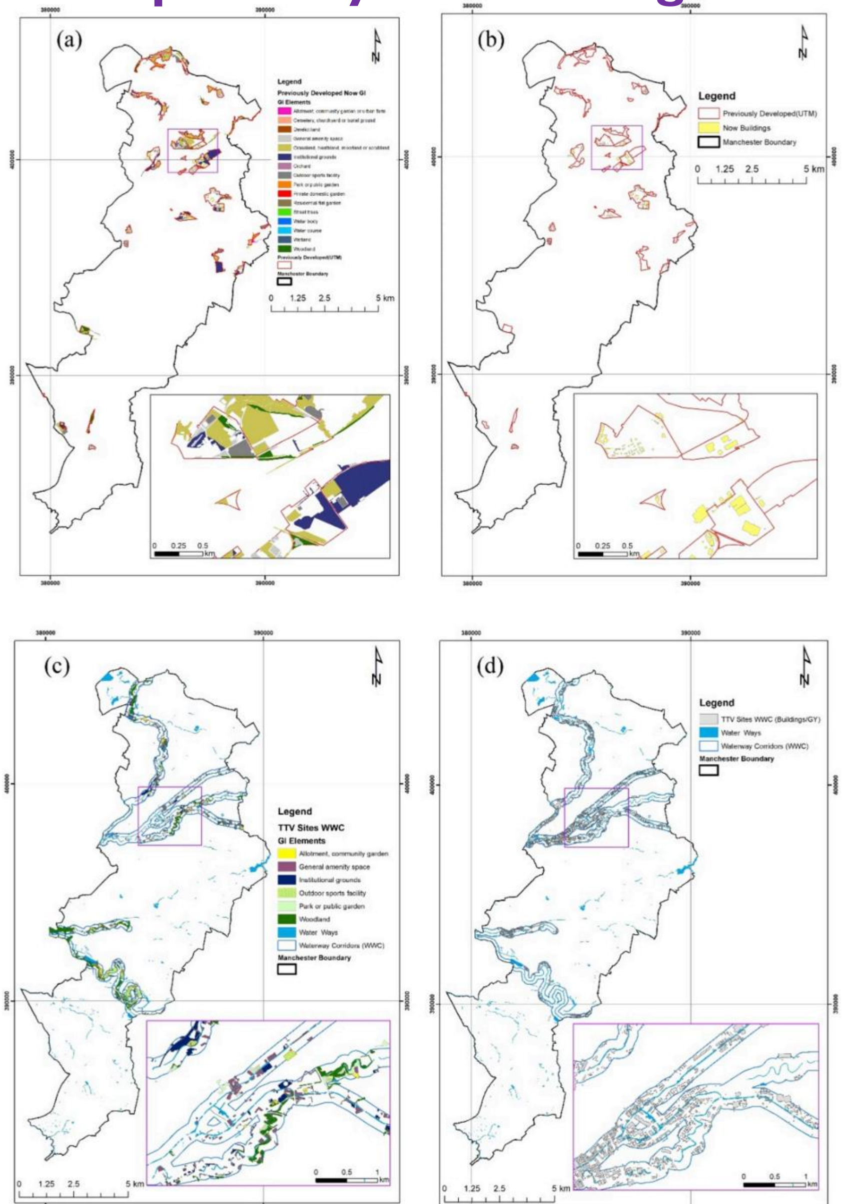
System 1- Modelled or spatial data

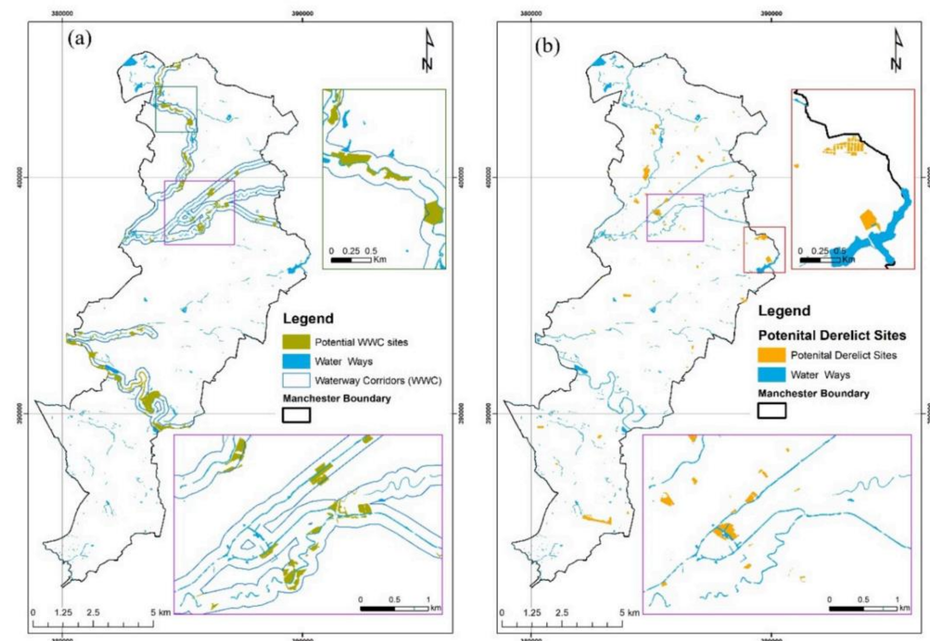
System 2- Modelling

System 3- Prediction using trained model

Geospatial Model coupling

Example study 2: Modelling Green infrastructure using ML (Cont…)



