Tracking global urban green space trends

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Urban green space

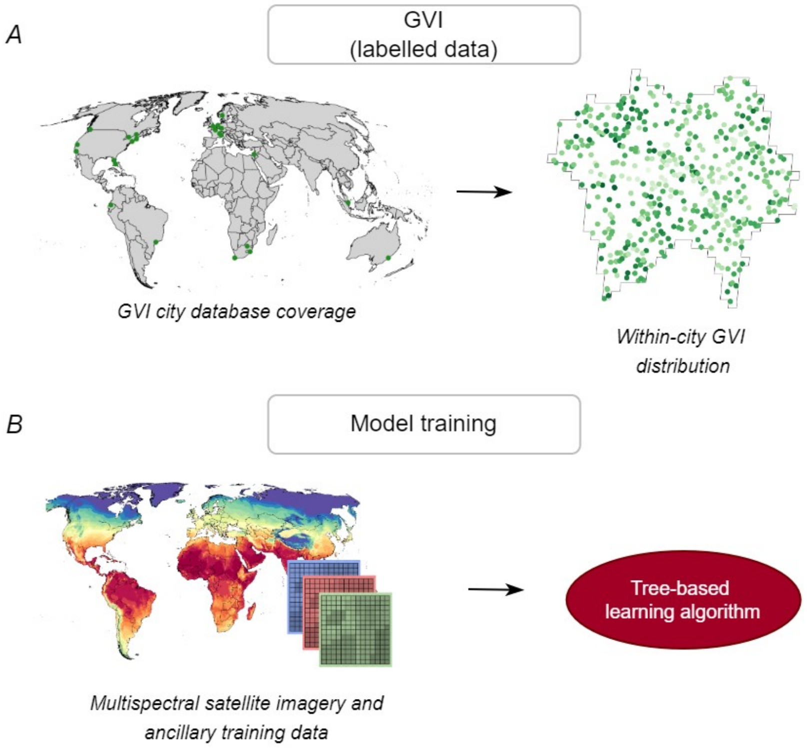
- **Urban green space (UGS) →** increasingly relevant indicator for evaluating the environmental and social sustainability of cities (*2022 Report of the Lancet Countdown*)

- **Provision of local ecosystem services** *(Derkzen et al. 2015)*, e.g. mitigating urban heat island effect (*Aram et al. 2019*), reducing impact of extreme precipitation events (*Farrugia et al. 2013*)

- Associated with increasing **well-being** of urban dwellers (*Reyes-Riveros et al. 2021*).

Study objectives

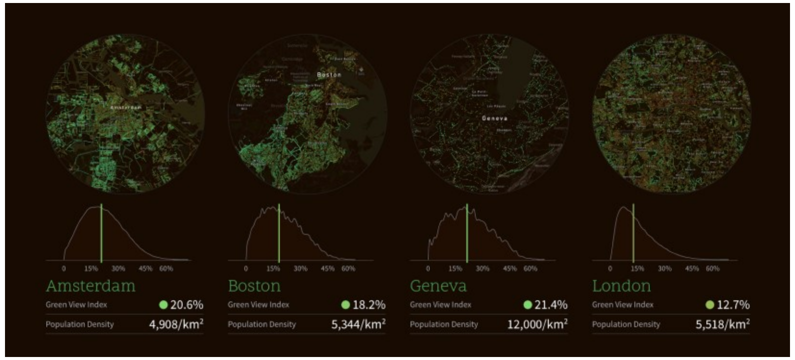
1. Train a **ML model** to predict **street-based vegetation presence (UGS) perception** indicator
2. Evaluate UGS **status and evolution in a global pool of large cities**
3. Enable **near-real-time tracking** of green space trends to support decision-making



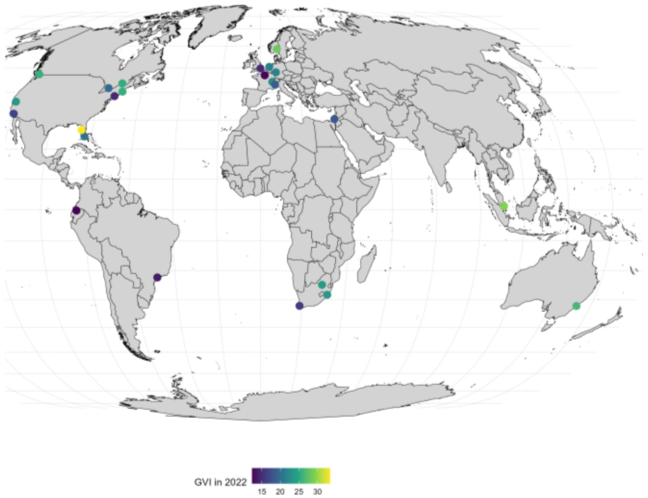
Labelled data: the Green View Index (GVI)

