



Asset Value Prediction Hue Vietnam

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Braun

AK – Fernerkundung Bochum 29.- 30.09.2025



Bundesministerium
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und Raumfahrt



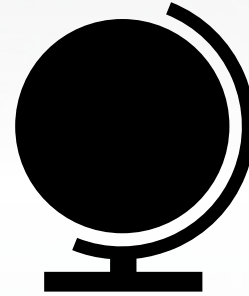




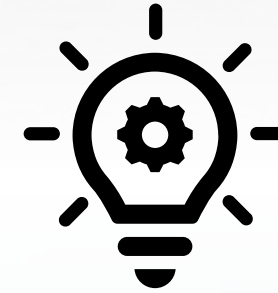
Justification/Intro



Support for decision
making by allocating
resources



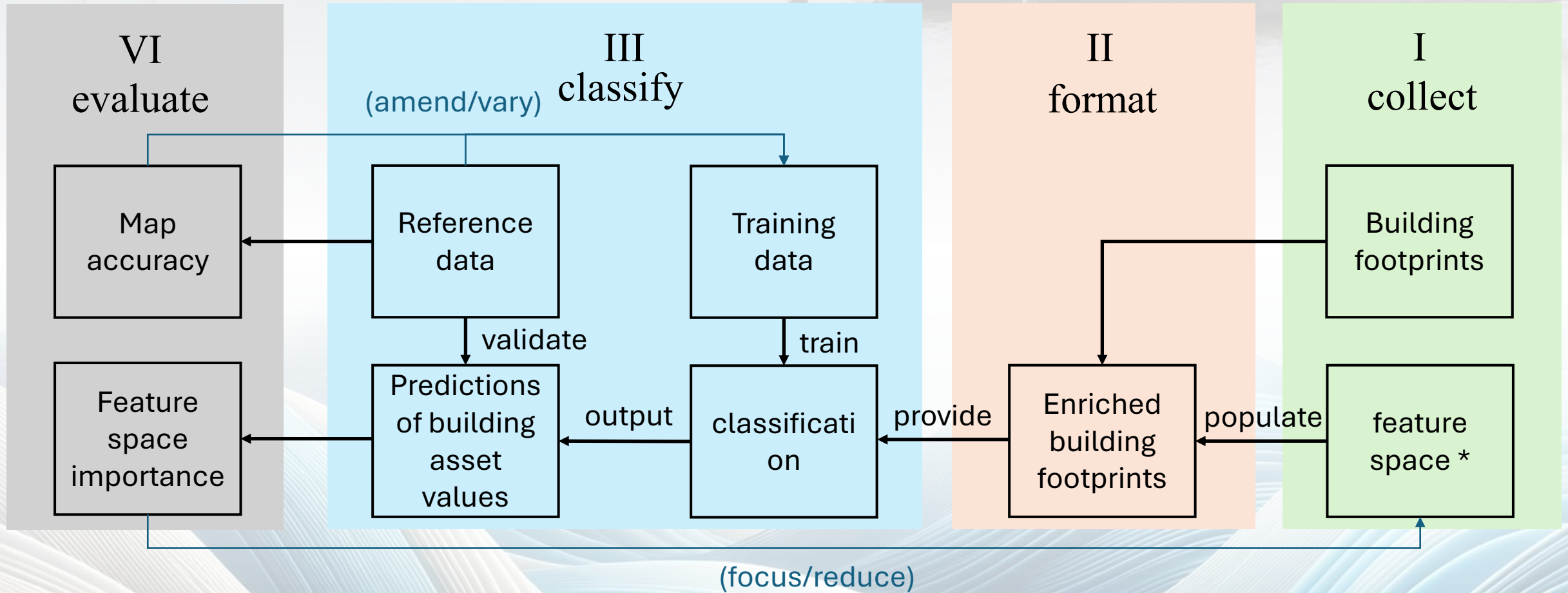
Remote Sensing and OSM
as global/generic source
of information



Benefits of AI for creation
of large area products of
human function



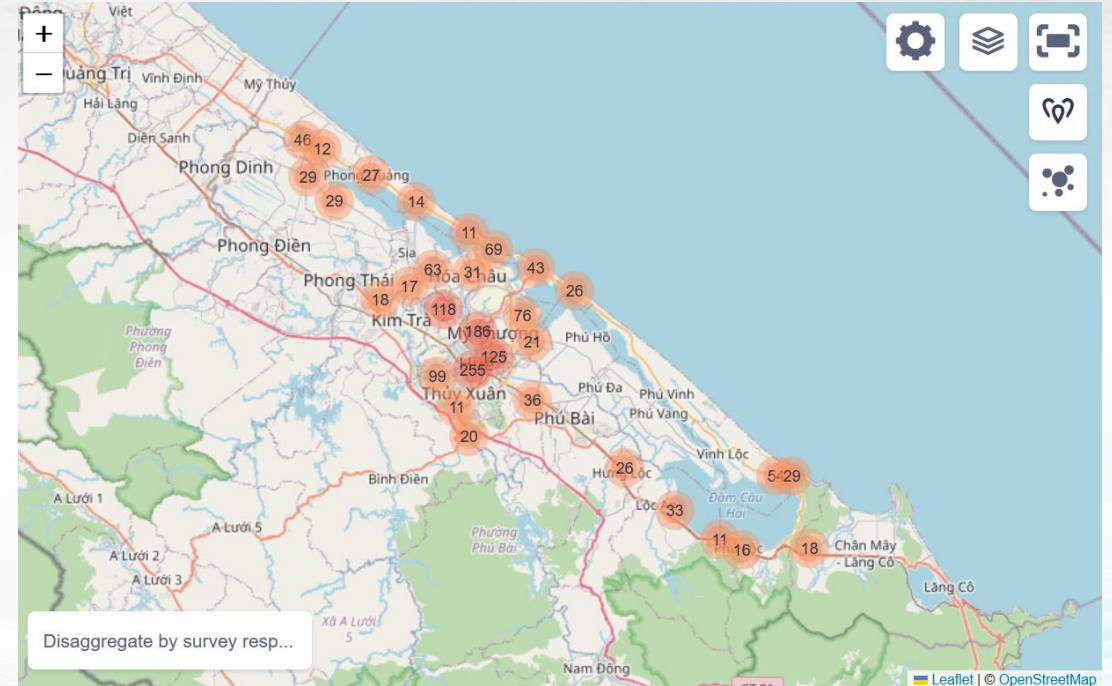
Prediction/classification of building asset values



*remote sensing data of different devices, auxiliary data

Method for Prediction of Building Asset Values

- I. Field Campaign (Mar 2023 & Mar 2024)
- II. Reference Data (n=1572)
- III. Categorize 49 Building Types
- IV. Map to 5 Govt. Cost Classes





Apartment Buildings



Social Housing - Low rise



Social Housing
Apartments



Individual
Houses (villa
style)



Individual
Houses

Method for Prediction of Building Asset Values

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- V. Train ML Model using generic feature space
(Auxiliary layers, OSM + Remote sensing)