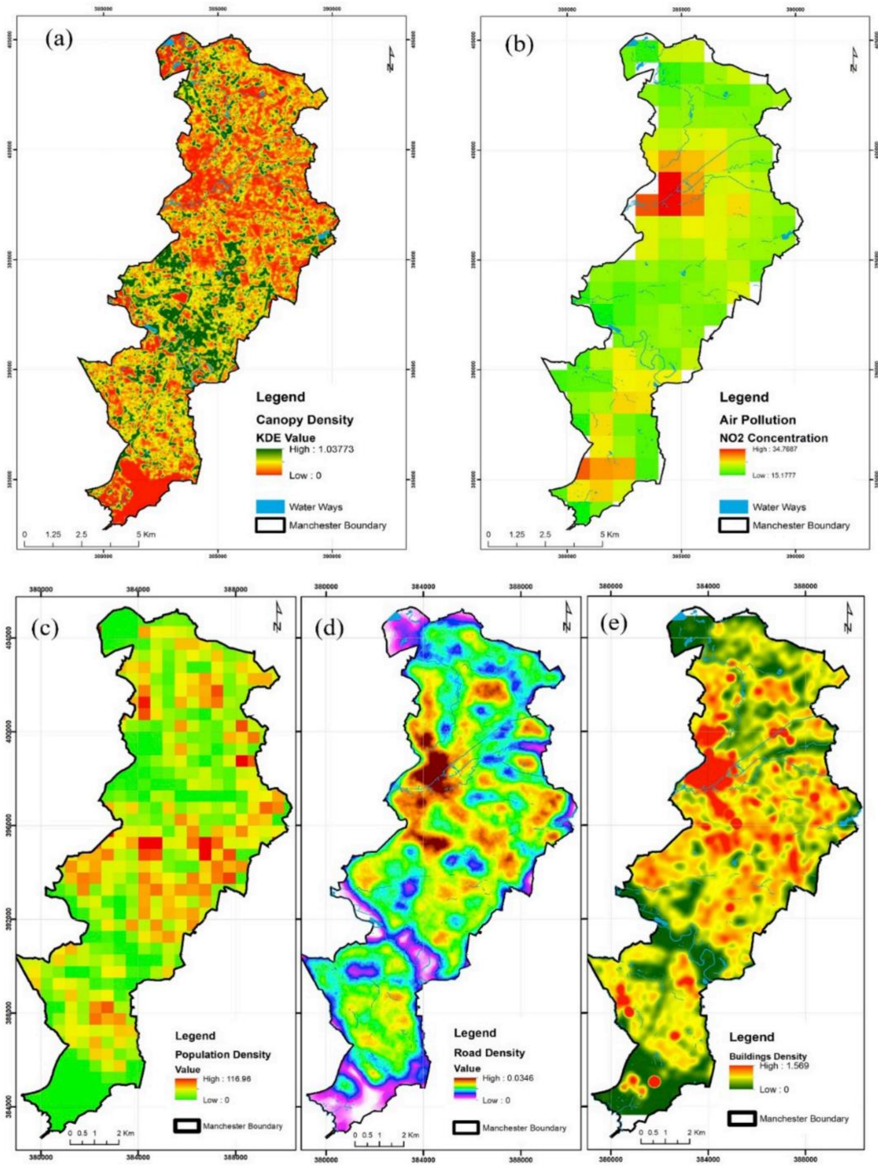


Prediction sties (150 along waterways, 112 derelict sites)

Training sties (3916 along waterways, 866 derelict sites)

Geospatial Model coupling

Example study 2: Modelling Green infrastructure using ML (Cont…)

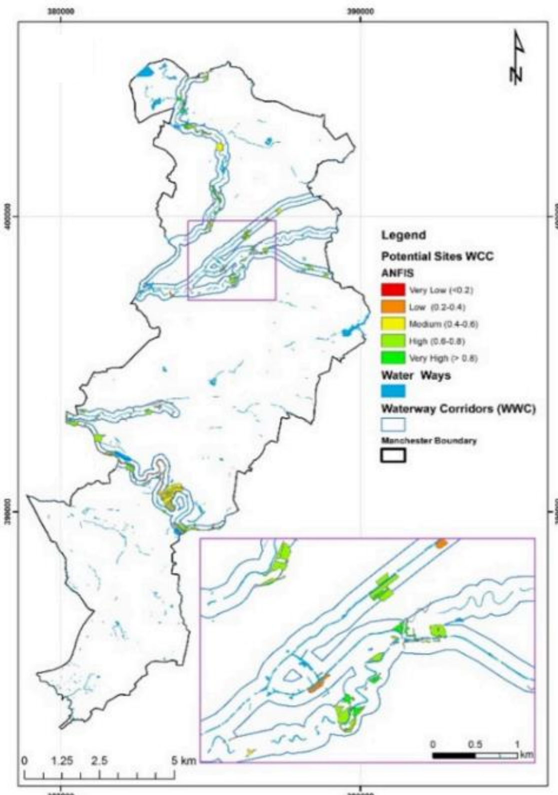


Input data from different spatial data sources, and modelled NO_2 data

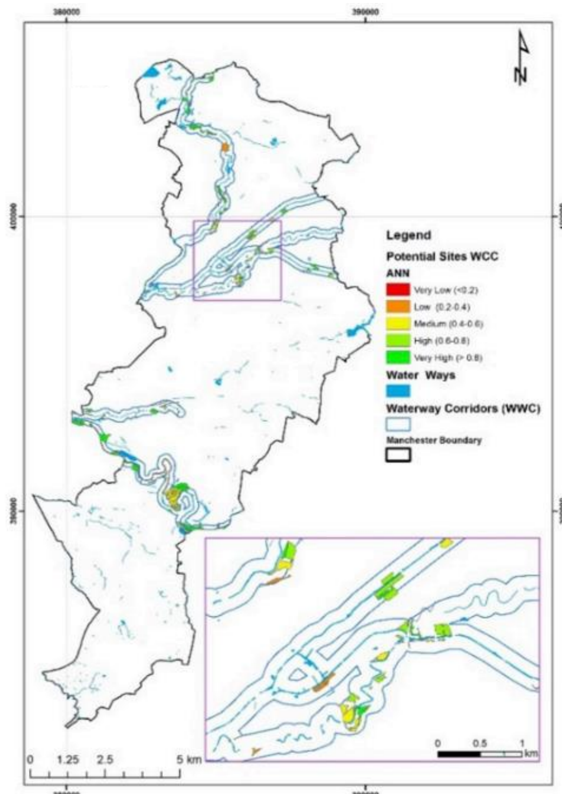
Geospatial Model coupling

Example study 2: Modelling Green infrastructure using ML (Cont…)

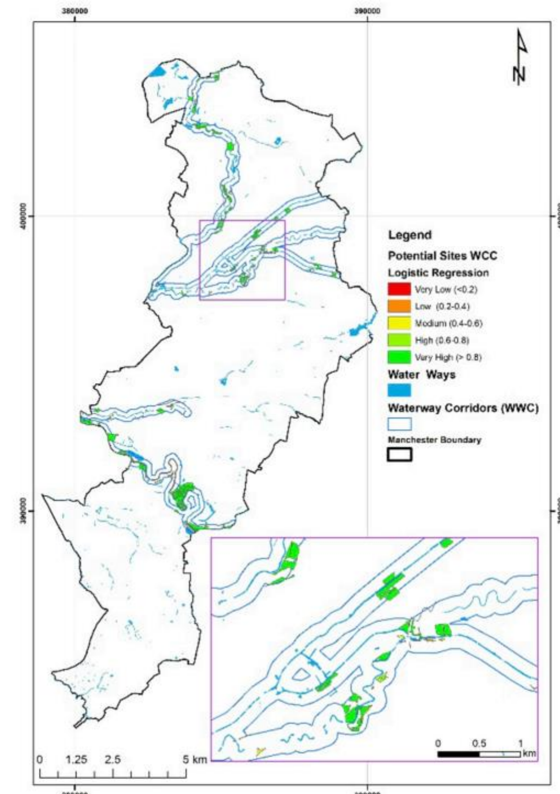
Prediction for Waterway corridor plots



ANFIS Prediction; RMSE: 0.29; **79.3% green**



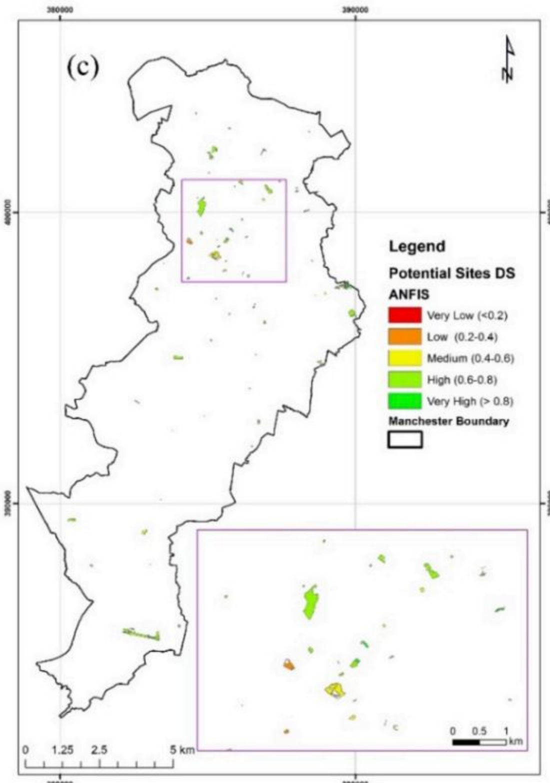
ANN Prediction; RMSE: 0.28; **80.7% green**