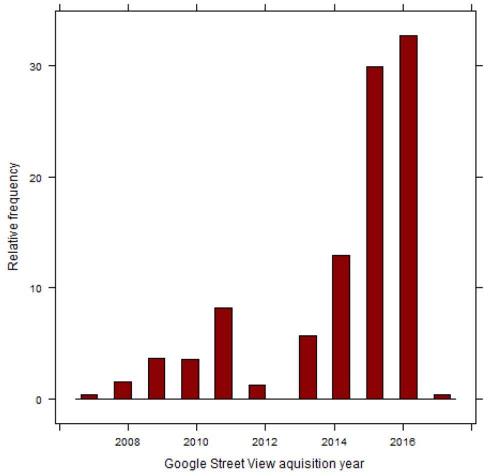
MIT Treepedia (http://senseable.mit.edu/treepedia)’s **Green View Index**, by which to evaluate and compare % of canopy cover, calculated using Google Street View panoramas
→ <u>human perception of the environment from the street level</u>

Seiferling et al. (2017); Xi et al. (2015); Li & Ratti (2018)



GVI – generation process and representative illustration (Ratti et al., Treepedia)





Global spatio-temporal distribution of labelled data

Training data and data preparation

Sources of predictors data

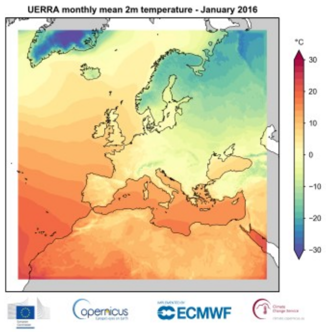
- Multispectral satellite imagery → Sentinel 2
- ERA5-Land historical climate → Copernicus
- Gridded population distribution → JRC GHS
- Global land cover map → Google
- GDP per capita → World Bank

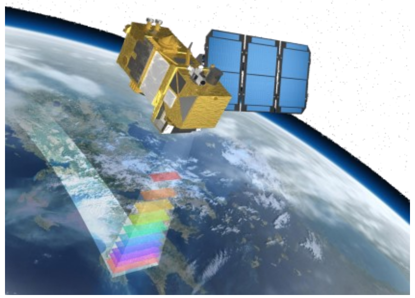
Data extraction

- Data extracted in **Google Earth Engine** (monthly averages)
- Data processing in **R** (parsing to GVI database)

Feature selection and engineering

- X-Y coordinates and polar coordinates
- 10-nearest neighbours spatial median of several key predictors





Methods

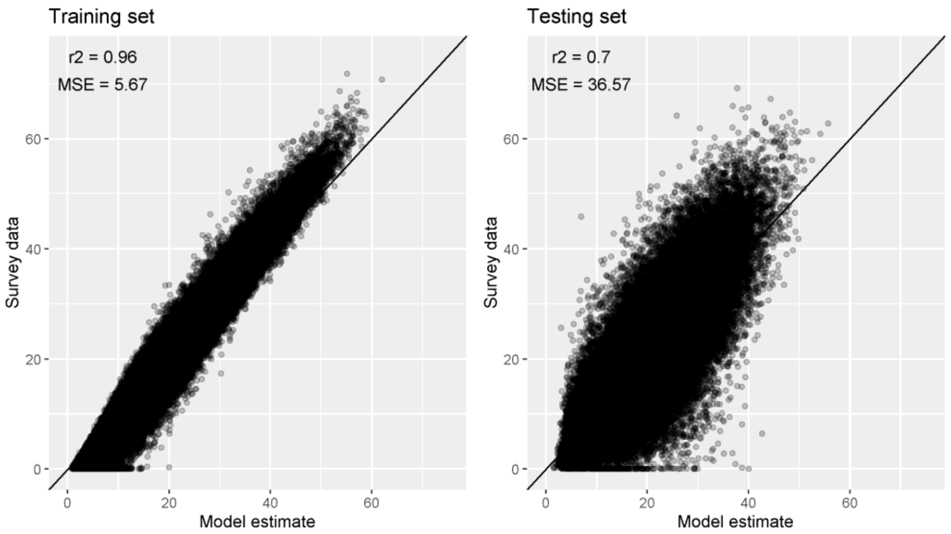
Model training & validation

- eXtreme Gradient Boosting (XGB) Regression
- *X*s → 24 features
- 10-fold spatial cross validation (SCV)
- Hyperparameters tuning based on Root Mean Squared Logarithmic Error (RMSLE)