Input feature space

OSM/Remote sensing/Demographics

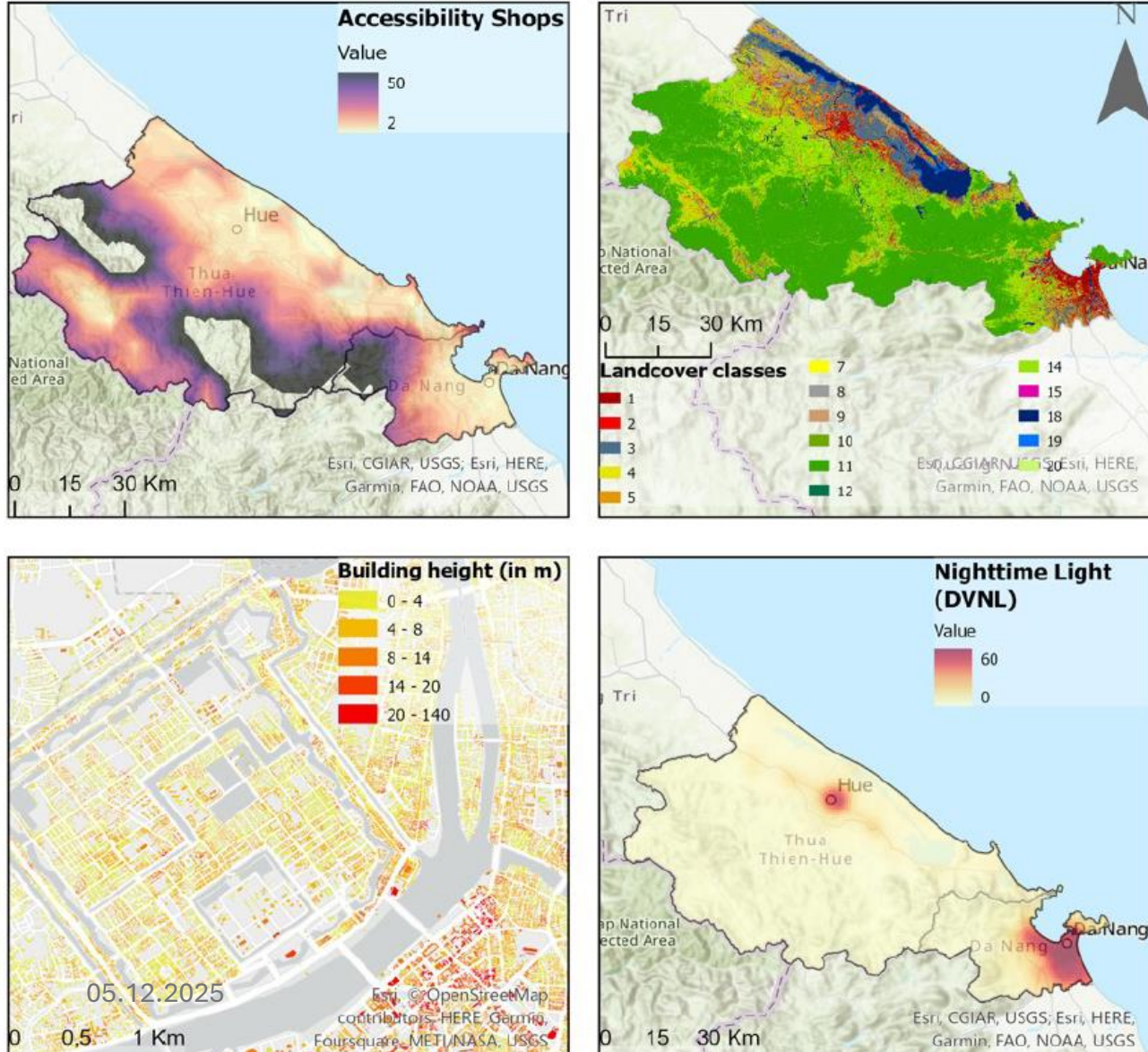


Dataset	What it measures	Resolution	Coverage (time)	Why we use it
Sentinel-1/2 via SEPAL & GEE	SAR backscatter; multispectral reflectance	10–60 m	2014/2015–present	Robust time-series and cloud-scale processing for land-surface dynamics.
OSM/OSRM accessibility	Network travel time/distance	n/a (network)	As of OSM snapshot	Reproducible isochrones and OD matrices for access analyses.
WSF Evolution & 3D	Settlement emergence; building fraction/height/volume	30 m / ~90 m	1985–2015; reference epoch for 3D	Urbanization timing and 3D urban form metrics.
JAXA LULC Vietnam	Annual land-use/land-cover classes	30 m	1990–2020	Consistent national LULC trajectories.
WorldPop	Gridded population counts (UN-adjusted)	~1 km or 100 m	Year-specific	Population exposure and normalization.
VIIRS Black Marble	Nighttime light radiance	500 m	2012–present	Human activity proxy and temporal dynamics.



Generic feature space

Different predictor variables used in the study



Remote Sensing Data:

- Satellite imagery and derived products
- Captures biophysical properties of surfaces

External Datasets:

- Accessibility metrics (e.g., access to shops, healthcare, education)
- Derived from sources like OpenStreetMap

Synergistic Effect:

- Combination enhances model performance
- Provides both physical and anthropogenic insights

Versatility:

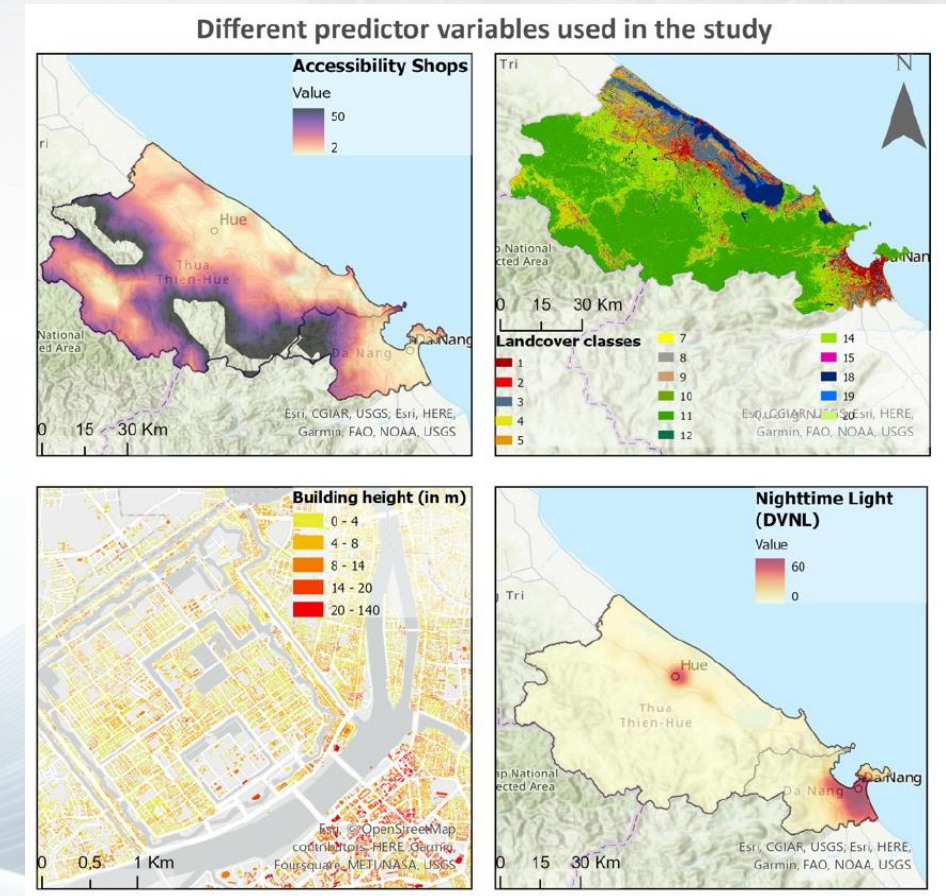
- Applicable to various predictive tasks across different domains

Feature Space Representation:

- Graphical depiction of combined data layers
- Highlights areas with varying accessibility

Method for Prediction of Building Asset Values

- I. Field Campaign (Mar 2023 & Mar 2024)
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- III. Categorize 49 Building Types
- IV. Map to 5 Govt. Cost Classes
- V. Train ML Model using generic feature space (Auxiliary layers, OSM + Remote sensing)
- VI. Classify 600k Buildings
- VII. Estimate Floors from Building Height
- VIII. Compute Asset Value (sq.m. cost × floor area)



Asset Value Prediction (RS+OSM as feature space)

Data Collection:

- Collected ~1,500 reference points on building types
- Building values obtained from investment plans

Training Classification Models:

