

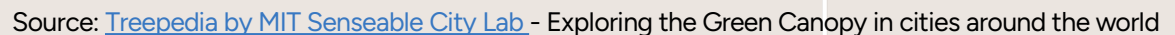


Street-Level Green View Index (GVI) Estimation from Satellite Image

Presenter: Jinghan Xu [jinghanx@kth.se]

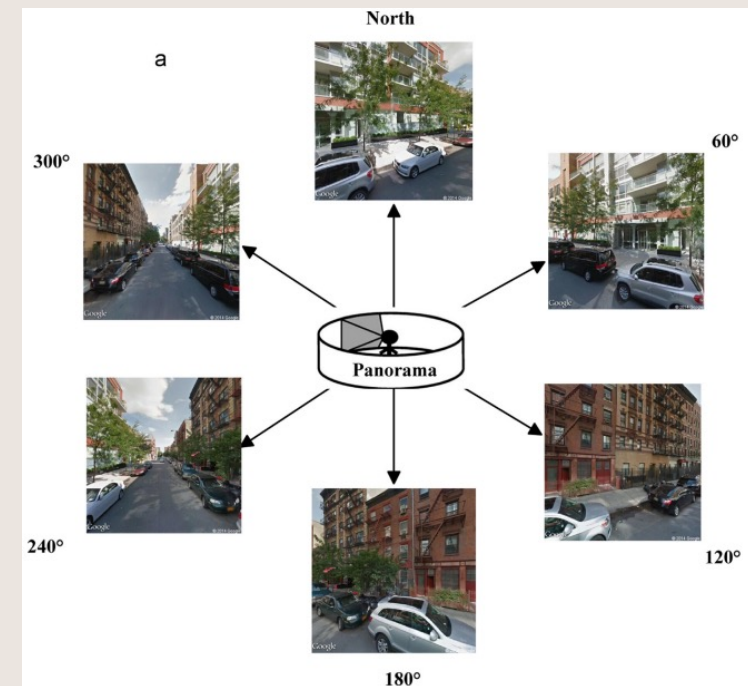
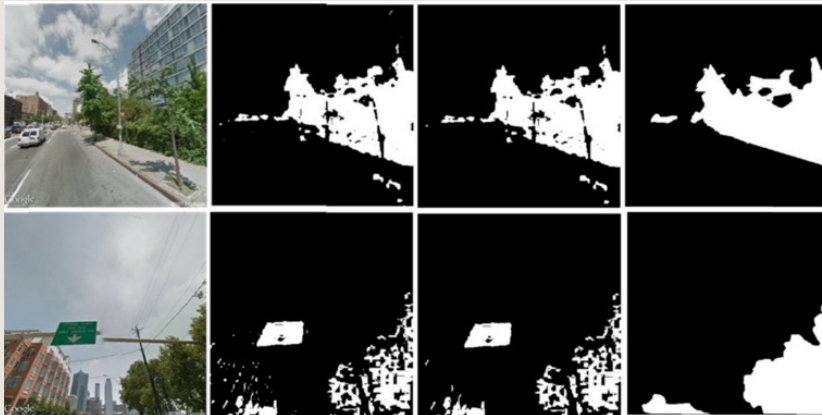
Supervisor: Yancheng Ling [Yancheng@kth.se], Zhenliang Ma [zhema@kth.se]

- An index to measure how much green one can experience when walking on the streets.
- Can be calculated by the percentage of green pixels in **street view images**.
- Can be used to describe **urban greenery quality**, e.g., how much the vegetations are benefiting citizens' living experience, especially along transport networks.



Background

- **GVI (Green View Index) Computing**
 - **Street view images** can be created as the previews of the panorama from Google Street Views, for a specified location (coordinate)
 - Simply, the green percentage can be calculated by **green pixels**, while some other more advanced semantic-based CV models are available.



Source: <https://doi.org/10.1016/j.ufug.2015.06.006>

Background

- **Current gap/limits - mostly computed using Street View Images, therefore:**
 - **Poor data availability:** low update frequency, high collecting cost, limitedly available area, for it requires vehicles to drive through.
 - **Difficult format-control:** different panorama collecting configuration, different update frequency.
 - **Computing resource-consuming:** each point requires several panorama previews to process



Question:

Can we make GVI calculation **less computing resource-consuming**, and **available at anytime & anywhere with low acquisition cost**?

Figure source: [ArchDaily](https://www.archdaily.com)

Background

- **Satellite imagery & remote sensing (RS):**
 - Collected by sensors installed on satellites.
 - Different materials / surfaces display unique spectral signature.