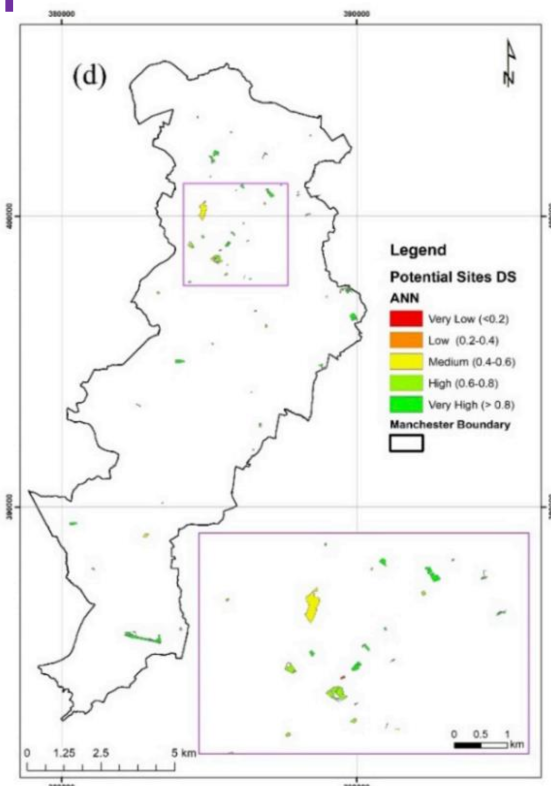
Logistic Regression Prediction; RMSE: 0.36; **74% green**

Geospatial Model coupling

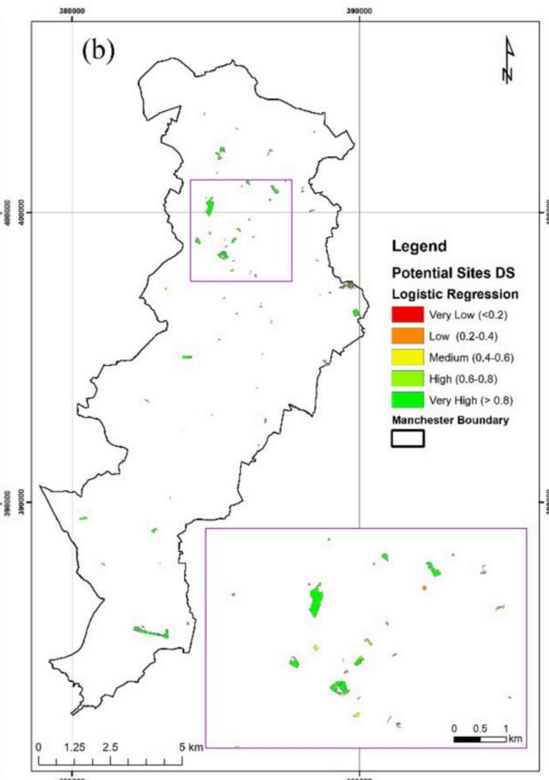
Prediction for Derelict plots



ANFIS Prediction; RMSE: 0.285; **61.6% green**



ANN Prediction; RMSE: 0.23; **53.6% green**



Logistic Regression Prediction; RMSE: 0.35; **34.8% green**

- **Derelict sites** are more **likely to become grey areas/buildings**, where water ways corridors plots are more likely to remain or become green areas.
- ML models **unable to explain the importance or significance** of the input variables
- Logistic regression models indicated, **site size, population density and air pollution** are significantly associated with green transformation likelihood.

Geospatial Model (coupling summary)

- Modelling **approaches are transferable**; can be applied in different studies, such as built environment- health, air pollution-health studies
- Different spatial and non-spatial **data can be integrated** within the modelling environment.
- Emerging algorithms are being introduced/integrated frequently.

Part -4: Spatial dimensions of greenspace and health research- current practice

Spatial Dimensions greenspace & health

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Review article

Spatial dimensions of the influence of urban green-blue spaces on human health: A systematic review

S.M. Labib*, Sarah Lindley, Jonny J. Huck

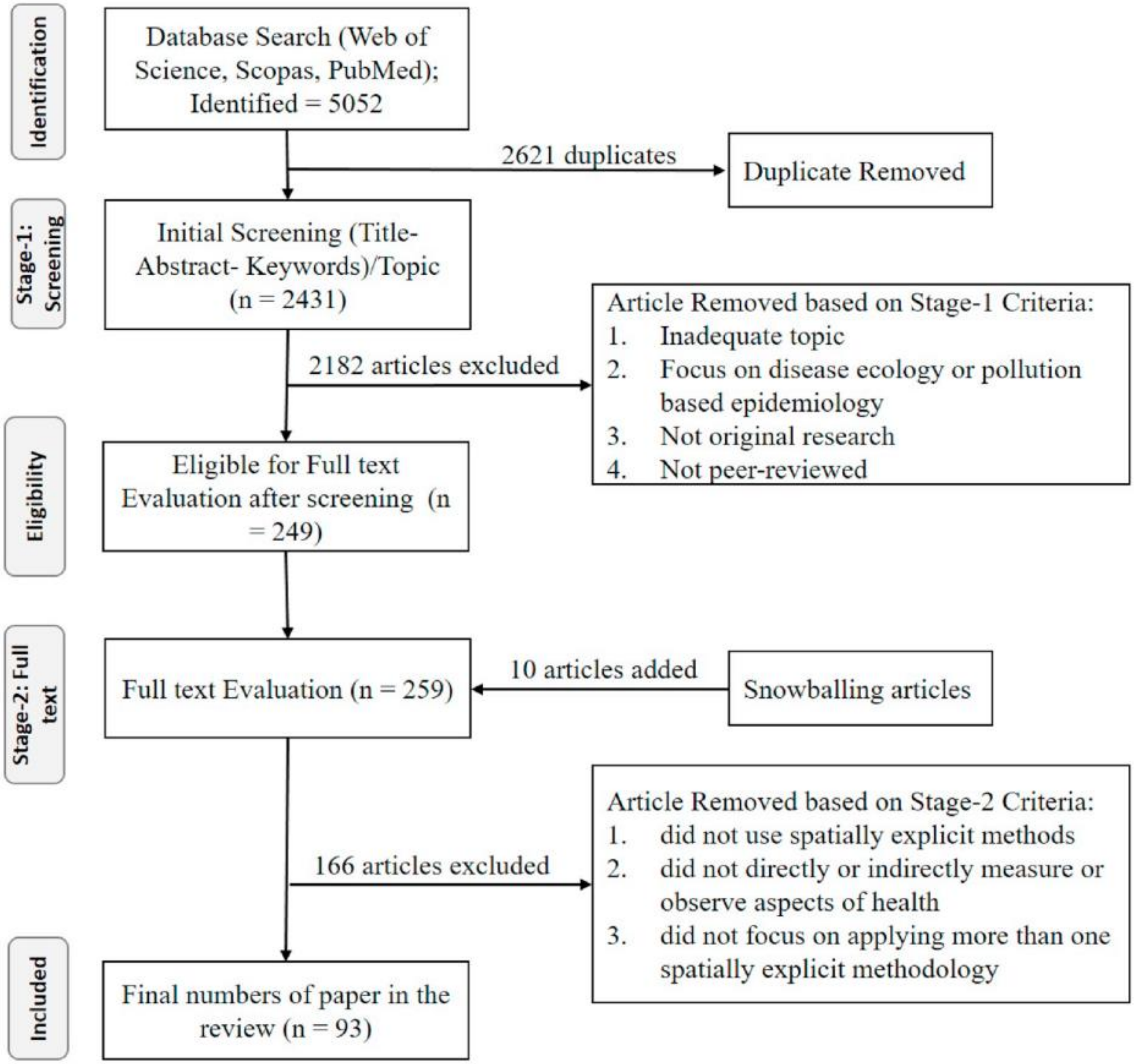
Department of Geography, School of Environment, Education and Development (SEED), University of Manchester, Arthur Lewis Building (1st Floor), Oxford Road, Manchester, M13 9PL, UK

