

Kick-Off Meeting

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# **Urban Green Space Mapping Through Remote Sensing for Frankfurt/Main, Germany**

# Omdena

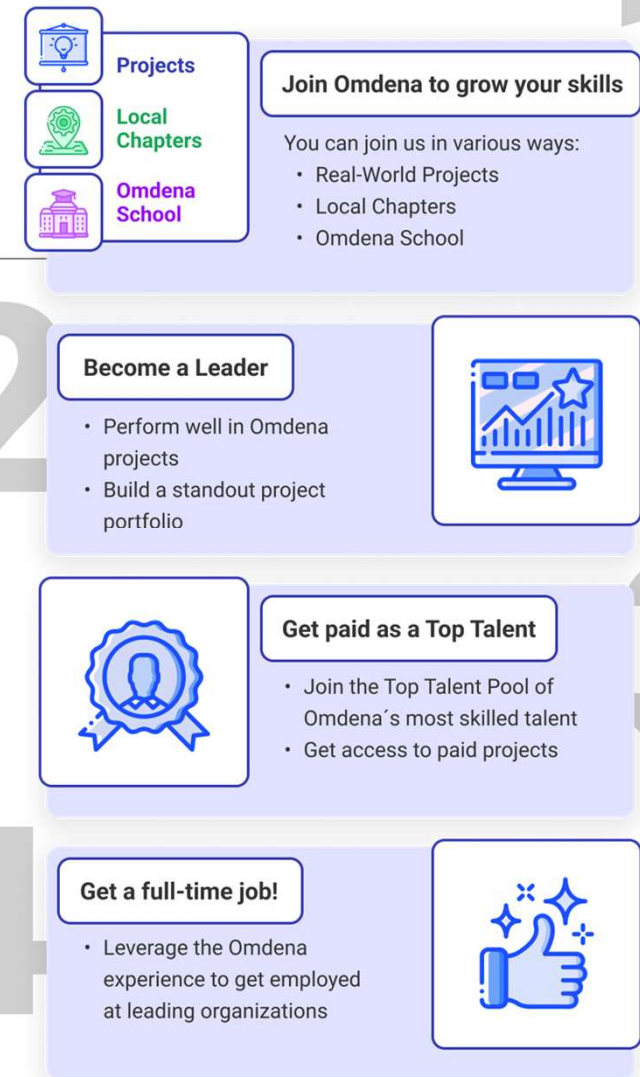
## Omdena Project Types:

- Local Chapter Challenges
- AI Innovation Challenges
- Top Talent Projects

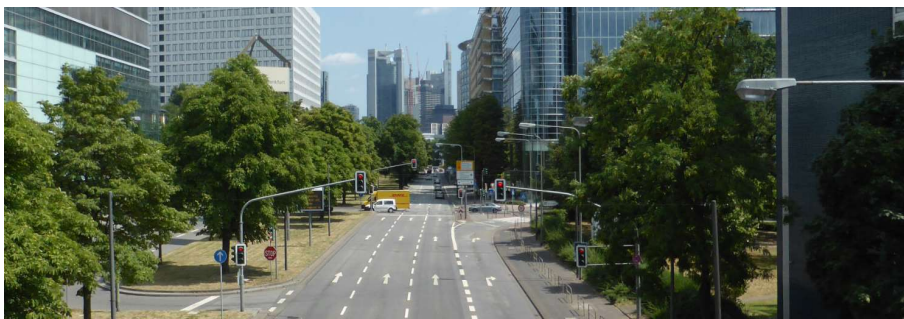
**The mission of Omdena Local Chapters** is to run open-source AI projects to solve challenges faced by local communities

- Chapters in 50+ countries
- Starting 10+ projects per month
- 80+ collaborators per project

**This is the first project of the Frankfurt Chapter**



# Urban Greenery



# Why map urban greenery – ‘cause you can plan and monitor it then

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## **SOTA of urban vegetation mapping:**

Ground observation of the entire urban greenery or purchasing imagery of high-resolution satellites is a costly affair. Thus, methods based on low-resolution missions such as Sentinel-2 are developed – often town-specific. Deep learning architectures can be thus trained to map individual trees for highly controlled image inputs. Benchmark studies so far are dominated by computationally expensive solutions – hindering their adoption.

## **SOTA of computer vision:**

Newly developed deep learning solutions claim to both be computationally more efficient and surpass detection limits. For example, in 2024 variations of the structured space state sequence model ‘mamba’ were adapted to remote sensing. Can it or alternative approaches from 2024 push both computational efficiency and detection limit?

## **The mission statement:**

Which services to monitor and plan urban greenery could we offer Frankfurt/Main and other cities? How reliable and precise while computational efficient can we get?



TABLE I: Classification results of Augsburg dataset in terms of F-1 score where  $\kappa$  = Kappa index, OA = Overall Accuracy, AA = Average Accuracy, respectively.

Class	HybridSN	ResNet	iFormer	Efficientformer	CoAtNet	SGU-MLP
Forest	0.88	0.83	0.91	0.88	0.85	<b>0.94</b>
Residential	0.89	0.83	0.89	0.9	0.87	<b>0.95</b>
Industrial	0.43	0.15	0.35	0.4	0.22	<b>0.63</b>
Low Plants	0.87	0.88	0.88	0.88	<b>0.98</b>	0.96
Allotment	0.13	0.1	0.13	0.11	0.09	<b>0.36</b>
Commercial	0.04	0.05	0.1	0.11	0.16	<b>0.28</b>
Water	0.35	0.19	0.21	0.25	0.19	<b>0.52</b>
OA×100	82.28	79.07	82.82	82.72	81.32	<b>91.82</b>
AA×100	55.76	43.57	52.96	52.81	49.9	<b>66.79</b>
$\kappa$ ×100	74.85	69.34	75.37	75.24	73.12	<b>88.22</b>