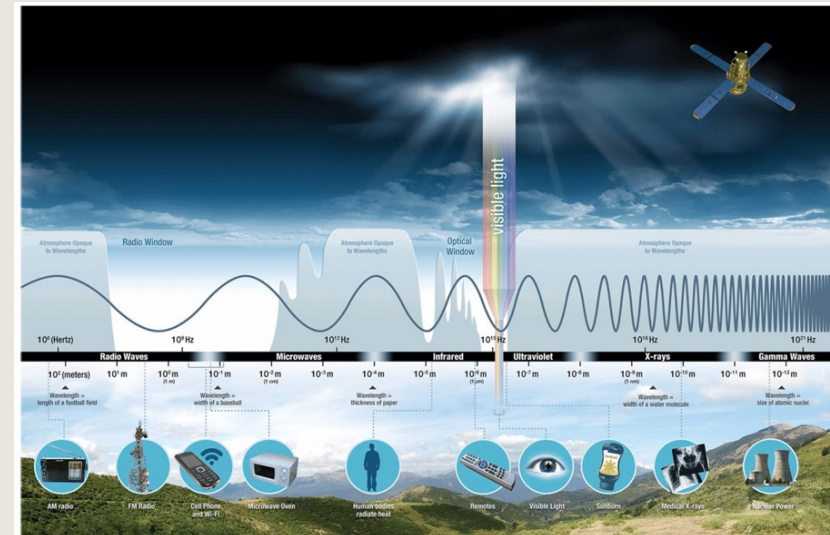
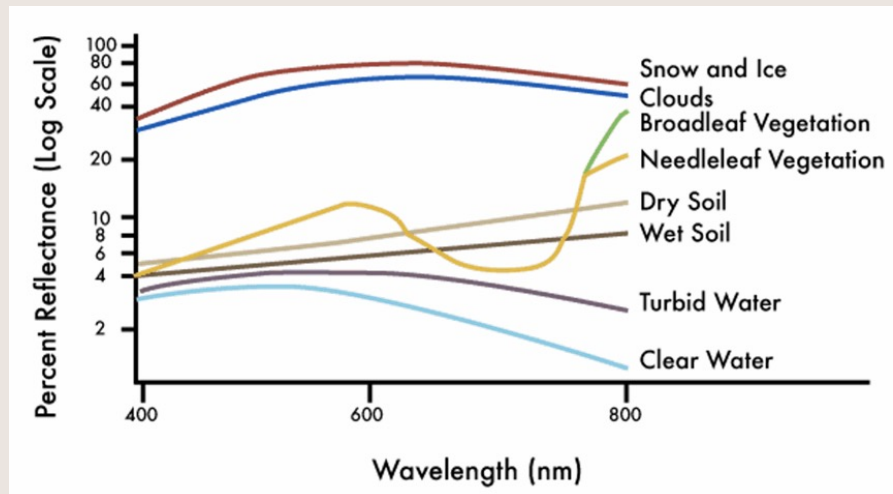










Figure source: NASA's Applied Remote Sensing Training Program

Methodology

- **Input features**

- Eight interpretable ground features derived from [Sentinel-2A](#) (updated every five days; open access. Resolution of used bands: 10-20 meters). Positive correlation to the described feature.

| | | |
|--|---|---|
|  NDVI Vege. Health & Density |  EVI Enhanced Vege. Index |  MNDWI Water Body Index |
|  UI Urban Index |  MSAVI Soil-Adjusted Vege. |  GNDVI Green Vegetation |
|  NDRE Chl Density |  BSI Bare Soil index | |

- Multiple buffer sizes for scale impact analysis, ranging from 200m to 1000m.
- **True label processing**
 - Computed based on Google Street View (GSV) images.
 - Four directions a point for GSV retrieval. Mean value to represent the ground truth GVI.
 - Semantic / color range-based kernel for vegetation detection -> pixel percentage as GVI value.



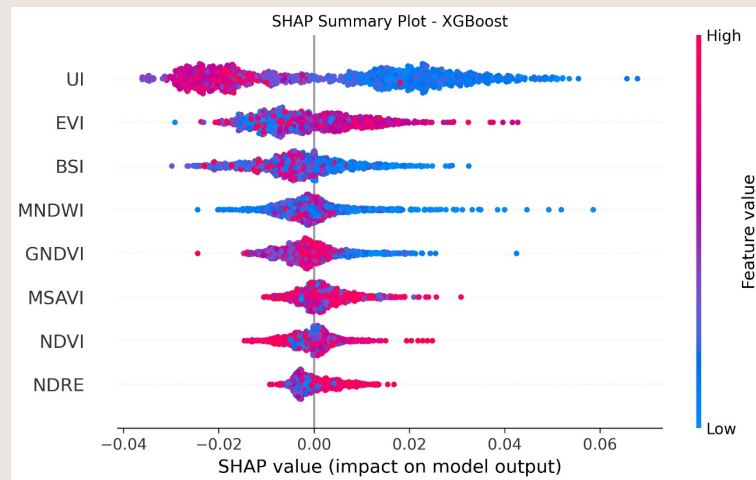
Methodology

- **Tree-based models**
 - Input mean-aggregated values for each sample.
 - Focus on large-scale impact.
 - Tested models: Random Forest, XGBoost, LightGBM, Gradient Boosting.
- **CNN-based models**
 - Input raster data for each sample.
 - Focus on fine-scale analysis.
 - Tested structures: light-weighted CNN, simplified CNN, ResNet18 backbone pretrained on ImageNet.
- **SHAP analysis**
 - Conducted for feature importance investigation and explainable results.