Prediction in out-of-sample locations

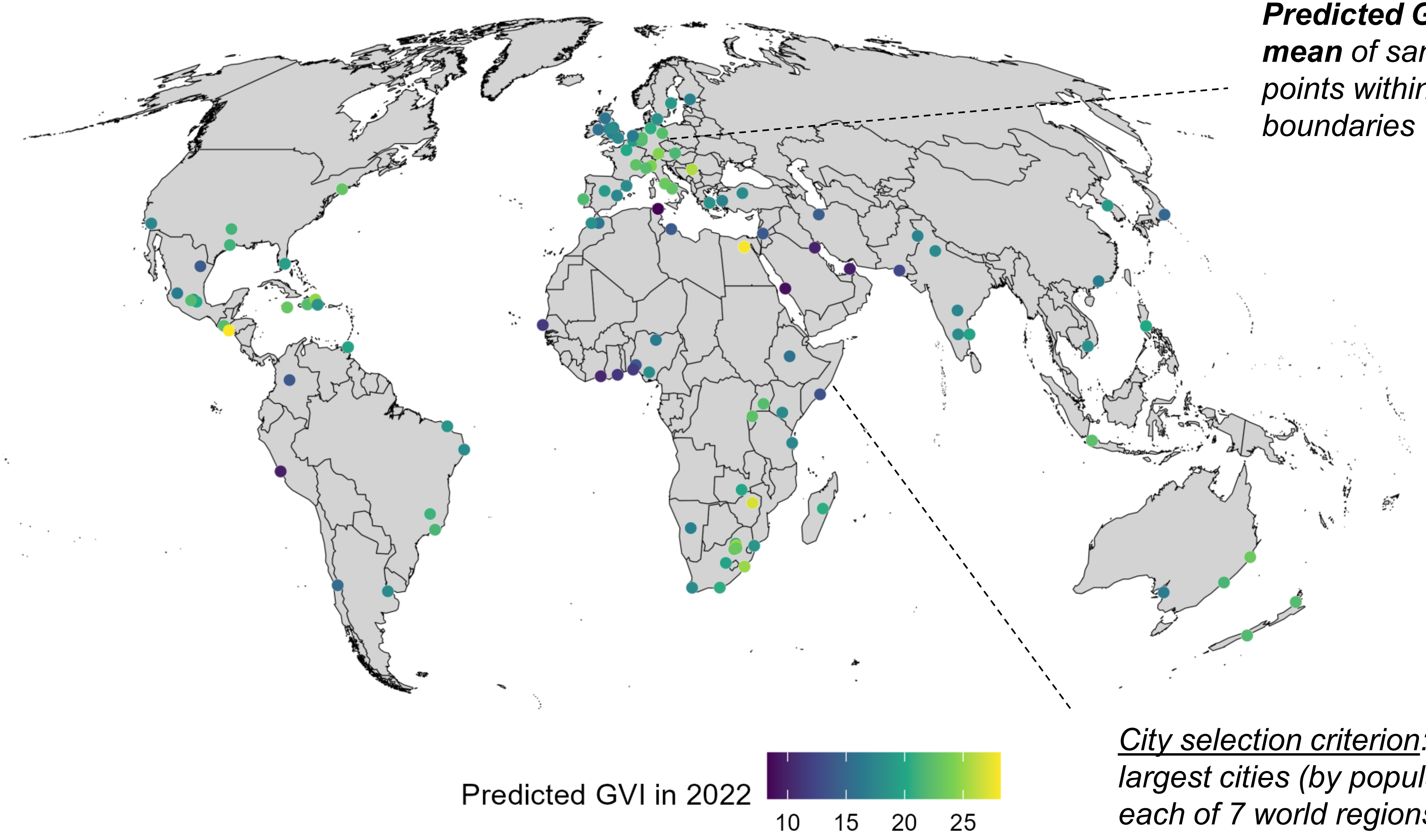
- Latin hypercube sampling (LHS) of points in 140 major global cities
- Extraction of predictor variables in points
- Model prediction