- Used collected data as training input

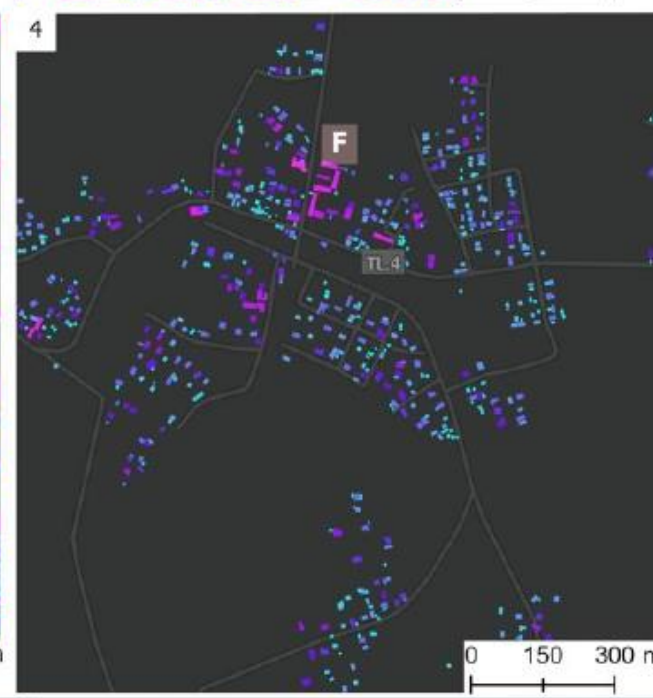
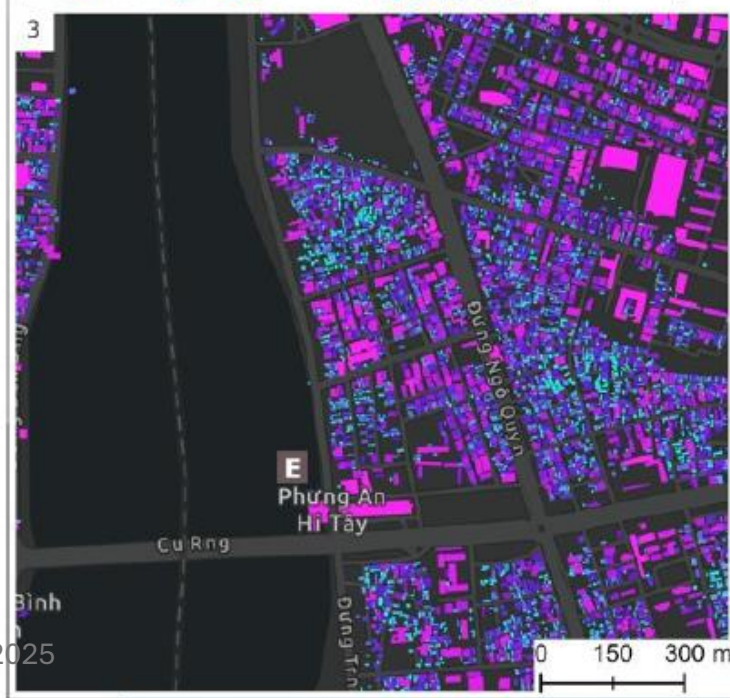
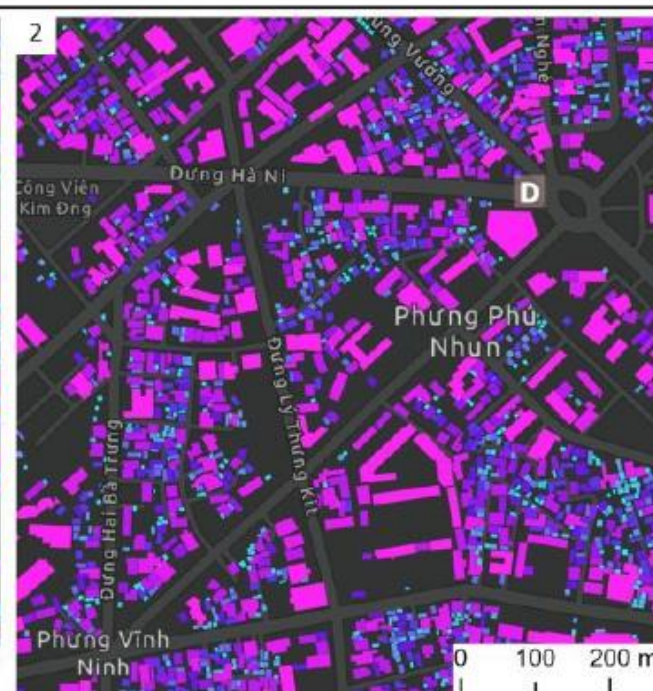
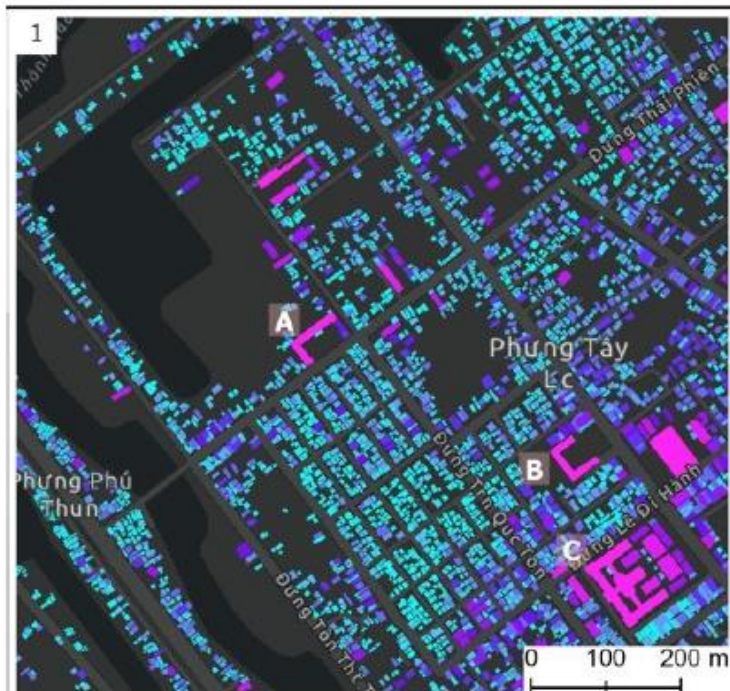
Remote Sensing Data Feature Space

- Biophysical properties of surfaces

OpenStreetMap (OSM) Feature Space

- Shop accessibility
- Access to healthcare
- Access to education





House value distribution of different districts

Buildings

Value Classes

- 1 (0 - 0.082 million USD)
- 2 (0.082 - 0.119 million USD)
- 3 (0.119 - 0.168 million USD)
- 4 (0.168 - 0.229 million USD)
- 5 (0.229 - 0.296 million USD)
- 6 (0.296 - 0.379 million USD)
- 7 (0.379 - 0.567 million USD)
- 8 (0.567 - 0.997 million USD)
- 9 (0.997 - 2.040 million USD)
- 10 (> 2.040 million USD)