## Outcome of benchmarked methods

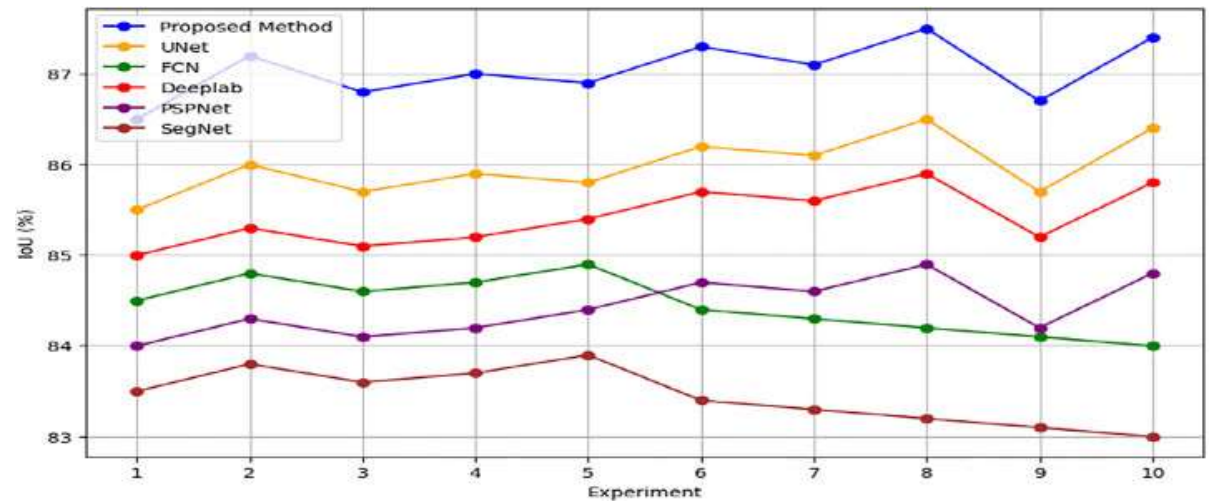
TABLE II: Classification results of Berlin dataset in terms of F-1 score where  $\kappa$  = Kappa index, OA = Overall Accuracy, AA = Average Accuracy, respectively.

Class	HybridSN	ResNet	iFormer	Efficientformer	CoAtNet	SGUMLP
Forest	0.71	0.64	0.69	<b>0.73</b>	0.65	<b>0.73</b>
Residential	0.8	0.81	<b>0.82</b>	0.81	0.76	<b>0.82</b>
Industrial	<b>0.49</b>	0.39	0.35	0.32	0.32	0.41
Low Plants	0.59	0.35	0.72	0.7	0.59	<b>0.72</b>
Soil	0.65	0.72	0.7	0.67	<b>0.75</b>	0.67
Allotment	0.44	0.28	0.34	0.29	0.3	<b>0.46</b>
Commercial	<b>0.45</b>	0.25	0.29	0.24	0.29	0.27
Water	<b>0.65</b>	0.53	0.49	0.38	0.28	0.48
OA×100	66.81	63.7	68.6	68.17	63.14	<b>70.79</b>
AA×100	62.67	58.23	62.84	60.05	60.53	<b>66.26</b>
$\kappa$ ×100	55.84	47.61	55.28	54.32	49.21	<b>58.06</b>

TABLE III: Classification results of Houston dataset in terms of F-1 score where  $\kappa$  = Kappa index, OA = Overall Accuracy, AA = Average Accuracy, respectively.

Class	HybridSN	ResNet	iFormer	Efficientformer	CoAtNet	SGUMLP
Healthy Grass	0.85	0.88	0.86	0.89	<b>0.9</b>	0.89
Stressed Grass	0.84	<b>0.9</b>	0.87	0.87	0.88	0.89
Synthetic Grass	0.84	0.78	0.5	0.58	0.72	<b>0.97</b>
Tree	0.87	0.89	0.92	0.91	0.93	<b>0.94</b>
Soil	0.96	0.94	0.93	0.95	0.85	<b>0.99</b>
Water	<b>0.73</b>	0.71	0.29	0.39	0.25	0.35
Residential	0.69	0.72	0.68	0.6	0.79	<b>0.81</b>
Commercial	0.69	0.39	0.68	0.56	0.6	<b>0.83</b>
Road	0.7	0.57	0.75	0.77	0.82	<b>0.85</b>
Highway	0.58	0.52	0.45	0.54	0.54	<b>0.89</b>
Railway	0.7	0.54	0.67	0.57	0.67	<b>0.82</b>
Parking Lot1	0.74	0.42	0.48	0.71	0.55	<b>0.96</b>
Parking Lot2	<b>0.94</b>	0.61	0.72	0.78	0.58	0.9
Tennis Court	0.84	0.77	0.74	0.73	0.56	<b>0.99</b>
Running Track	0.64	0.82	0.83	0.61	0.92	<b>0.95</b>
OA×100	75.62	68.16	71.03	71.66	72.67	<b>87.91</b>
AA×100	76.44	71.42	72.86	70.69	75.62	<b>89.33</b>
$\kappa$ ×100	73.59	65.49	68.71	69.25	70.56	<b>86.91</b>

### Deep learning and generative adversarial networks Vs Traditional methods (ISPRS Potsdam IoU %)



<https://pmc.ncbi.nlm.nih.gov/articles/PMC11257302/>

<https://arxiv.org/pdf/2308.05235>

# Your learning outcome of this project

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(1) Conquer new topics in Data Science and Deep Learning through **collaboration** – a systematic way of entering new knowledge fields such as:

- spatial data
- computer vision
- U-net/mamba/SGU-MLP/etc

(2) Listen to talks of local stakeholders in urban vegetation planning

(3) Get inspiration for what is technically possible in urban planning enhanced through environmental sensing and AI