- *identify the different* ***data, scales and geospatial methods*** *utilised in studying greenspace and its relation to human health in urban areas;*
- *investigate* ***how results vary*** *(e.g., significant vs insignificant, positive vs negative) according to the type of association between greenspace and health indicators and their relation to spatial data and methods; and*
- *identify the* ***limitations and prospects of spatial data and analytics*** *in representing and associating greenspace and human health.*

doi: https://doi.org/10.1016/j.envres.2019.108869

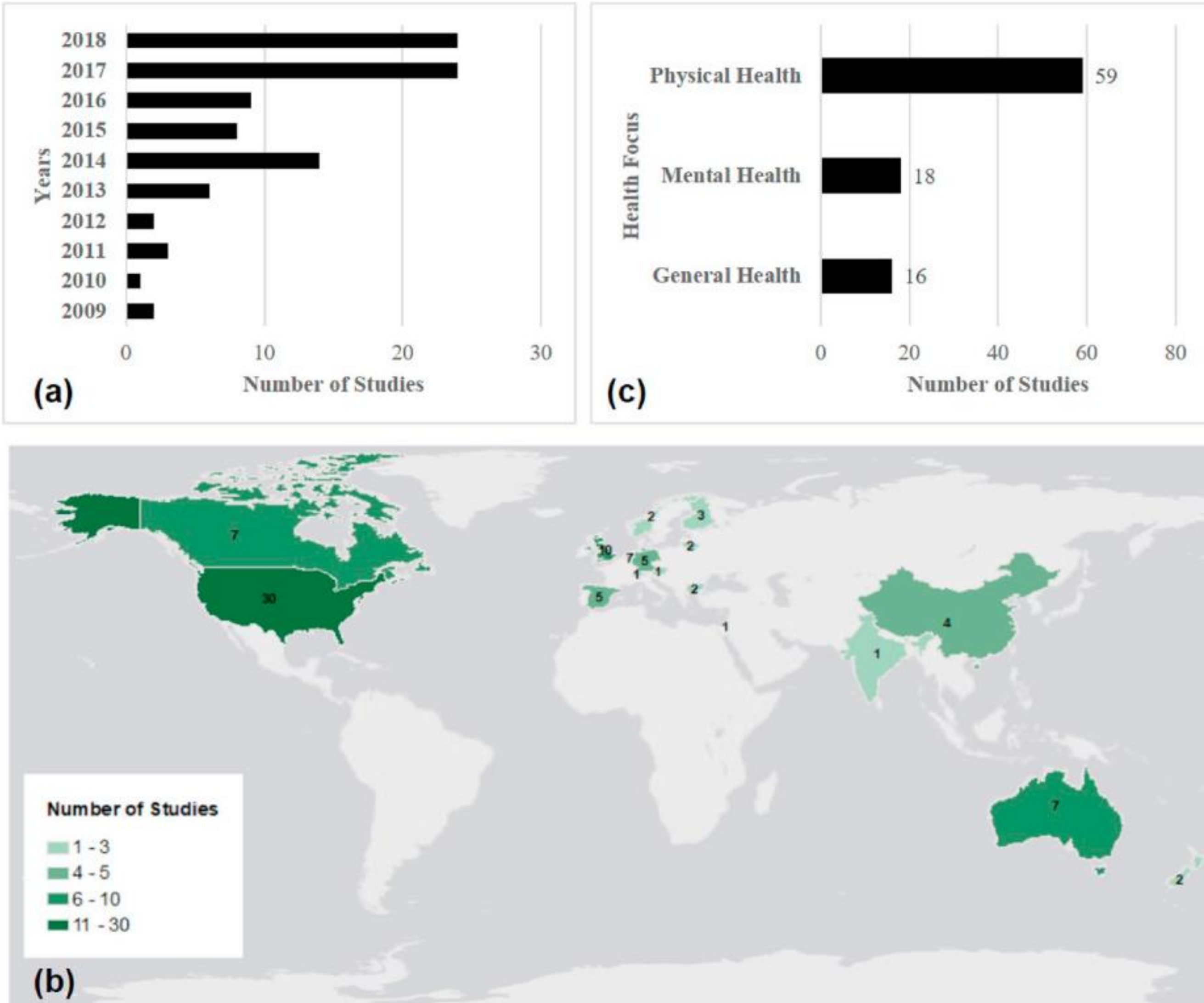
Spatial Dimensions greenspace & health

PRISMA



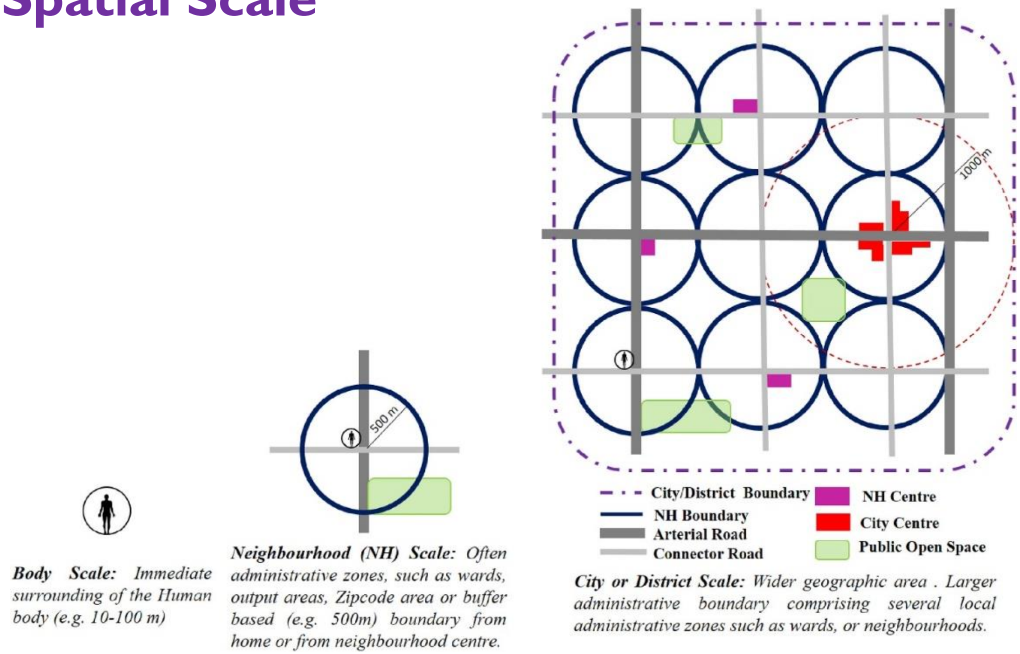
Spatial Dimensions greenspace & health

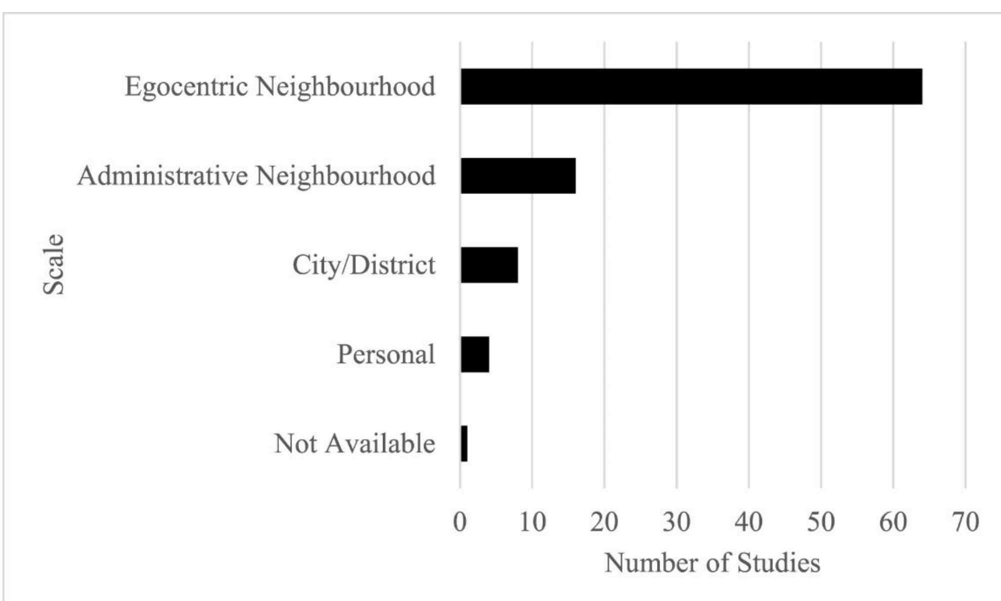
General characteristics of the studies



Spatial Dimensions greenspace & health

Spatial Scale





- Commonly used scales: **body, neighbourhood and City/districts**
- Neighborhood: (1) **egocentric** (e.g., a buffer around the home location) or (2) **allocentric** (e.g., using a pre-defned administrative unit)
- Majority of the studies focused on **ego-centric neighborhood**, applying different buffer distances (e.g., 400, 500, 800 m)