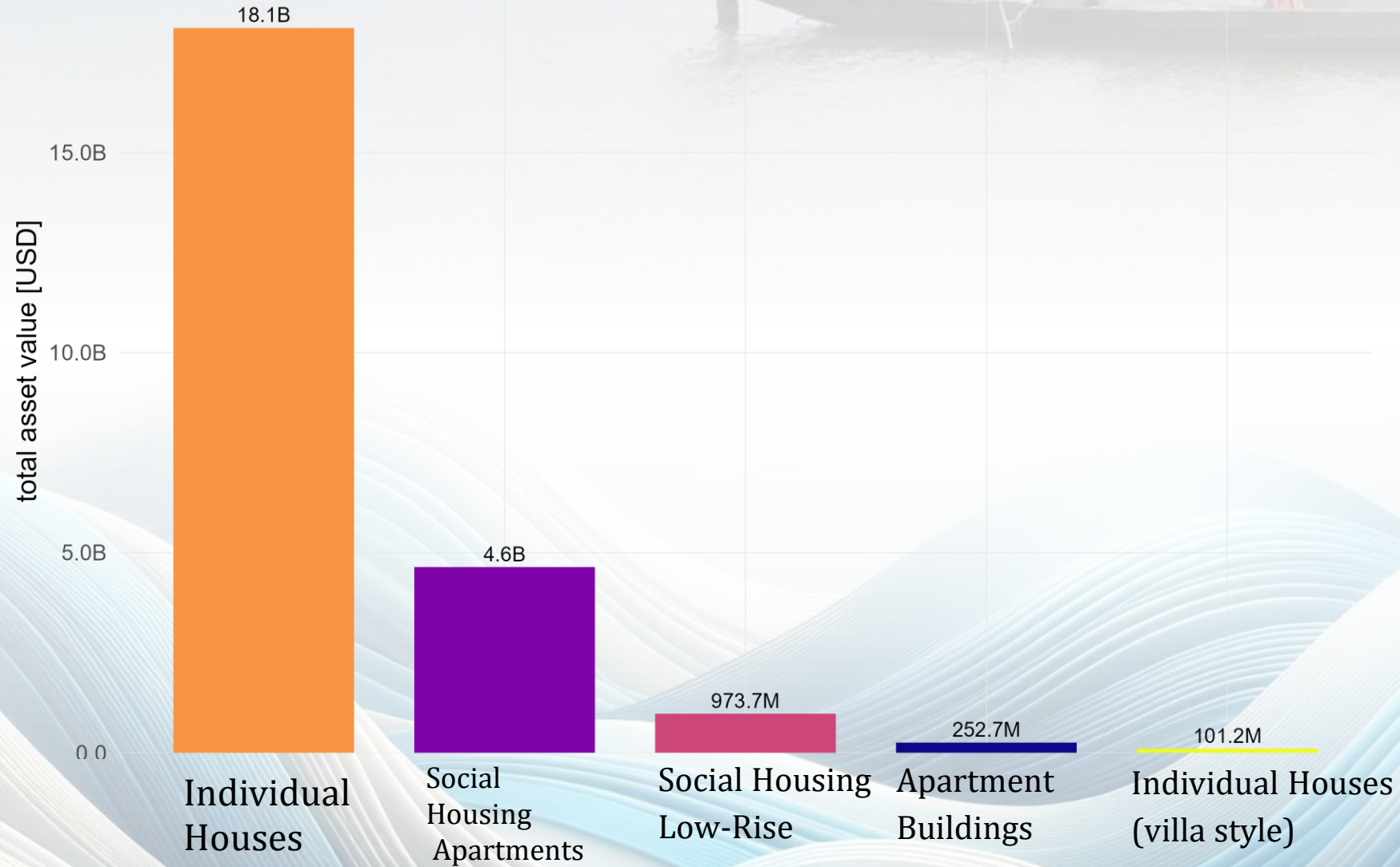
Author: Eric Offermann
 Source: Esri Community Maps Contributors, Esri, HERE, Garmin, Foursquare, METI/NASA, USGS; Esri, FAO, NOAA, USGS; Esri, © OpenStreetMap contributors, HERE, Garmin, Foursquare, METI/NASA, USGS; Esri, HERE, Garmin, FAO, NOAA, USGS; Esri, USGS





Total asset value by category

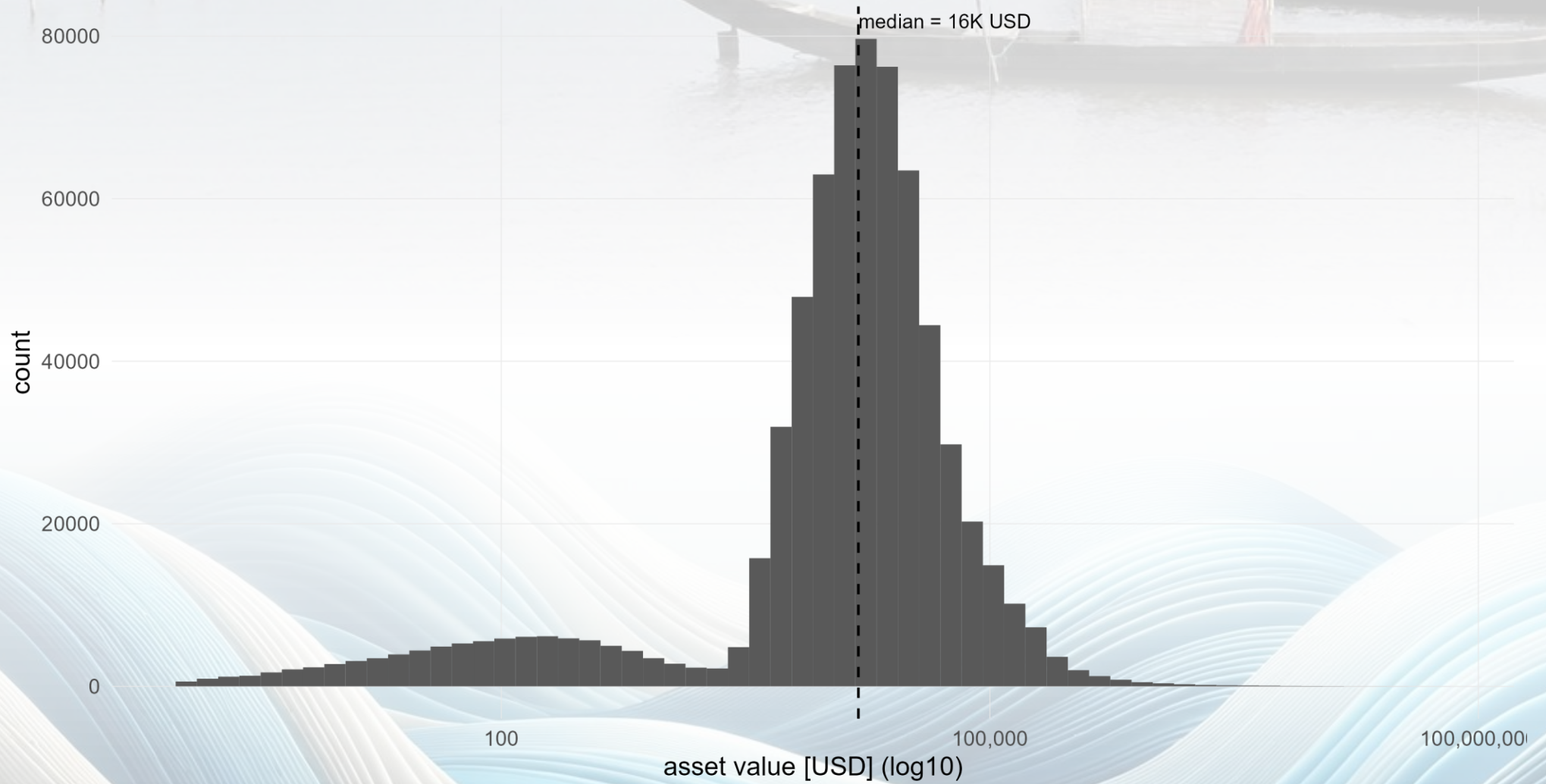
Bars labeled with totals; counts per cat: 5=676,204 2=8,846 4=1,968 1=176 6=1,415





Per-building asset values (log scale)