# **The Project Team**

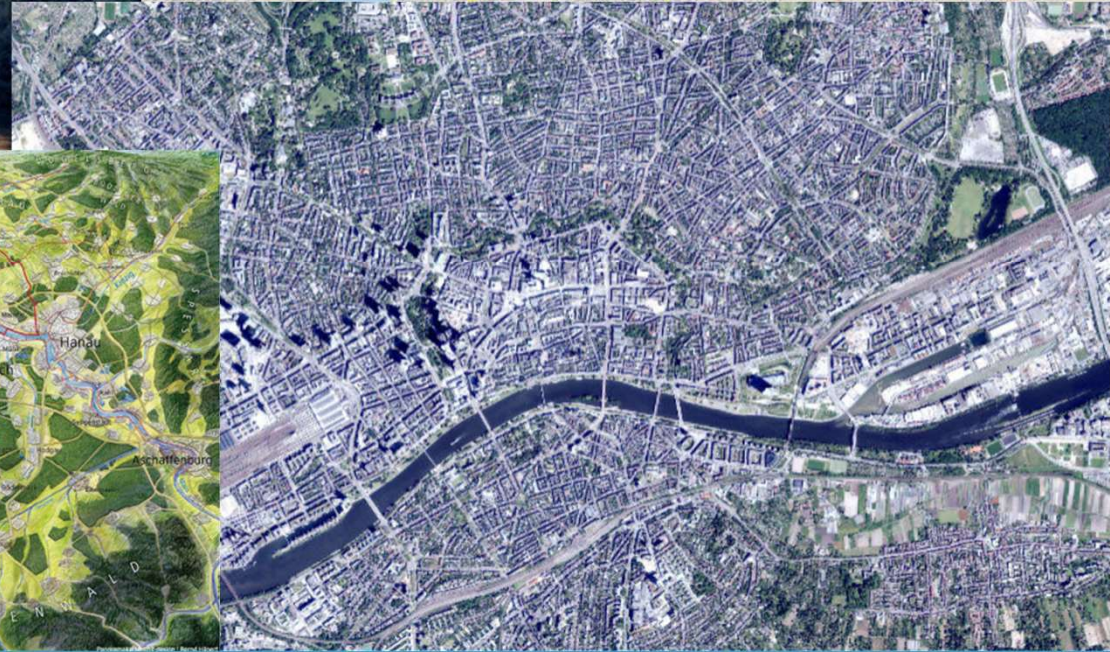
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# The location and data

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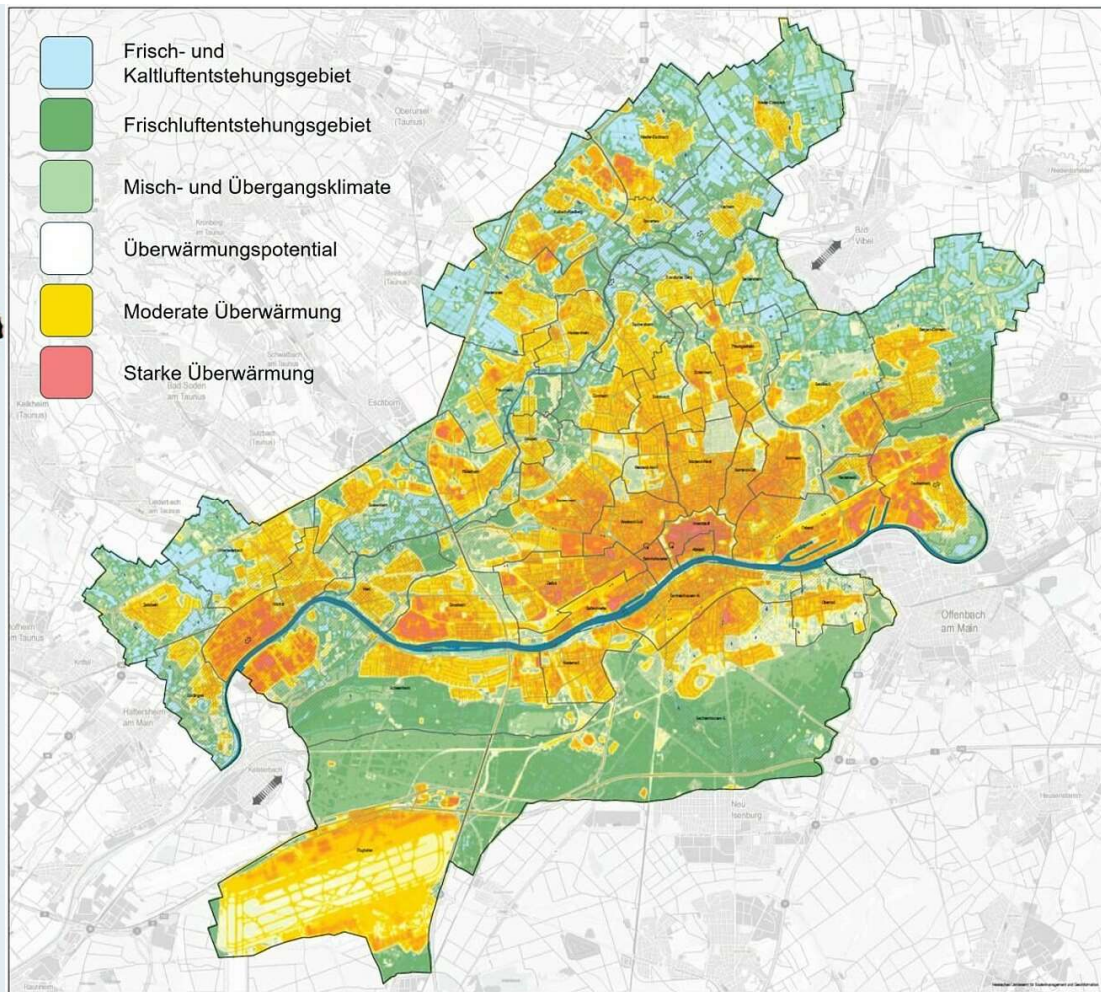
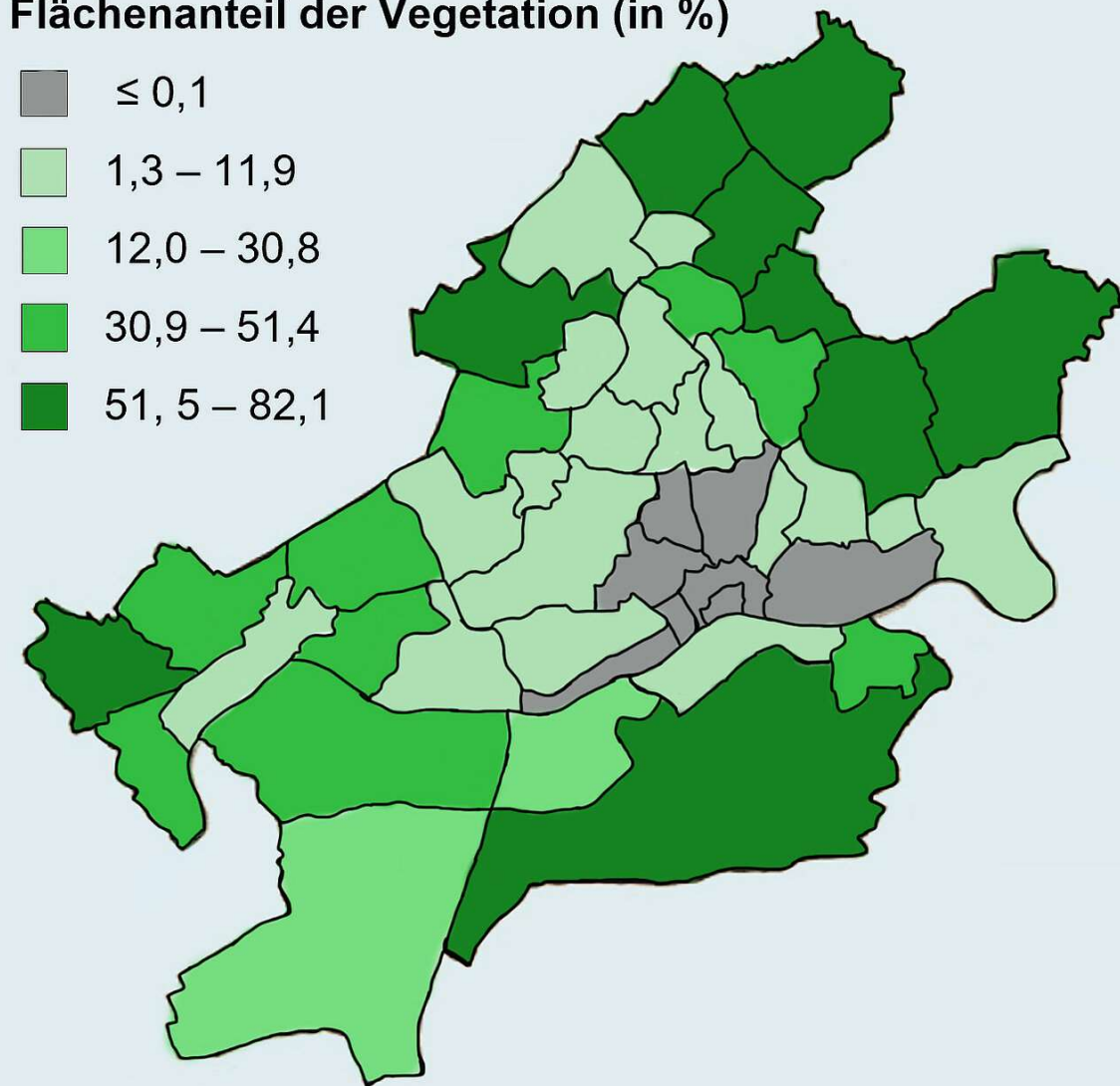
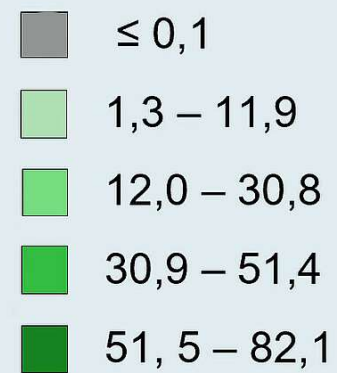