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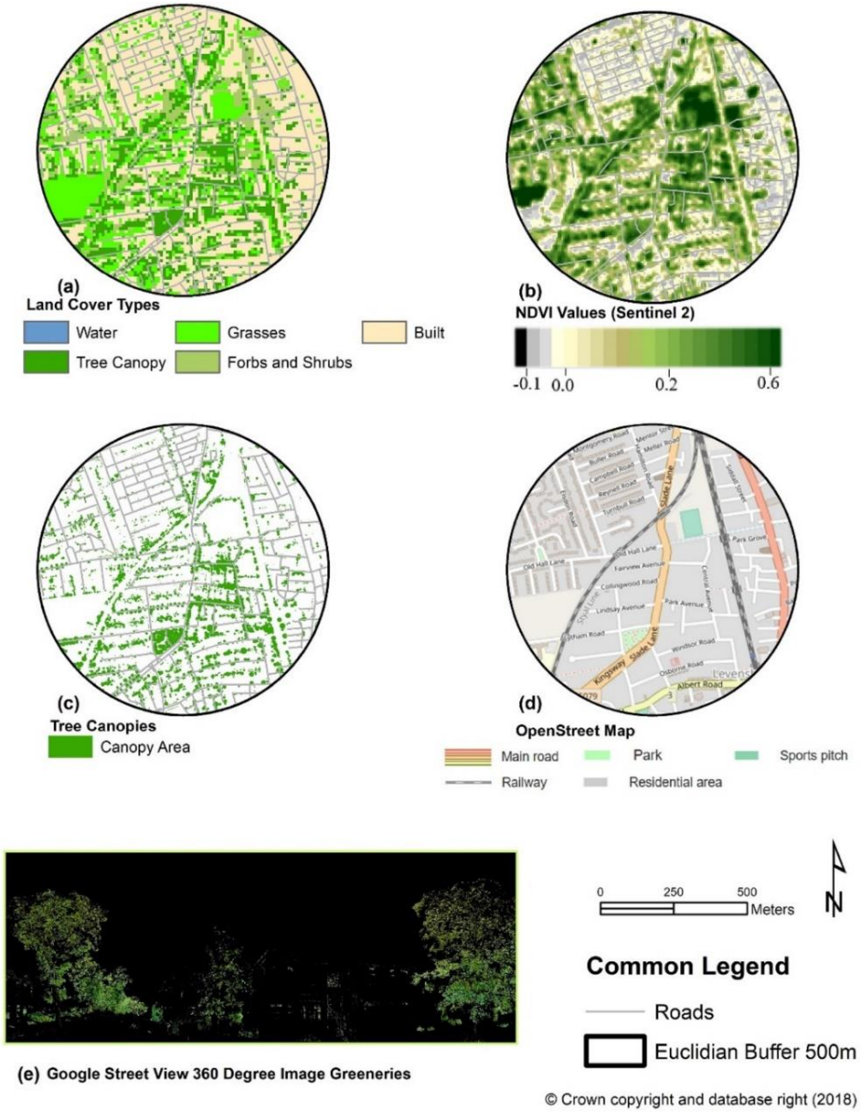
Commonly used greenspace metrics



- Commonly used **Greenspace metrics:** Land use land cover (n =47), NDVI/EVI/SAVI (n = 36), Canopy coverage (n = 5), Street view images (n = 3), 3D viewshed (n = 3).
- Land use and Land cover data often collected at **large spatial scale** (e.g., 1:100,000); CORINE, Urban Atlas data (minimum greenspace size 25ha).
- NDVI or satellite image indices often are estimated from **Low spatial resolution satellite**, mostly Landsat (30m), and MODIS (250m).
- **Street view data are emerging**, only available along streets.

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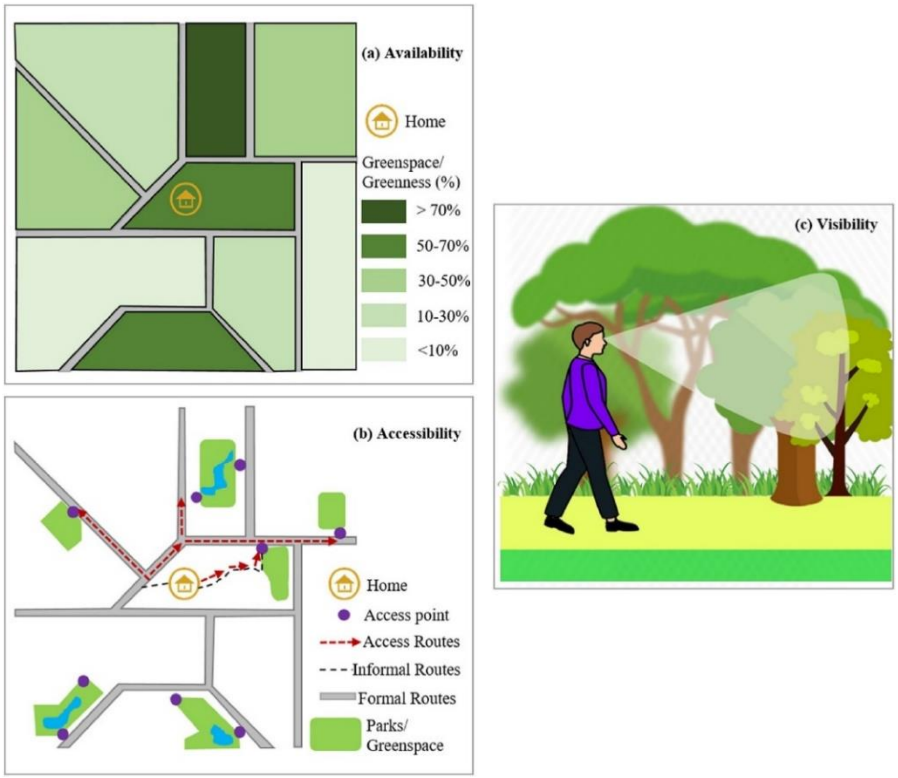
Spatially explicit greenspace exposure assessment



- **Availability** of greenspace or greenness in different neighbourhoods (e.g., percentage, numbers, mean NDVI, and area/size). Most common (n = 75).
- **Accessibility** to greenspace from home (e.g., numbers of accessible parcels, distance to parcels) (n = 48). Measured using both shortest distance, and fixed distance (e.g., 400m).
- **Visibility** of greenspace while travelling or around the home. **Least studied** (n = 6).
- Most studies use **proximity, and overly functions in ArcGIS/QGIS**.