Case study

• Single-city analysis

- ~6,300 sampled locations in densed area of Helsinki.
- Tree-based model tested, R-square: 0.670; buffer size: 1000m; resolution: 20m).
- SHAP analysis conducted for feature importance investigation.



| Model | Test R ² | Test MSE | Test MAE |
|-------------------|---------------------|---------------|---------------|
| Linear Regression | 0.3054 | 0.0021 | 0.0345 |
| Ridge | 0.3071 | 0.0021 | 0.0345 |
| Lasso | -0.0008 | 0.0030 | 0.0431 |
| ElasticNet | -0.0008 | 0.0030 | 0.0431 |
| Decision Tree | 0.4015 | 0.0018 | 0.0284 |
| Random Forest | 0.6600 | 0.0010 | 0.0218 |
| Gradient Boosting | 0.6554 | 0.0010 | 0.0226 |
| XGBoost | 0.6704 | 0.0010 | 0.0221 |
| LightGBM | 0.6687 | 0.0010 | 0.0221 |
| SVR | 0.0512 | 0.0028 | 0.0447 |
| KNN | 0.5901 | 0.0012 | 0.0248 |

Case study

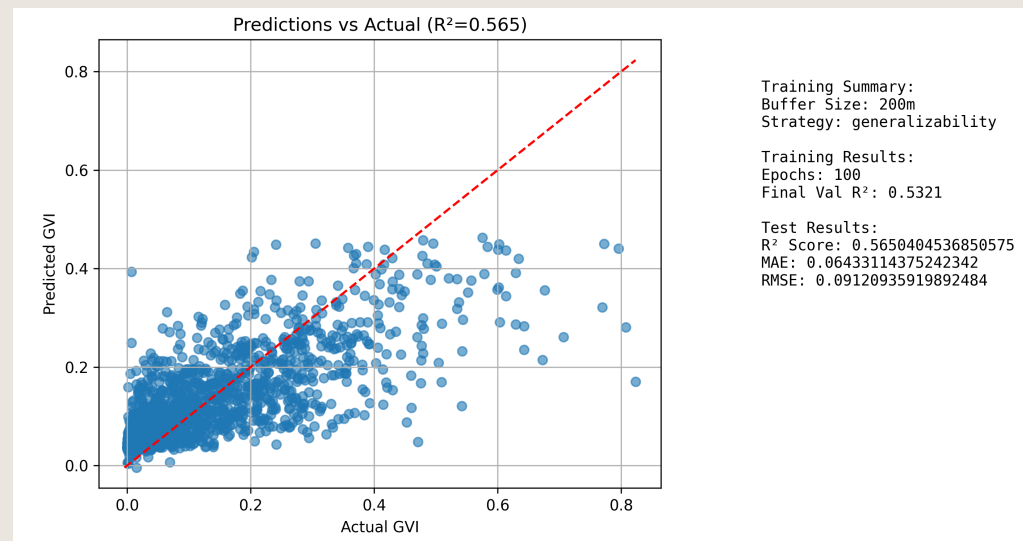
- **Multi-city analysis**

- Totally ~11,000 samples from 13 European cities:

- Sweden / Stockholm
- Finland / Helsinki
- Denmark / Copenhagen
- Germany / Berlin, Hamburg, Dusseldorf
- Spain / Barcelona
- UK / London, Manchester
- Greece / Athen
- Italy / Bologna, Milan
- Estonia / Tallin

- Generalizability test for CNN training

- Forming test set using samples from unseen cities (marked with underlines).
- Test R-Square = 0.565 (buffer size: 200m; resolution: 20m)



Key findings and discussions

- **For the single-city analysis (Helsinki):**
 - Tree-based models, despite poor generalizability, performs better under large buffer (1000m).
 - In SHAP analysis, UI, BSI, and EVI dominate for feature importance, while NDVI is not the most influencing among vegetation-related features.
- **For the multi-city analysis, the CNN models:**
 - Display better performances under smaller buffer (200m), and show potentials in good generalizability.
 - Achieve higher accuracy in low-value samples. This may be due to lack to of high-value samples for the model to learn about the patterns, or high-value cases require finer scales of information.

References

1. Yang J, Zhao L, McBride J, et al. Can you see green? Assessing the visibility of urban forests in cities[J]. Landscape and Urban Planning, 2009, 91(2): 97-104.
2. Li X, Zhang C, Li W, et al. Assessing street-level urban greenery using Google Street View and a modified green view index[J]. Urban forestry & urban greening, 2015, 14(3): 675-685.
3. Chen C, Wang J, Li D, et al. Unraveling nonlinear effects of environment features on green view index using multiple data sources and explainable machine learning[J]. Scientific Reports, 2024, 14(1): 30189.
4. Zhang L, Wang L, Wu J, et al. Decoding urban green spaces: Deep learning and google street view measure greening structures[J]. Urban Forestry & Urban Greening, 2023, 87: 128028.