Population: 800,529 (2024)  
Size: 248 square kilometers  
Population density: 3,200 inhabitants per square kilometer  
Number of jobs: 734,000 (2022)  
**Daily commuters: 1.34 million to 430k people**





# Flächenanteil der Vegetation (in %)

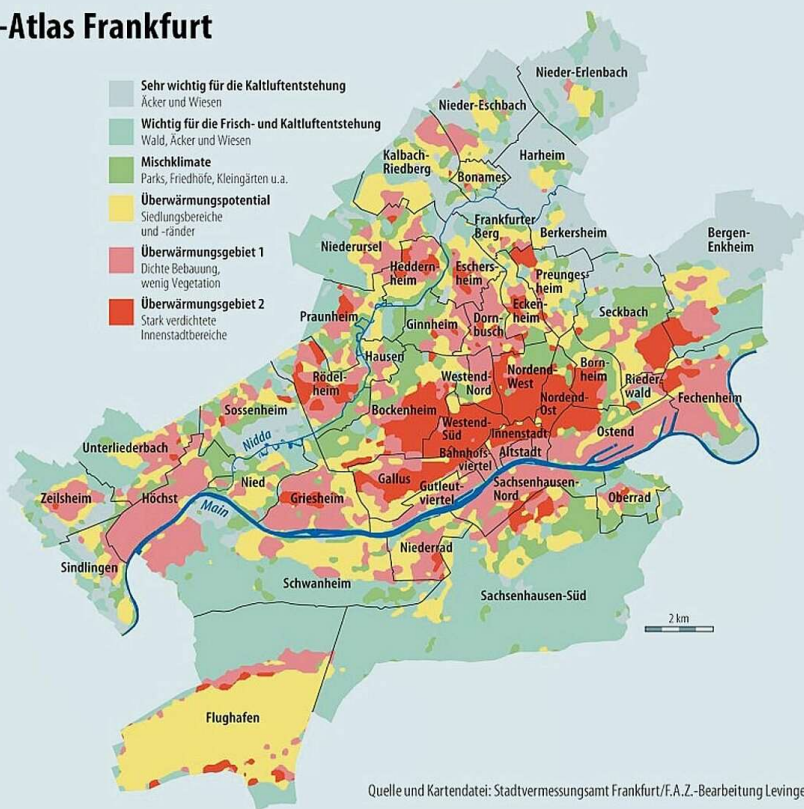


Share vegetation space: 40 %  
 Share building space: 40 %  
 Number of city trees: ~200'000