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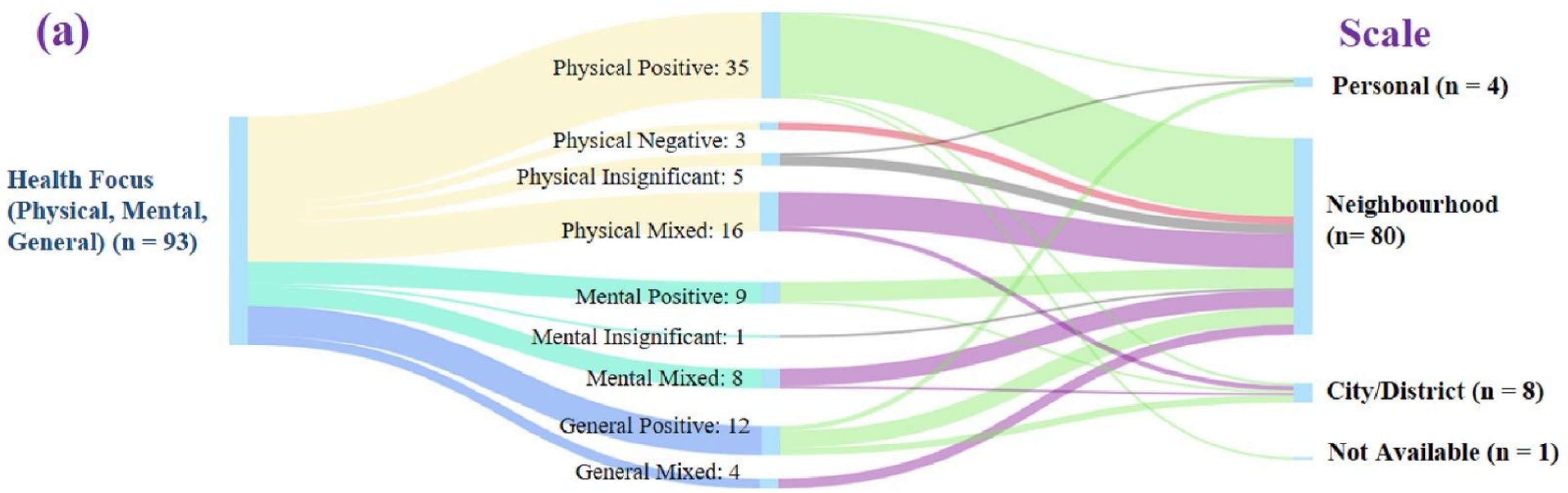
Analytical approaches and key results

- A mix of **subjective** (e.g., self reported, GHQ12, SF36) and **objective** (e.g., anthropometric information, GPS tracking) health indicators (e.g., BMI, MVPA).
- Most studies based on **statistical modelling** (e.g., logistic, linear regressions) and correlation analysis. **Very few applied spatial models** (e.g., regression with lag)



- Majority of the studies **found positive associations** at each scale. Mixed or insignificant associations also observed at all scales.
- Neighbourhood scale has more **variations in study results**, as it is most commonly used, and there are **a lot of variations in conceptualising** neighbourhood (e.g., different buffer distances).

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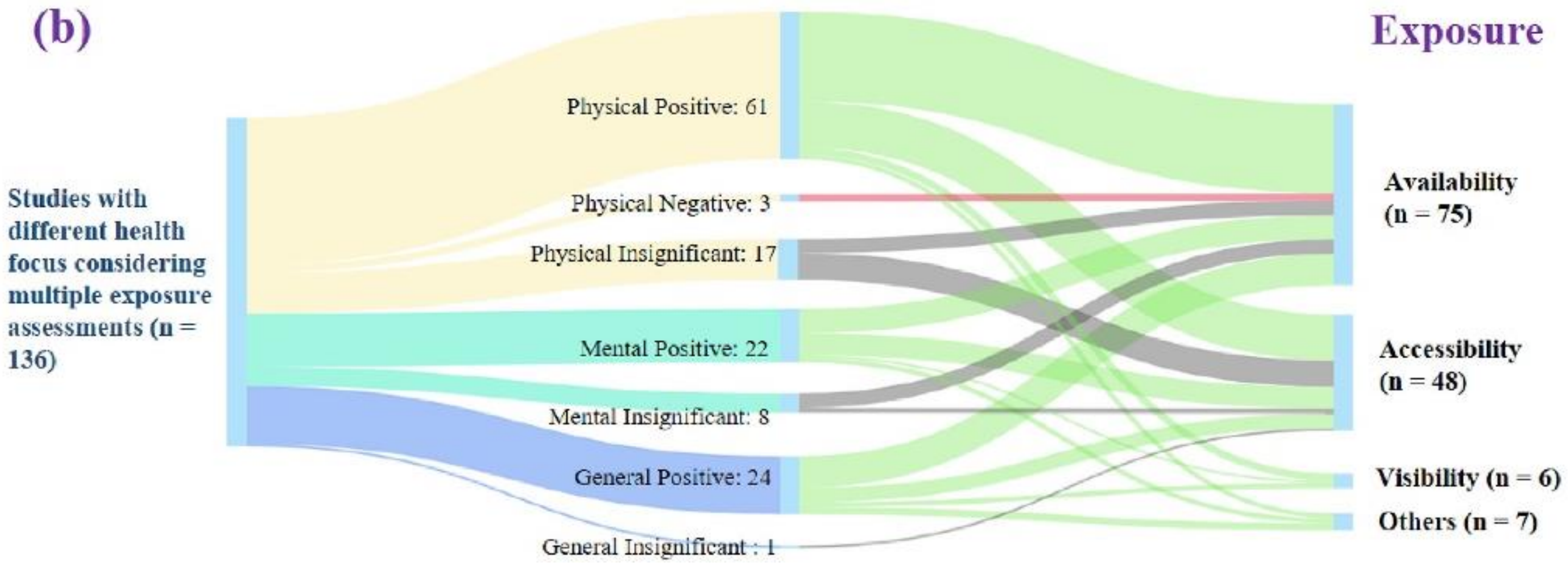
Analytical approaches and key results (Cont…)



- Majority of the studies **found positive associations** between health greenspace exposure.
- Mixed associations and insignificant associations observed depending on how the exposure measured. Such as **availability within 400m vs 1600m; the resolution of spatial data (MODIS vs. Landsat); shortest distance vs. fixed distance.**
- All visibility exposure studies found significant positive associations.
- **Absence of integrated approach of modelling exposure.** Depends on different pathways.