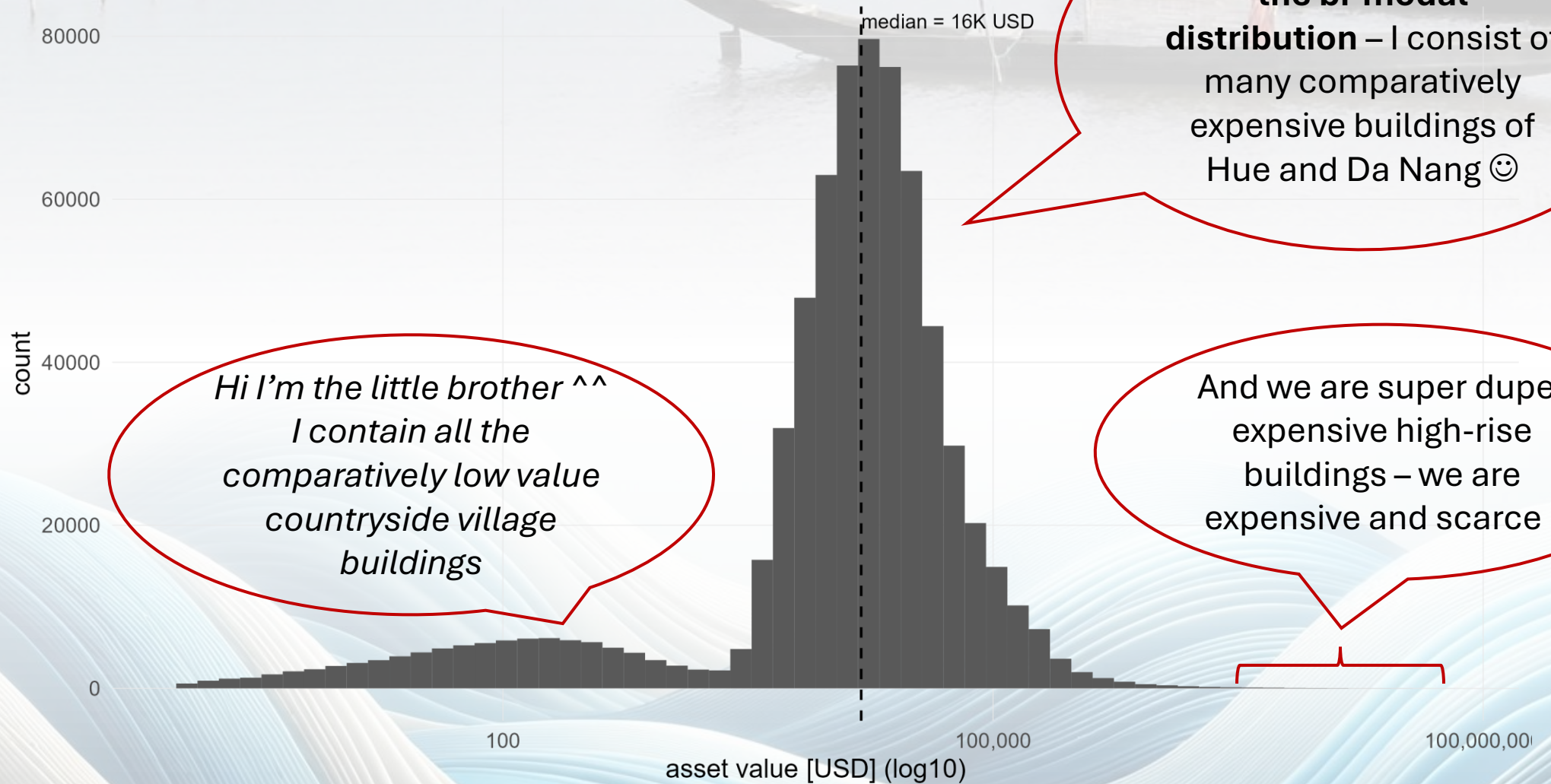
Dashed line shows the sample median





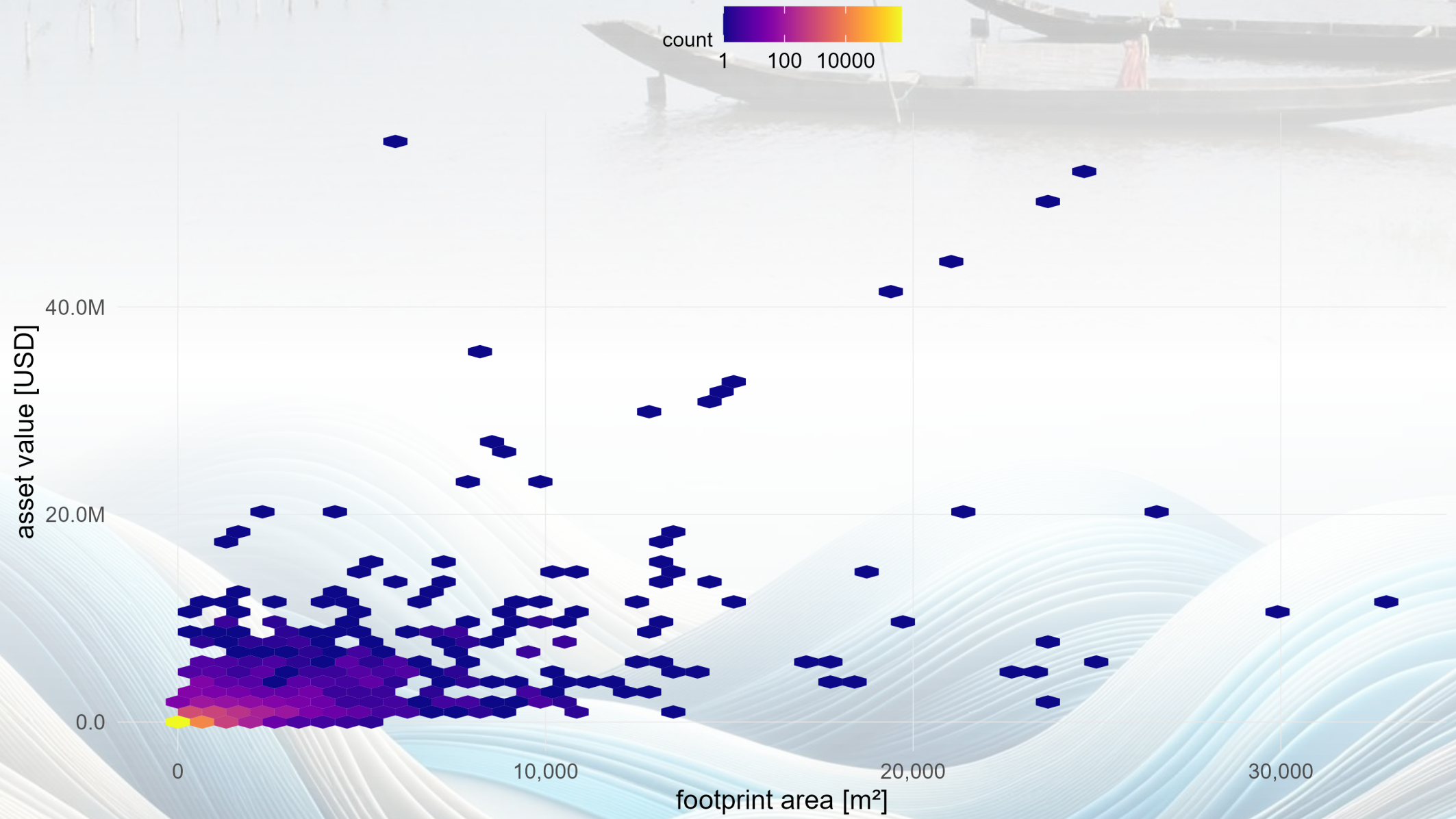
Per-building asset values (log scale)