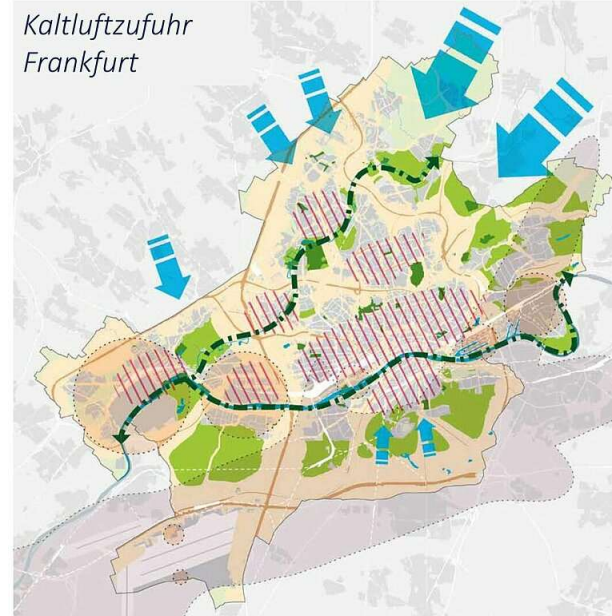


# Besides vegetation wind management shapes urban heat

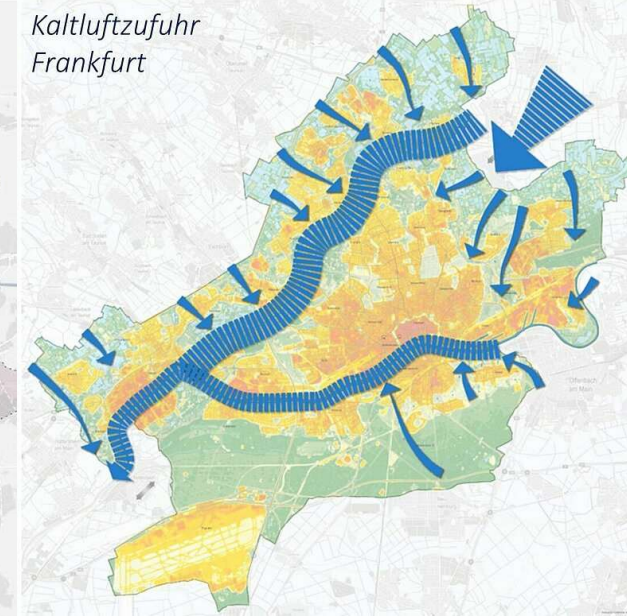
## Klimaplan-Atlas Frankfurt



Kaltluftzufuhr  
Frankfurt

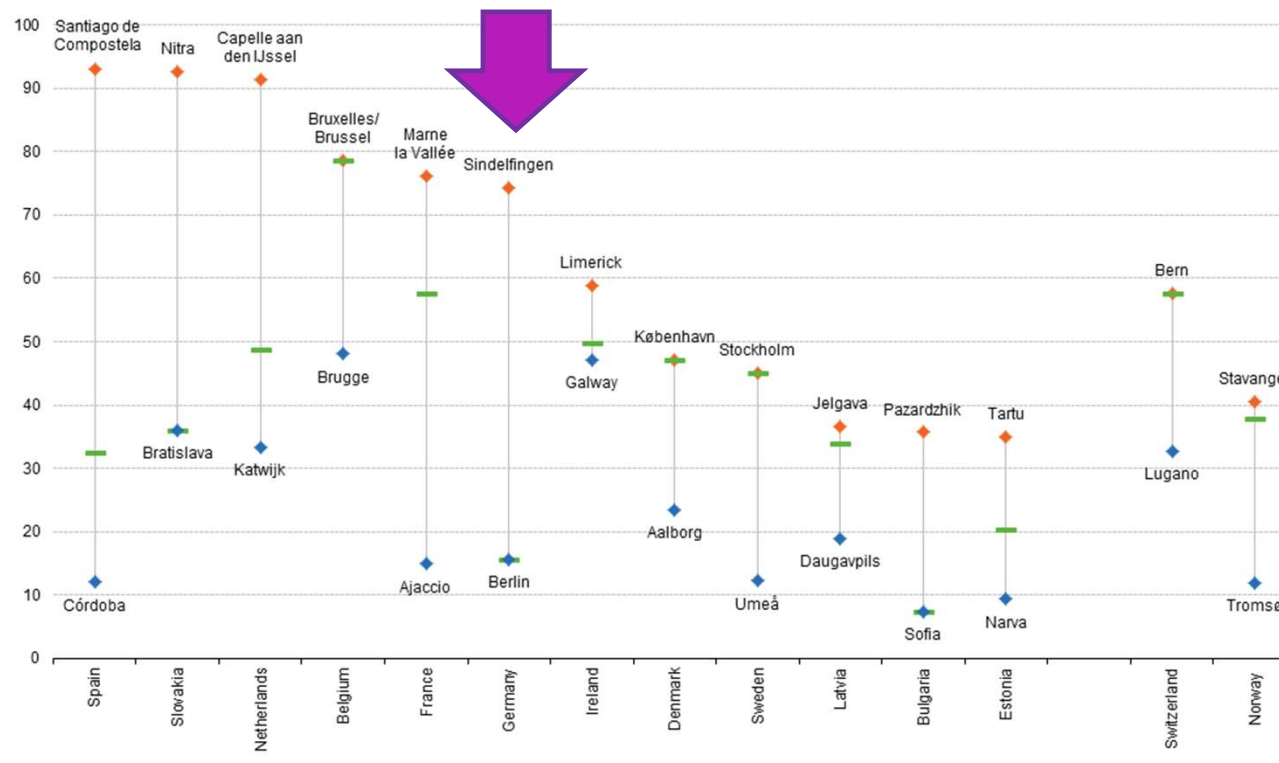


Kaltluftzufuhr  
Frankfurt



While Frankfurt's skyline is representative of modern global cities, its **topographical variance**—with hills, rivers, and surrounding forests—may be more pronounced than in many other urban centers.

## Fun facts about Frankfurt...



- Frankfurt/Main is a leading commuter hub
- The RheinMain region contributes 5-6% of Germany's GDP
- It is home to the European Central Bank
- Its airport handles: 6-7% of total EU passenger traffic, 4-5% of total EU flight movements, 12-15% of the EU's total cargo volume

# As a developed city Frankfurt monitors its green extensively...

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Frankfurt has approximately 58% of its space compromised by green space (including e.g. private gardens) – that is below the German average (86%) but well above the European average (42%)

Public parks make up only 4.3% of the city space

City-wide initiatives for green monitoring or more green:

- Grünflächenamt
- Umweltamt Frankfurt
- Klima-Büro Frankfurt
- AI Frankfurt
- Frankfurt Green City
- Frankfurt frischt auf
- Altes Neuland Frankfurt

## ***BUT***

Green space is not evenly distributed over the town

Only 1.3% of the town budget (~4 billion Euros annually) are spent on environmental concerns – 1/5th of that is spent on garbage disposal

## Besides Sentinel-2 imagery, this project is based on this data:

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Web-view of Frankfurt city data: <https://geoportal.frankfurt.de/karte/>