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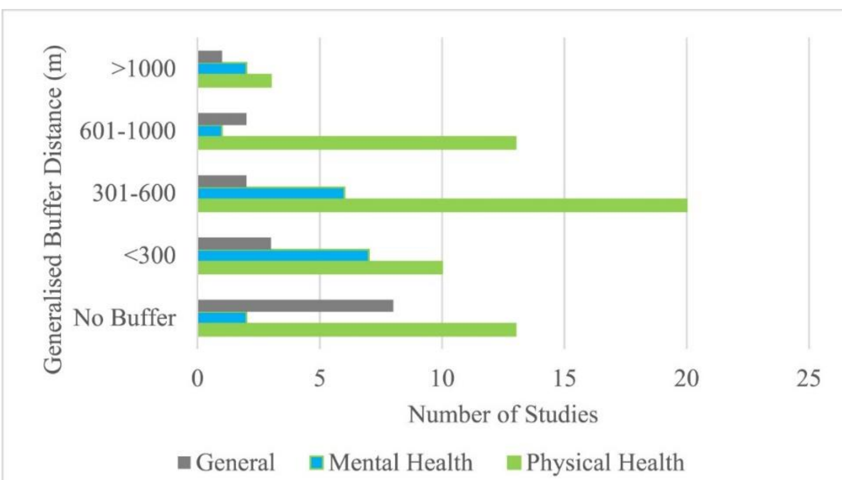
#Issue-1 Scale of analysis, distances, and MAUP



- **Spatial unit of aggregation and analysis** is a major concern. It influences both measurements and associations.
- Different buffering approaches (e.g. Euclidian, Network), and administrative units produced **different exposure areas, and spatial aggregation** of model inputs.
- **Physical health focus studies usually use larger distance than mental health.**

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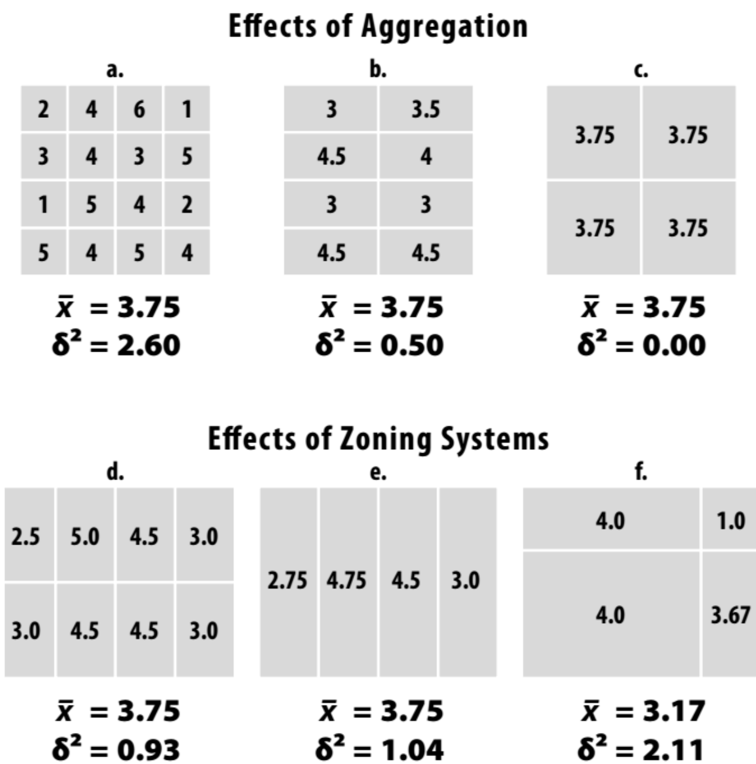
#Issue-1 Scale of analysis, distances, and MAUP (cont…)



Source: Dark and Bram, (2007)

- Varying distances, spatial units, and buffering approaches result in **Modifiable Areal Unit problem- MAUP** (scale effect/ aggregation, zone effect).
- Aggregating into **larger spatial scale reduce variance**, cause inconsistency in the model.
- Studies used **larger buffers** to measure greenspace exposure usually found significance associations, but **effect sizes become inconsistent,** as covariance among variables affected**.**
- Zoning of the exposure areas also effect the variance, and hence influence the associations.

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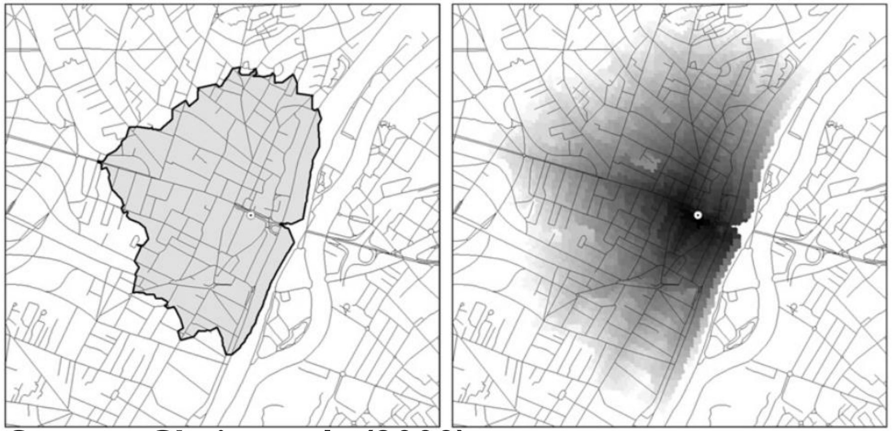
#Issue-1 Scale of analysis, distances, and MAUP (cont…)



Source: Chaix et al., (2009)

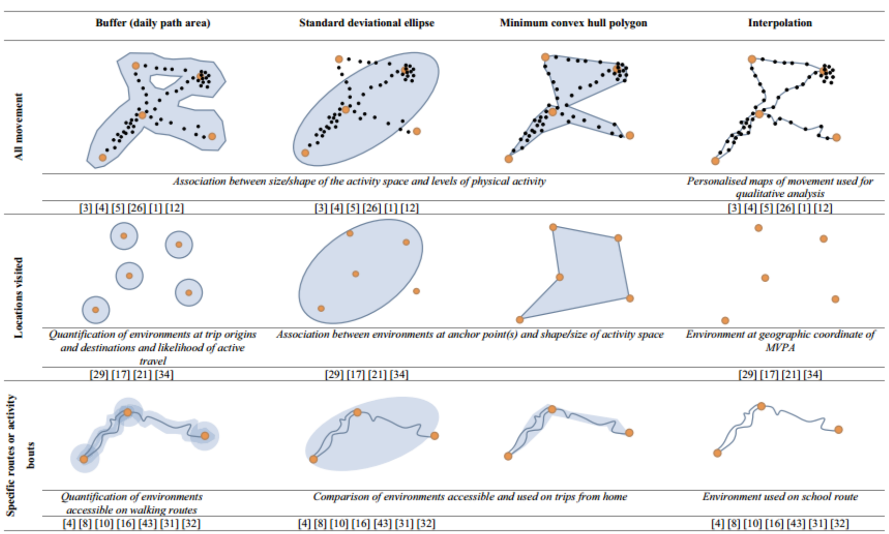


Fig. 2. Methods used to delineate activity spaces with descriptions of example applications. Anchor point (for example: home/work/school/sports club location). Geo-located movement. Activity space.

Source: Smith et al., (2019)

Some potential solutions:

- Select an unit of analysis, or buffer distance that **do not cause over aggregation of exposure** or health variables. Need sensitivity analysis. [My upcoming paper detailed with this issue]
- **Use a weighted/fuzzy distance** approach, when do not know what distances more appropriate (Chaix et al., 2009), for which health focus.
- Use **activity space** to determine more realistic exposure area. Smith et al., (2019) detailed some sate-of-the art approaches in activity space delineation.