Spatial cross validation – representative example



Training and testing accuracies measured by R-squared

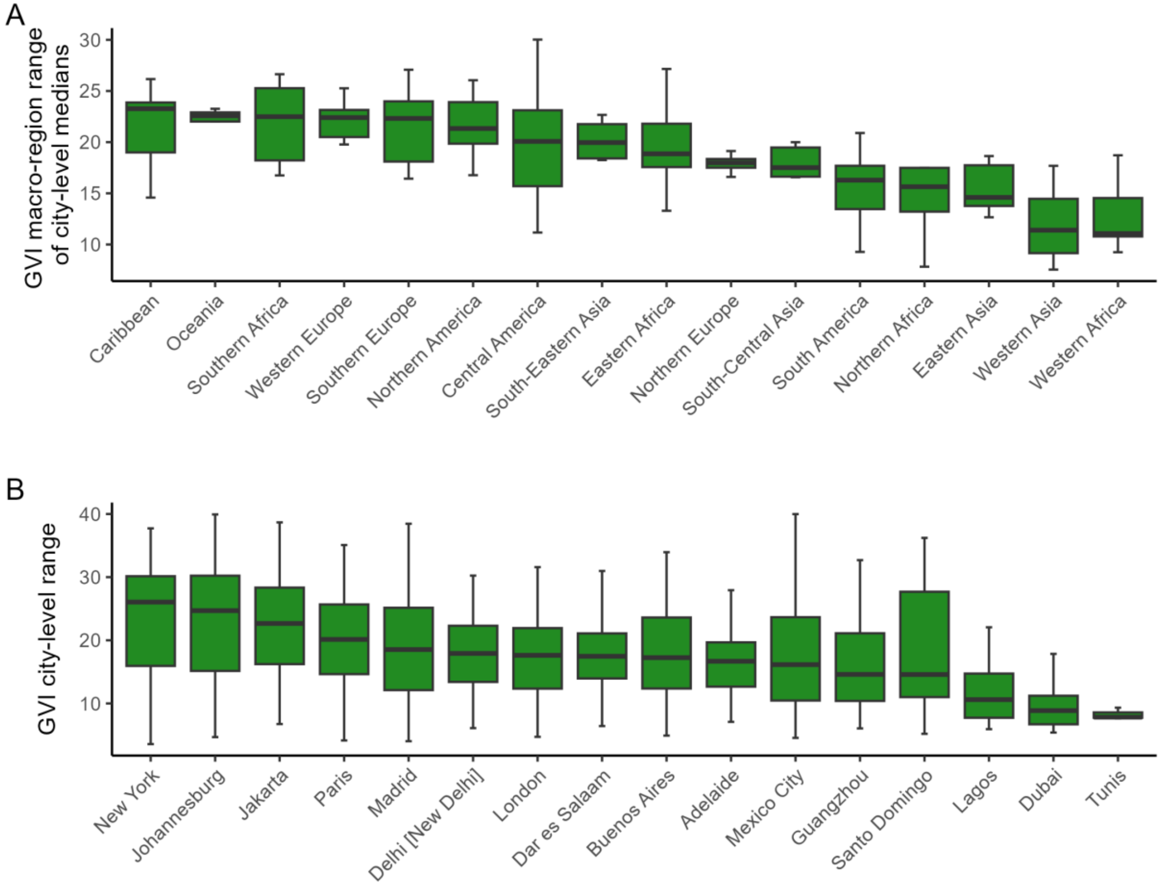
Results – mapping global UGS



Predicted GVI, mean *of sampled points within city boundaries*

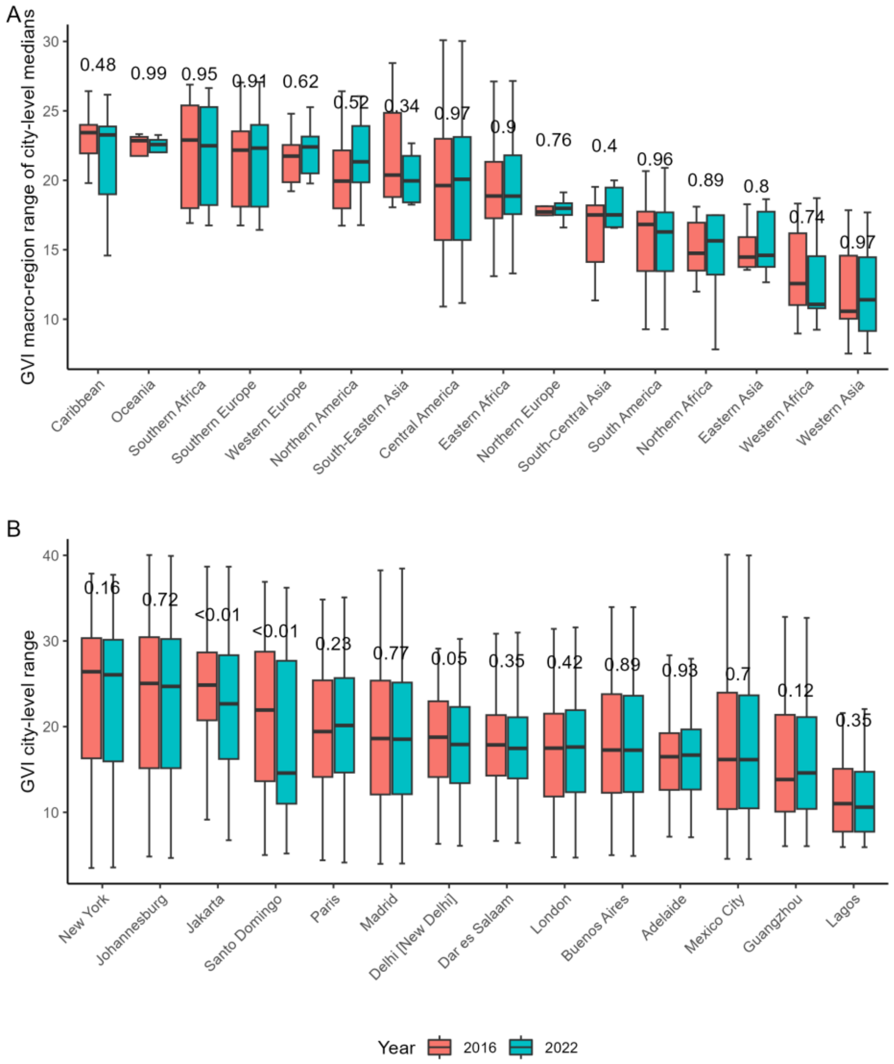
<u>City selection criterion</u>: 20 largest cities (by population) in each of 7 world regions

Results – UGS regional and city heterogeneity



- The **cities with the highest density of UGS** are found to be in the Caribbean, Oceania, Southern Africa, and South-western Europe
- Among the **greenest cities among the world metropolitan cities**, New York, Johannesburg, and Jakarta stand out.