HR air photos of Frankfurt as tiff (summer of 2023): <https://www.govdata.de/suche/daten/atkis-dop-20>

HR air photos of Frankfurt as WMS (summer of 2023):  
[https://www.geoportal.hessen.de/mapbender/php/mod\\_showMetadata.php?resource=layer&languageCode=de&id=54451](https://www.geoportal.hessen.de/mapbender/php/mod_showMetadata.php?resource=layer&languageCode=de&id=54451)

Inventory (with species name) of urban city trees: <https://data.europa.eu/data/datasets/73c5a6b3-c033-4dad-bb7d-8783427dd233?locale=en>

Open Street Map Frankfurt: <https://www.openstreetmap.org/relation/62400#map=15/50.11209/8.67581>

Biotop Kartierung Frankfurt am Main: <https://offenedaten.frankfurt.de/dataset/biotopkartierung-2021-wfs-und-wms-frankfurt-am-main>

Rain-runoff map Frankfurt am Main: <https://offenedaten.frankfurt.de/dataset/starkregengefahrenkarten-wms-2021-frankfurt-am-main>

For WMS/WFS data, you can access them through python or download the GUI freeware QGIS



# Methodology and project plan

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# What resolution does to your remote image...

HyMap (3.6 m)

simulated EnMAP (30 m)

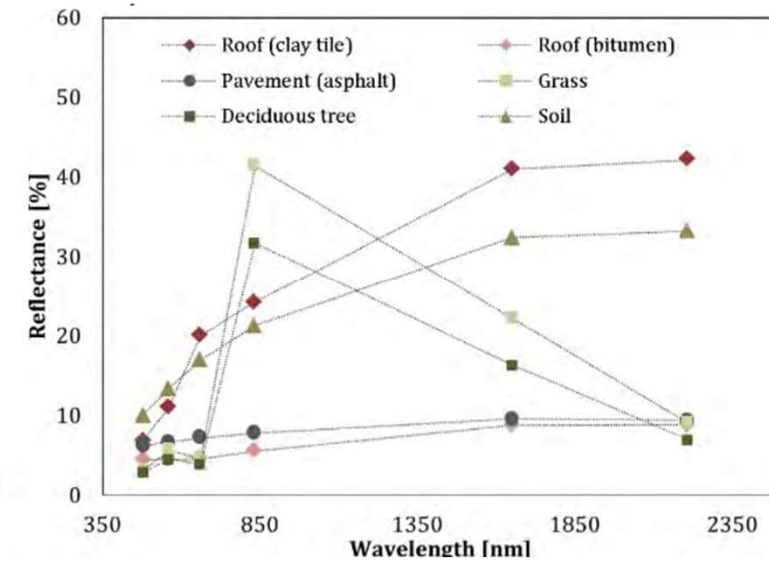
dense-urban area



peri-urban area



Landsat ETM+ (30 m; 6 spectral bands)



# The Problem Statement again...

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Urban green space can be smaller than the coarse pixel resolution

How to approach this:

Superresolution

<https://arxiv.org/pdf/2302.11494>

„Simple“ Spectral Unmixing

Includes advanced kernel-based methods

Spectral Clustering

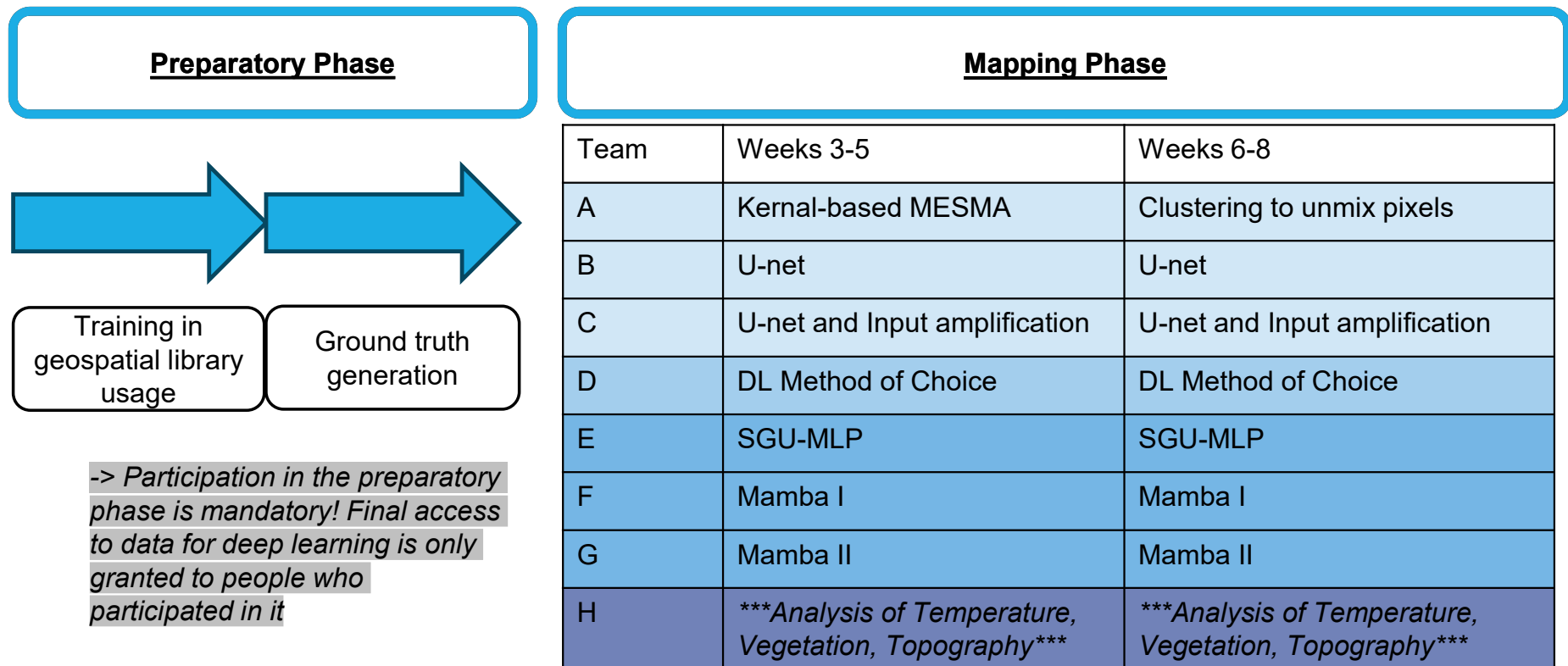
unsupervised

Supervised ML

Deep Learning

**\*\*State of the art?**

# Project Plan – Weekwise



# The preparatory phase

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**Challenge: append map of urban vegetation in Open Street Map with information from 20cm \* 20cm resolution air photographs**