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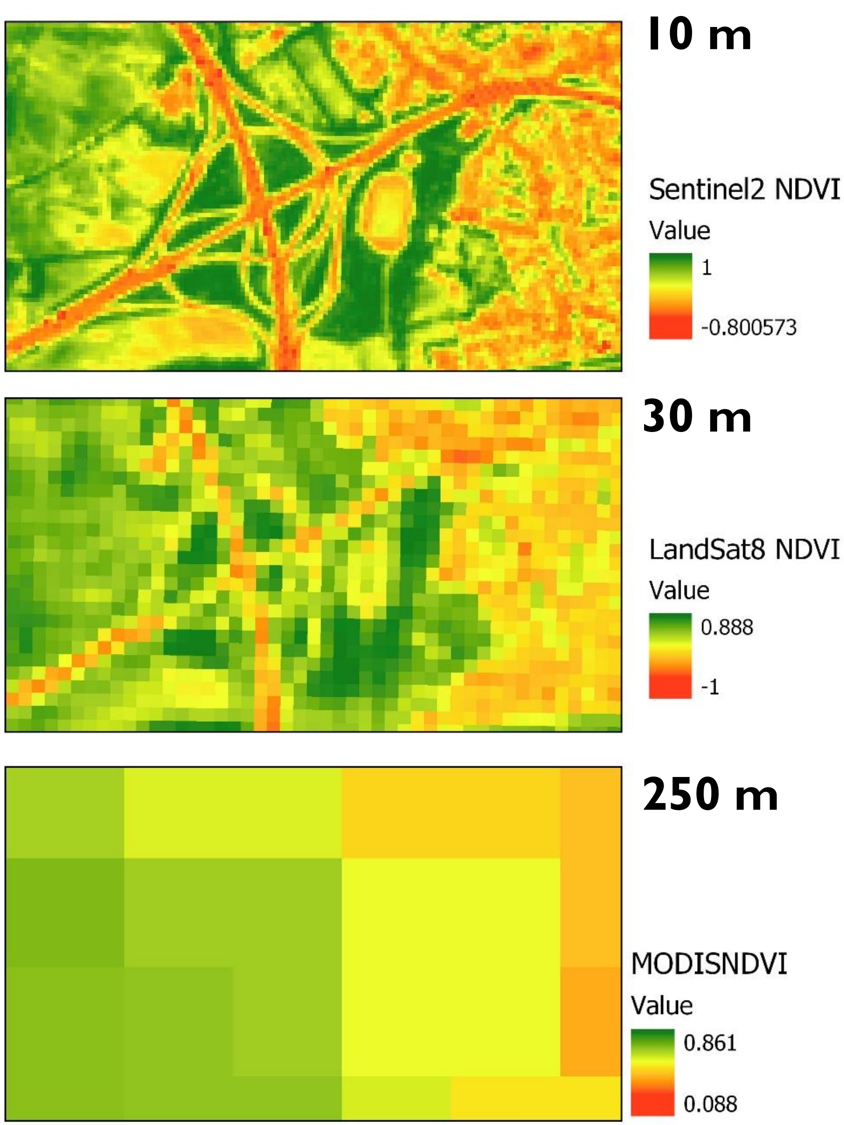
#Issue-2 Resolution of images and data capturing scale



- Resolution of the metrics of greenness can cause **misclassification of greenness**, and result in under or over estimation of exposure.
- Low spatial resolution could also **result in insignificant/ mixed** association with health outcomes (also Reid et al., 2018).
- Scale of analysis/ aggregation area sensitive to data resolution.

Some potential solutions:

- Use the **best resolution data** available, currently Sentinel-2 is the better free option (**Part 2, case study 1**)
- Select an aggregation unit/ exposure area/scale that **does not over aggregate** already misclassified exposure. [My upcoming paper investigated this for satellite images]

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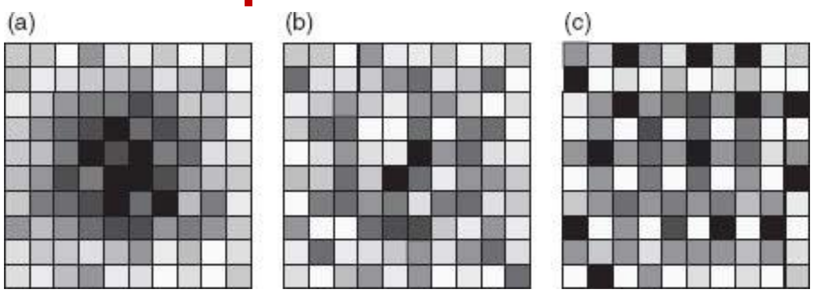
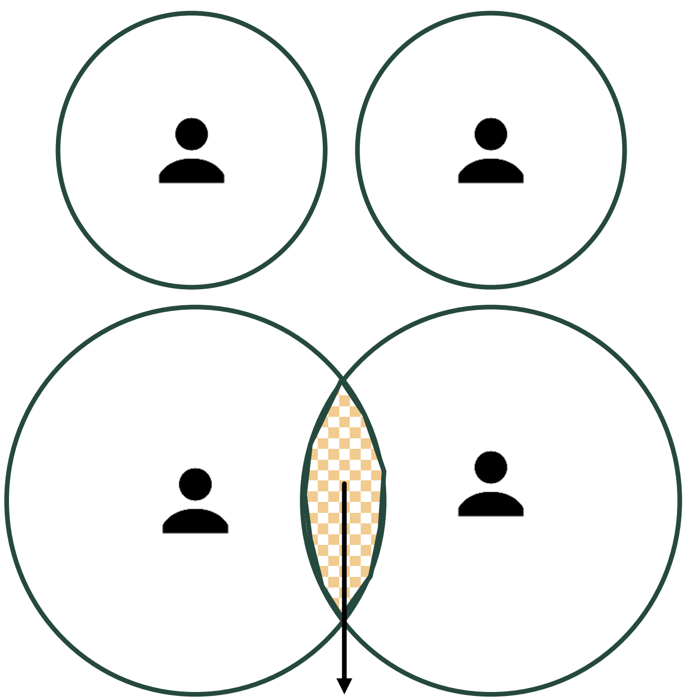
#Issue-3 Spatial autocorrelation



(a) Positive spatial autocorrelation. (b) Spatial randomness. (c) Negative spatial autocorrelation (Source: Fortin and Dale, 2009)



Larger buffer distances produce overlapping exposure areas, add autocorrelation

- All spatial data **usually have some autocorrelation, mostly positive.**
- Autocorrelation among observations can be **introduced with overlapping exposure areas**.
- Auto-correlated variables usually has less information, **reduced effective sample size, and vulnerable to Type-I error**, when using in a non-spatial modelling approach (e.g. linear regression).
- Spatial autocorrelation observed in few **greenspace and health studies**, most studies did not checked.

Some potential solutions:

- Test autocorrelation (e.g., Moran 'I)
- Apply spatial smoothing, or randomization.
- Apply **spatially explicit regression** (e.g., Geographically weighted regression, Bayesian spatial model), and test application of ML algorithms (**Part 3, example 2**).

Take home message

Part-1

- Spatial data and methods are integrated in environmental epidemiological studies
- ***Environmental exposure assessment*** frequently dependent on spatial methods.

Part-2

- A lot of spatial data available, can be used in different epidemiological studies.
- Free, ***open and easy access to big-spatial data*** via platforms like Google earth engine, OpenstreetMap. A lot of open access analytical tools available.

Part-3

- Spatial modelling framework provide opportunities to integrate multiple data, and models
- Adopting new algorithms allowing robust modelling
- ***Transferable modelling approach***

Part-4

- Applying spatial data, methods ***require careful attention*** in selecting data types, scale of analysis, and methods.
- ***Scale, resolution, MAUP, and autocorrelation*** can influence the associations among variables.
- Fine resolution data, ***appropriate scale, and spatially explicit modelling*** should be used environmental epidemiological studies.

Q-A

Thank you…
Any Questions!

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