- On the other hand, cities in East Asia and Northern and Western Africa are among the **least UGS-dense cities**
- For example, Lagos, Guanghzhou, and Mexico City show **low levels of UGS.**

Results – UGS evolution: 2016-2022



- Repeating predictions for 2016 and 2022, we can assess **IF and HOW MUCH the distribution of GVI in each city has changed.**

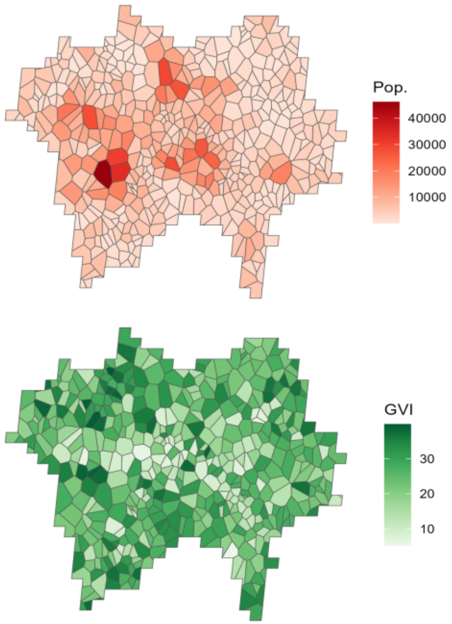
- Then, we can produce both **summaries** at the macro-regional level (panel A) and distributions at the city-level (panel B)

- The **p-value** shows the probability of a statistical change in the GVI mean value

- 2022-2016 is a relatively **short** period of time to observe a statistically significant change within a city