Use method described here:

<https://www.mdpi.com/2220-9964/10/4/251>

[https://heidata.uni-](https://heidata.uni-heidelberg.de/dataset.xhtml;jsessionid=a64fd55022cde3237c69553fbfb4?persistentId=doi%3A10.11588%2Fdata%2FUYSAA5&version=&q=&fileTypeGroup)

[heidelberg.de/dataset.xhtml;jsessionid=a64fd55022cde3237c69553fbfb4?persistentId=doi%3A10.11588%2Fdata%2FUYSAA5&version=&q=&fileTypeGroup](https://heidata.uni-heidelberg.de/dataset.xhtml;jsessionid=a64fd55022cde3237c69553fbfb4?persistentId=doi%3A10.11588%2Fdata%2FUYSAA5&version=&q=&fileTypeGroup)

<https://mirror.netcologne.de/CCC/events/sotm/2019/h264-hd/sotm2019-1899-eng->

[Assessing\\_the\\_Completeness\\_of\\_Urban\\_Green\\_Spaces\\_in\\_OpenStreetMap\\_hd.mp4](https://mirror.netcologne.de/CCC/events/sotm/2019/h264-hd/sotm2019-1899-eng-)

<https://senseable.mit.edu/treepedia>

Sample changes and visually expect them.

# The preparatory phase - teams

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## **Week 1:**

Each participant can join 1 out of 8 teams – each team covers a different geographic area

The teams practice together the use of geospatial libraries in python

## **Week 2:**

Code to append Google Street Maps will be provided

The teams can test and improve the code for their region

The teams will visually inspect samples of their results

*\*\*\*Additionally, vegetation will be compared with Biotop Map*



# Some reading for the Mapping Phase

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## MESMA and Clustering:

- [https://zhouyuanzxcv.github.io/files/papers/Zhou%20et%20al\\_2020\\_Unmixing%20urban%20hyperspectral%20imagery%20using%20probability%20distributions%20to%20represent%20endmember%20variability.pdf](https://zhouyuanzxcv.github.io/files/papers/Zhou%20et%20al_2020_Unmixing%20urban%20hyperspectral%20imagery%20using%20probability%20distributions%20to%20represent%20endmember%20variability.pdf)
- <https://www.cedric-richard.fr/Articles/chen2011novel.pdf>
- <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0124608>
- <https://arxiv.org/pdf/2001.07307>
- [https://www.researchgate.net/profile/Rob-Heylen-2/publication/264564339\\_A\\_Review\\_of\\_Nonlinear\\_Hyperspectral\\_Unmixing\\_Methods/links/53f485700cf2888a7491048d/A-Review-of-Nonlinear-Hyperspectral-Unmixing-Methods.pdf](https://www.researchgate.net/profile/Rob-Heylen-2/publication/264564339_A_Review_of_Nonlinear_Hyperspectral_Unmixing_Methods/links/53f485700cf2888a7491048d/A-Review-of-Nonlinear-Hyperspectral-Unmixing-Methods.pdf)
- <https://www.mdpi.com/2072-4292/16/15/2851>

## U-net:

- <https://sh-tsang.medium.com/review-recurrent-u-net->

[for-resource-constrained-segmentation-a50c769e2b50](https://www.researchgate.net/profile/Tony-Boston/publication/384330477_Deep_learning_convolutional_neural_networks_for_Landsat-derived_land_cover_mapping/links/66f4bb89906bca2ac3c9bc17/Deep-learning-convolutional-neural-networks-for-Landsat-derived-land-cover-mapping.pdf)

- [https://www.researchgate.net/profile/Tony-Boston/publication/384330477\\_Deep\\_learning\\_convolutional\\_neural\\_networks\\_for\\_Landsat-derived\\_land\\_cover\\_mapping/links/66f4bb89906bca2ac3c9bc17/Deep-learning-convolutional-neural-networks-for-Landsat-derived-land-cover-mapping.pdf](https://www.researchgate.net/profile/Tony-Boston/publication/384330477_Deep_learning_convolutional_neural_networks_for_Landsat-derived_land_cover_mapping/links/66f4bb89906bca2ac3c9bc17/Deep-learning-convolutional-neural-networks-for-Landsat-derived-land-cover-mapping.pdf)

## Input Amplification:

- <https://www.sciencedirect.com/science/article/pii/S2352938524000168>

## SGU-MLP:

- <https://ieeexplore.ieee.org/document/10399888>

## Mamba:

- <https://github.com/ReaFly/Awesome-Vision-Mamba>
- <https://www.mdpi.com/2072-4292/16/19/3622>

# Inspiration for the vegetation/temperature/topography team

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- **Estimate biomass:** [https://news.ku.dk/all\\_news/2023/10/new-study-finds-hidden-trees-across-europe-a-billion-tons-of-biomass-is-overlooked-today/](https://news.ku.dk/all_news/2023/10/new-study-finds-hidden-trees-across-europe-a-billion-tons-of-biomass-is-overlooked-today/)
- **Sponge city:** <https://ascelibrary.org/doi/full/10.1061/JSWBAY.0000862>
- **Vegetation against heat islands:** <https://www.kth.se/en/seed/forskning/alg/pagaende-forskningsprojekt/stockholm-heat-1.1092946>
- **Monitoring trees:** <https://datasmart.hks.harvard.edu/fighting-climate-change-data-driven-urban-forestry>
- **Public Tree Map App:** <https://www.hackforla.org/projects/public-tree-map.html>
- **Biodiversity Mapping:** <https://environmentalsolutions.mit.edu/news/artificial-intelligence-for-urban-biodiversity-mapping/>

**From Dec 8th, 2024**

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 **Duration**  
~ 8 weeks

**Planned Output: a Medium blog post with main author „Local Chapter Frankfurt“  
and links to all contributors**

See here for an example: <https://www.omdena.com/blog/image-analysis-fires>

## Member Rules & Guidelines

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- English is the language to be used for any communication about the project (Slack,mail,...)
- Only contributions to slack channels count as contributions – private messages do not
- The preferred coding environment are colabs/kaggle notebooks
- You can create shared git projects with your team instead if you all agree on it
- **IMPORTANT: always track your use of computational resources!!!**
- It seems likely that the primary coding language is python
- if you want to use R or Java, you can use python libraries interfacing R/Java with python, such as e.g. rpy2 or Py4J
- otherwise discuss in your team to use alternative coding language

# Project Management Tools that could be used within teams

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Trello Boards for keeping track of ToDos?