Dashed line shows the sample median

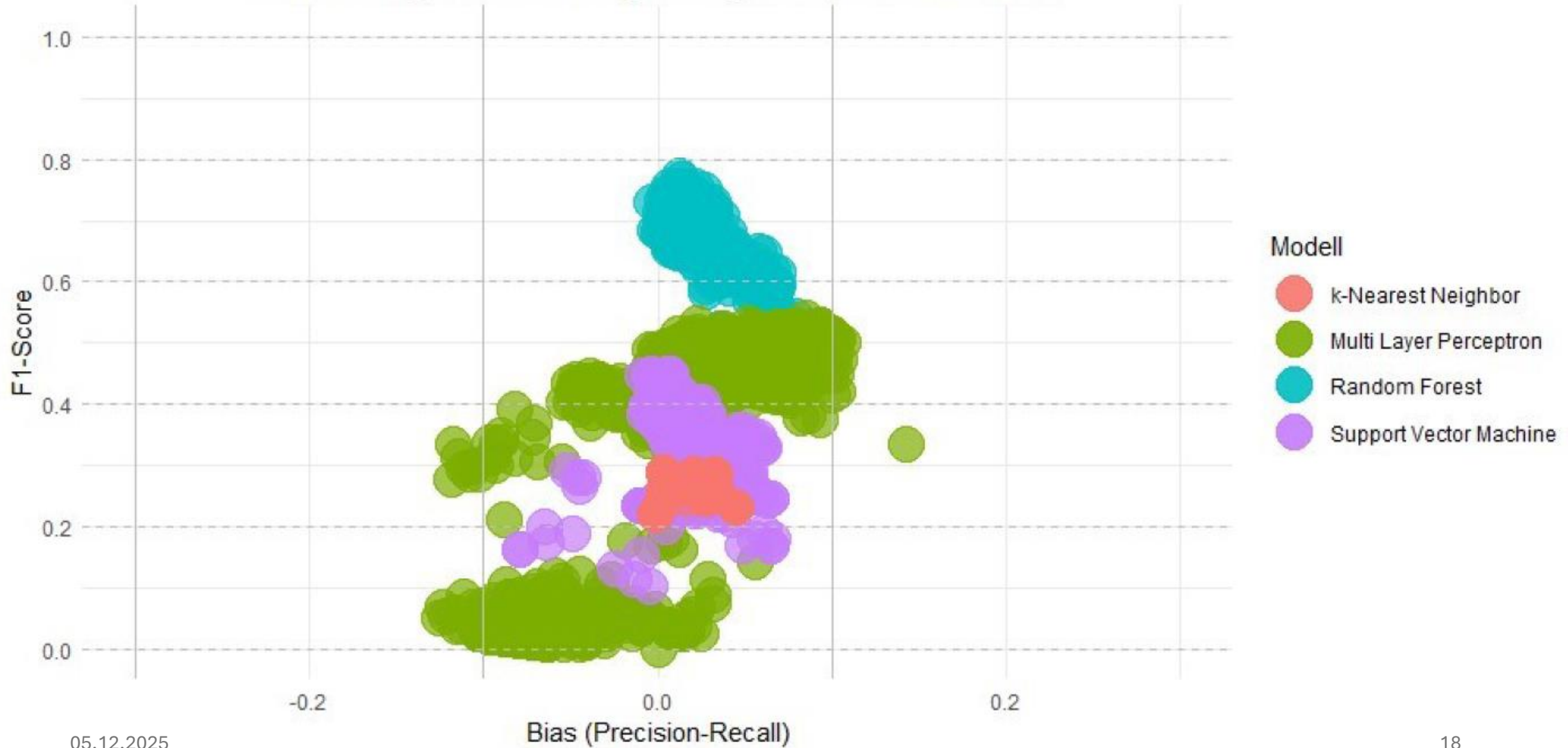


Area vs value — hexbin density

Color scale shows log count per hexbin



Accuracy





Conclusion and Outlook

- Scalable per-building replacement value mapping for Thua Thien Hue using **remote sensing, OpenStreetMap, and auxiliary layers**.
- Reference data: 1,572 labeled points from field campaigns in March 2023 and March 2024.
- Pipeline: 49 building types mapped to 5 government cost classes; heights → floor counts; area × unit cost → per-building value.
- Coverage: approximately 600,000 buildings classified and valued.
- Applications: prioritization, flood loss modeling, and on-the-fly aggregation in support of FloodAdaptVN decision making.
- Reproducibility: KoBo field forms and GitHub repository; generic feature space transferable to other provinces and cities.
- Limitations: class imbalance for high-rise types, OSM completeness, height estimation and unit-rate uncertainties.
- Next steps:
 - Update to current Ministry of Construction unit rates and add uncertainty bands.
 - Extend mapping to the wider central Viet Nam region; perform external validation.
 - Integrate with flood hazard layers to generate impact and adaptation scenarios.
 - Publish GeoNode layers and API endpoints; run stakeholder calibration workshops.

Vielen Dank

Thank You

धन्यवाद

谢谢

Merci à toi

Cảm ơn



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EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN



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Overall descriptive statistics

buildings (n): 688,609

total asset value (USD): 24,073,354,356 (24.07B)

USD distribution:

min : 1 (1)
p25 : 7,246 (7.25K)
median: 15,587 (15.59K)
mean : 34,959 (34.96K)
sd : 243,013 (243.01K)
p95 : 103,596 (103.60K)
max : 55,689,716 (55.69M)

footprint area total (m²): 61,154,788 (61.15M)

GFA total (m²) : 90,550,386 (90.55M)

floors (min / p25 / median / mean / p95 / max): 1 / 1 / 1 / 1.33 / 2 / 45



Facilitation **FRAME**

FLOOD ADAPT
VN

← → ↻ frameavn.org/#/ 130% ☆

FRAME Search 🔍

FRAME

Flood Flood Risk Information System for Adaptation Measures and Evaluation in Central Vietnam

All resources Datasets Maps Documents GeoStories Dashboards Scenarios About FloodAdaptVN home Imprint English

Featured

BẢN ĐỒ LỚP PHỦ BỀ MẶT NĂM 2020

admin View

ĐÓNG XE Ô TÔ KHI LŨ ĐẠT BÁO ĐỘNG III (...)

admin View

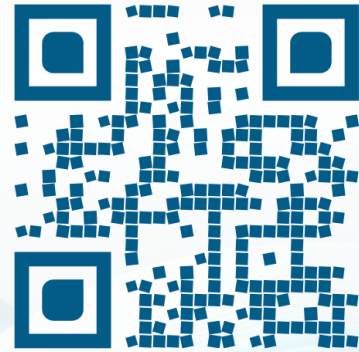
Usecases overview EN

Johannes Weixler View

Future-Proofing Urban Flood Resilienc...

Johannes Weixler View

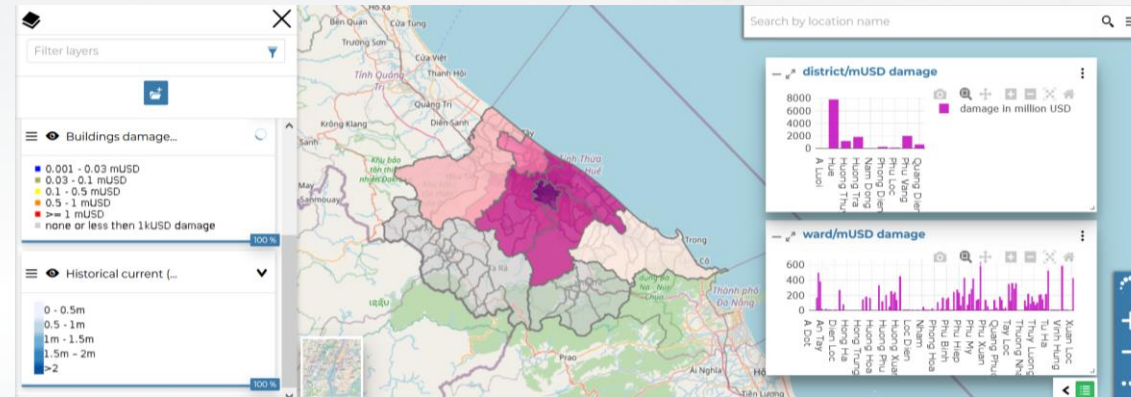
geonode.org Developers About





Facilitation **FRAME**

a) on the fly data aggregation feature via widgets



b) individual buildings and flood impact analysis



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☒ ☒ Expected Annual Impact (EAI)

- ☒ ☒ Current estimated Expected Annual I...
 - 0-0.5 mill. VND
 - 0.5-1 mill. VND
 - 2-3 mill. VND
 - 3-10 mill. VND
 - 10-100 mill. VND
 - 100-1000 mill. VND
 - 1000-7000 mill. VND
- ☐ Estimated Expected Annual Impact (E...
- ☐ Estimated Expected Annual Impact (E...
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- ☐ Estimated Expected Annual Impact (E...