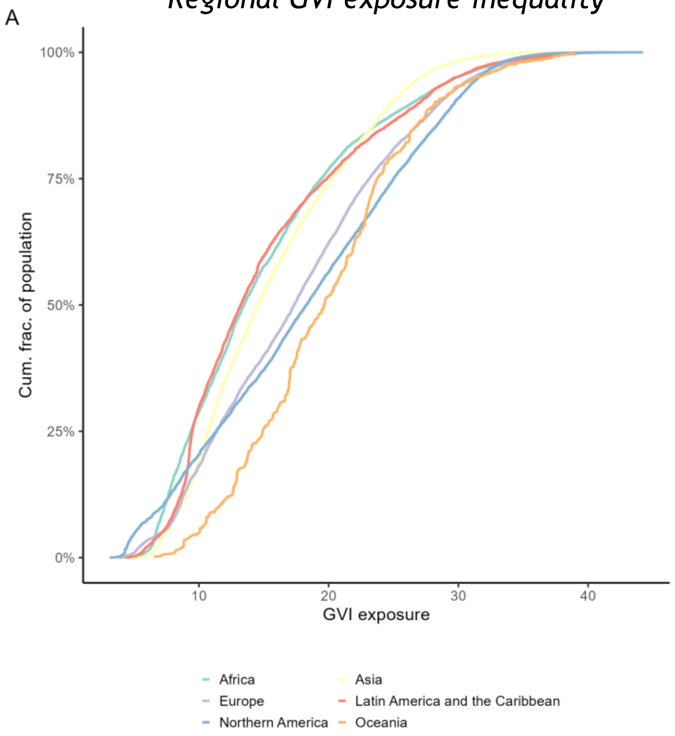
- Examples of stat-sig change are found in **Jakarta, Santo Domingo, where GVI has decreased significantly.**

Results – within-city UGS distribution

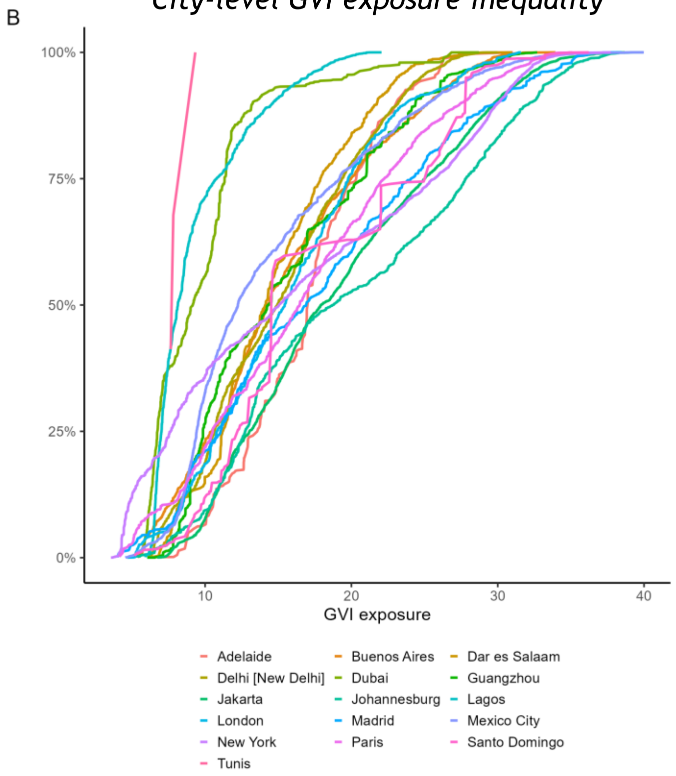


Example: predicted GVI and pop. distribution in Rome, Italy

Regional GVI exposure inequality



City-level GVI exposure inequality



- **Within-city** GVI vs. population distribution **UGS distribution inequality** analysis
- E.g., about 50% of **European** cities dwellers live in areas with GVI>20, against only 25% in **Latin America, Asia, And Africa**
- **Emblematic case:** in Cairo only **25%** of population exposed to GVI > 12, irrespective of **average GVI of 19.**

Conclusions

- Urban green space → **unequally distributed** both across and within the subset of the major global cities analysed.

- On average, mean UGS of **18.5** estimated, varying from **8.9 to 28.2** across cities.

- **Greenest cities** in **Southern Africa, the Caribbean, and Western Europe**, while regions with the **least UGS** are **Eastern and Western Asia, and West Africa.**

- Globally, based on the major global cities analysed, between 2016-2022 **UGS has diminished by 0.33 GVI points (-1.75% from 2016).** Yet, **6-year period is rather short** to observe a statistically significant change in mean city-level UGS in most cities.

- **Within-cities,** population exposure to UGS is **most equal** in Oceania and Southern Europe, and **most unequal** in Latin American, Asian and African cities.

- Global UGS policies can benefit from **near-real-time assessment and tracking**, also under the viewpoint of **environmental justice**. Particularly crucial in the developing world!

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Thank you!

Preprint **soon** available at

Earth ArXiv

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