<https://trello.com/>

Zotero for keeping track of research?

<https://www.zotero.org/>

Milanote and Obsidian for keeping track of team ideas?

<https://milanote.com/>

<https://obsidian.md/>

GitHub Projects and ZenHub for keeping track of coding?

<https://www.zenhub.com/>

## OMDNA'S CORE VALUES

Omdena's most basic principle is the desire to learn and grow. **Through curiosity, a person constantly asks questions and seeks answers.**



**Curiosity**



**Compassion**

Every member is motivated to help others, especially the less fortunate. **With compassion we ask ourselves "how can we help?"**

Collaboration among diverse talents allows us to bridge gaps in understanding between different mindsets, share knowledge, and unite people and values. It also helps harness crowd wisdom, diversity and inclusion. **Through collaboration, we collectively build ethical solutions.**



**Collaboration**



**Consciousness**

Because there are so many divisions in this world, we need to understand that deep down we are all one, we live on one planet and our future is interconnected. **Through consciousness, we think and act collectively as one.**



## Projects/Labs to follow

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- [MIT Senseable City Lab](#): Founded the Treepedia “Green View Index” Project, Dust Tracker, and more (blending local/ground/IoT and remote sensing data and approaches)
- [MIT Sustainable Urbanization Lab](#): Putting urban sustainable design into context with social, policy, and economics research.
- [Microsoft Planetary Computer](#): Similar to Google Earth Engine
- [US Forest Service’s Urban Forestry Programs](#)
- <https://www.lup-umwelt.de/en/urbangreeneye/>
- <https://urbancanopy.io/about>
- <https://www.isprs.org/education/benchmarks/UrbanSemLab/semantic-labeling.aspx>
- <https://spacenet.ai/challenges/>
- <https://opportunities.spacein africa.com/register-for-the-mjini-hackathon/>

# Some more reading

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Reviews from 2021 about Urban Green Space Mapping:

- <https://www.sciencedirect.com/science/article/abs/pii/S1618866720307639>
- <https://www.mdpi.com/2072-4292/14/4/1031>

Example of limit of green space mapping in urban areas

- [https://thilowellmann.de/wp/wp-content/uploads/2018/11/HaaseJ%C3%A4nickeWellmann\\_FrontBackyardGreen\\_AcceptedManuscript.pdf](https://thilowellmann.de/wp/wp-content/uploads/2018/11/HaaseJ%C3%A4nickeWellmann_FrontBackyardGreen_AcceptedManuscript.pdf)

Vegetation indices

- <https://www.sciencedirect.com/science/article/pii/S1470160X24011026>
- <https://journals.vilniustech.lt/index.php/GAC/article/download/18724/12263>
- [https://d1wqtxts1xzle7.cloudfront.net/84839310/j.rse.2012.10.02920220425-1-1ibpxp0-libre.pdf?1650876954=&response-content-disposition=inline%3B+filename%3DQuantifying\\_tree\\_mortality\\_in\\_a\\_mixed\\_sp.pdf&Expires=1729243529&Signature=RKZZAnCubdlNggjklkofw4~EztKwSyoWCiYtaeMO~OHnz8iwp-quks3~ZDXYR50UJUUp9507EMezA8p20R2GhcZemKNKA4K27m4AjPsMEcRMGf34r-uC2uuDIHEzah5tu-T3Do3SHeAmteNxjn8dQ0JekBNnAqSx2ASK9d3NXcTRteWWCDoSgHpkjsf5~0~YTE5RB~-jlQeG33hr6-IVQWBdpuQG5~~rWnOaUG~Qz9d3tsdLe8ky8pC7ZcDXFyKW-J0hdC08HRIKr1A535R6BOEKEdvx~VXqNC63eUVY8TsfEFyTOJBpFg3GB8yl3gWTK3oxApTEwSeBTnTjL5w\\_\\_&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA](https://d1wqtxts1xzle7.cloudfront.net/84839310/j.rse.2012.10.02920220425-1-1ibpxp0-libre.pdf?1650876954=&response-content-disposition=inline%3B+filename%3DQuantifying_tree_mortality_in_a_mixed_sp.pdf&Expires=1729243529&Signature=RKZZAnCubdlNggjklkofw4~EztKwSyoWCiYtaeMO~OHnz8iwp-quks3~ZDXYR50UJUUp9507EMezA8p20R2GhcZemKNKA4K27m4AjPsMEcRMGf34r-uC2uuDIHEzah5tu-T3Do3SHeAmteNxjn8dQ0JekBNnAqSx2ASK9d3NXcTRteWWCDoSgHpkjsf5~0~YTE5RB~-jlQeG33hr6-IVQWBdpuQG5~~rWnOaUG~Qz9d3tsdLe8ky8pC7ZcDXFyKW-J0hdC08HRIKr1A535R6BOEKEdvx~VXqNC63eUVY8TsfEFyTOJBpFg3GB8yl3gWTK3oxApTEwSeBTnTjL5w__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA)

<https://towardsdatascience.com/best-libraries-for-geospatial-data-visualisation-in-python-d23834173b35>

<https://python.plainenglish.io/unlocking-the-power-of-python-top-gis-and-remote-sensing-libraries-for-data-analysis-bb968e3139e9>

<https://www.coursera.org/learn/spatial-data-science?>

<https://www.coursera.org/learn/remote-sensing>

<https://www.esri.com/training/mooc/>

[https://eo4society.esa.int/wp-content/uploads/2021/02/D3T2b\\_LTC2015\\_vanderLinden.pdf](https://eo4society.esa.int/wp-content/uploads/2021/02/D3T2b_LTC2015_vanderLinden.pdf)

<https://sentiwiki.copernicus.eu/web/s2-mission>

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Thank you everyone!  
Keep in touch on Slack!

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