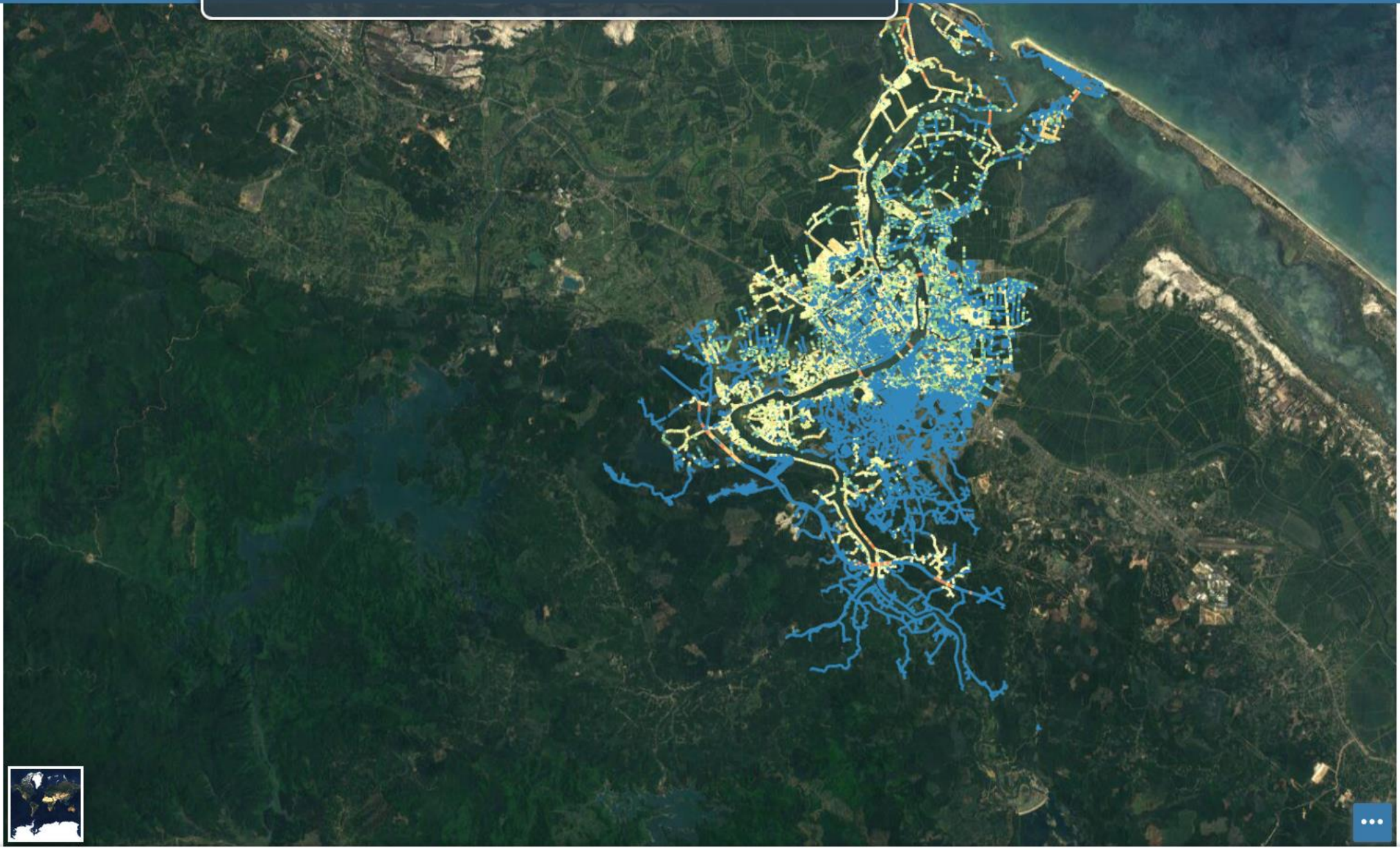
☐ Early Warning System

☐ Natural Urban Water Bodies

☐ Agroforestry

☐ Sustainable Forest

Florian Waldschmidt



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Method



FRAME_xTungRasterF2022_check.r • OSM_Isochrones_v7.R •

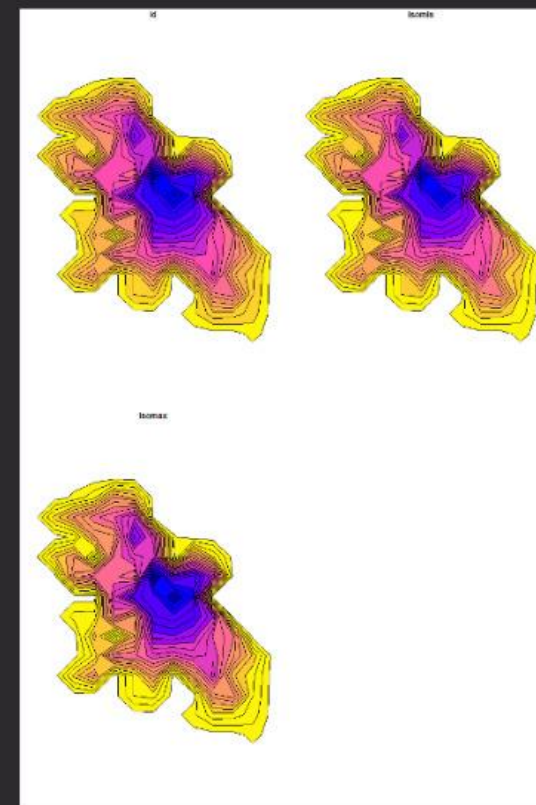
plot.png ×



C: > Users > Michael Schultz > OneDrive > code > OSM_Isochrones_v7.R

```
4
5 wd = 'C:/Users/Michael Schultz/OneDrive/FAVN/20230811_OSMaccessi
6 #pn = 'TTH_key_healthcare_v6.shp' # name of point data set
7 pn = 'TTH_key_shop_v1.shp' # name of point data set
8 #pn = 'TTH_key_education_v1.shp' # name of point data set
9
10 # program starts here
11
12 setwd(wd) # set work dir
13
14 x = st_read(pn, quiet = T)
15
16 # make isochrones
17 isochrones_list = list() # Initialize a list to store isochrone
18 # Loop through each point in x and get the isochrone
19 for(i in 1:nrow(x)){
20
21   iso = osrmIsochrone(Loc = x[i, ], breaks = seq(0, 50, 2)) # g
22   iso = isochrones_list[[i]] # call iso crone
23   iso = st_transform(iso, crs = 32648) # project to UTM zone 48
24   r = raster(extent(iso), res = 30) # Adjust the resolution as
25   projection(r) = projection(iso)
26   r_rasterized = rasterize(iso, r, field = "isomax") # Rasteriz
27 # output
```

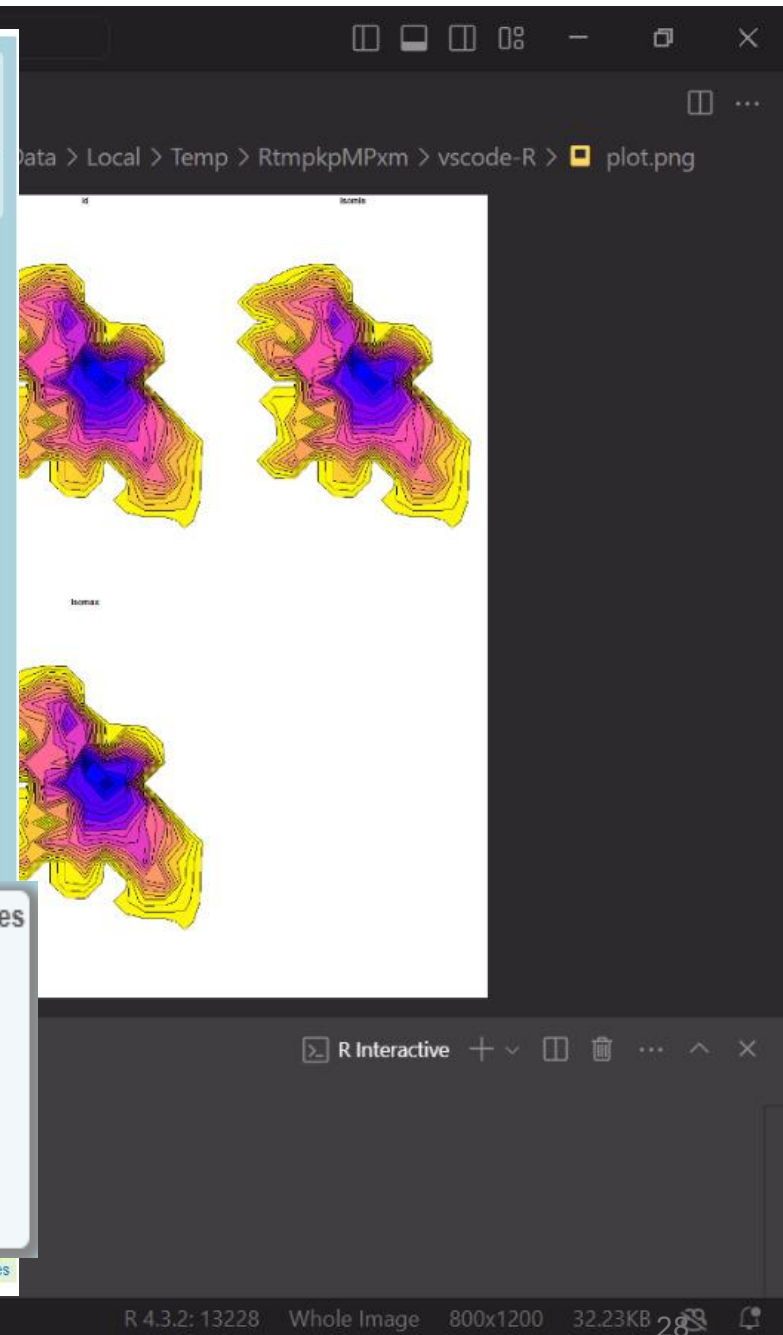
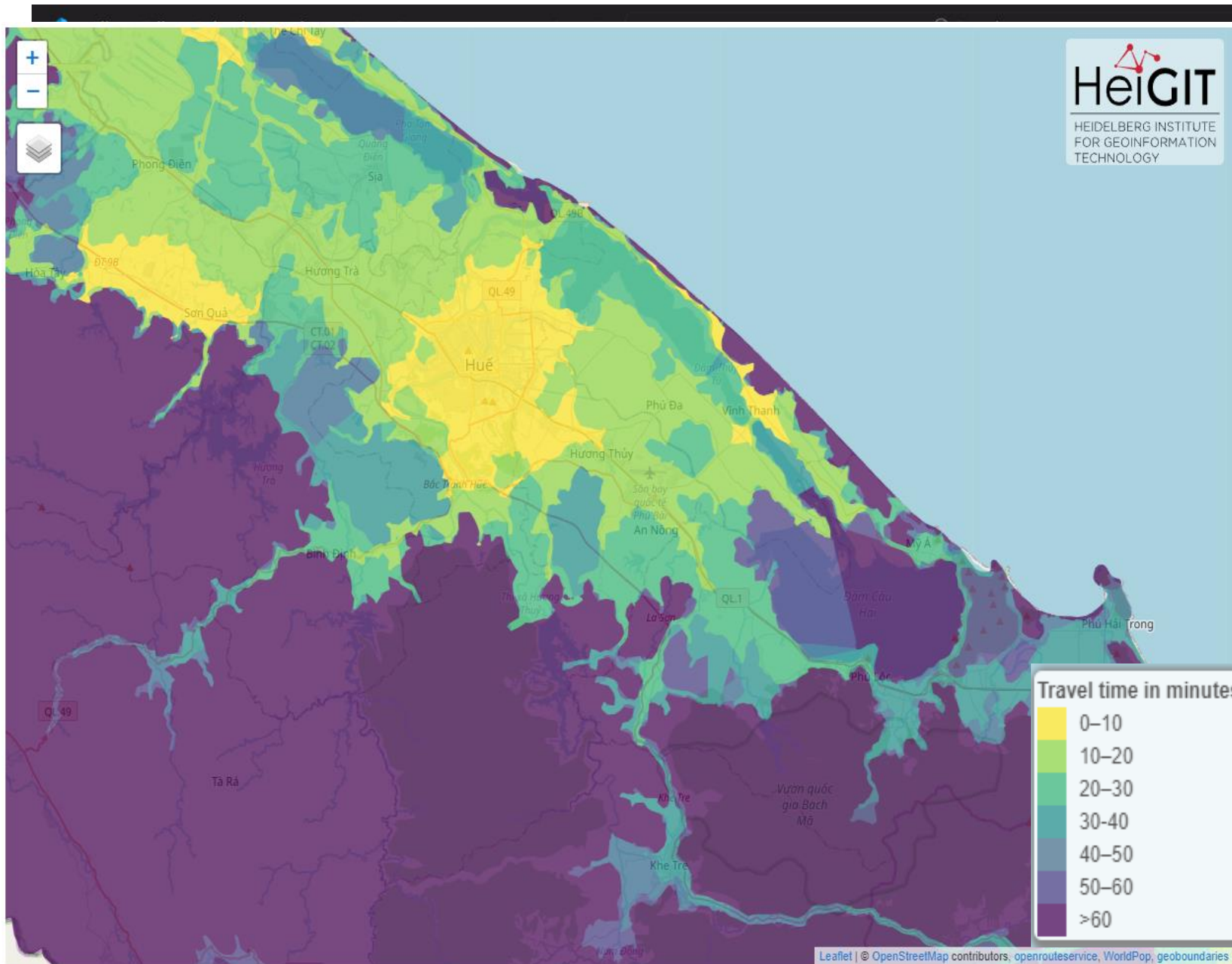
C: > Users > MICHAEL~1 > AppData > Local > Temp > RtmpkpMPxm > vscode-R > plot.png



PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

```
7 7 16 18 MULTIPOLYGON (((108.0565 16...
8 8 18 20 MULTIPOLYGON (((108.0565 16...
9 9 20 22 MULTIPOLYGON (((108.0565 16...
10 10 22 24 MULTIPOLYGON (((108.0565 16...
> plot(iso)
>
```

R Interactive + ▾ □ □ □ ... ^ ×





Input training data

- Ground truth campaign 2023/24
<https://kf.kobotoolbox.org/#/forms/aAY7brXZq5urtpvsRTpd9r/data/map>
- We estimate construction replacement value United States Dollar (USD) for every building polygon using nationally announced investment unit rates per square meter by housing class and floor count. Rates and rules follow Vietnam Ministry of Construction Decision 610/QĐ-BXD (announcement of 2021 construction investment unit costs) (Ministry of Construction, Socialist Republic of Viet Nam, 2022), applied at Q4/2022 price level with 1 USD = 22,890 VND

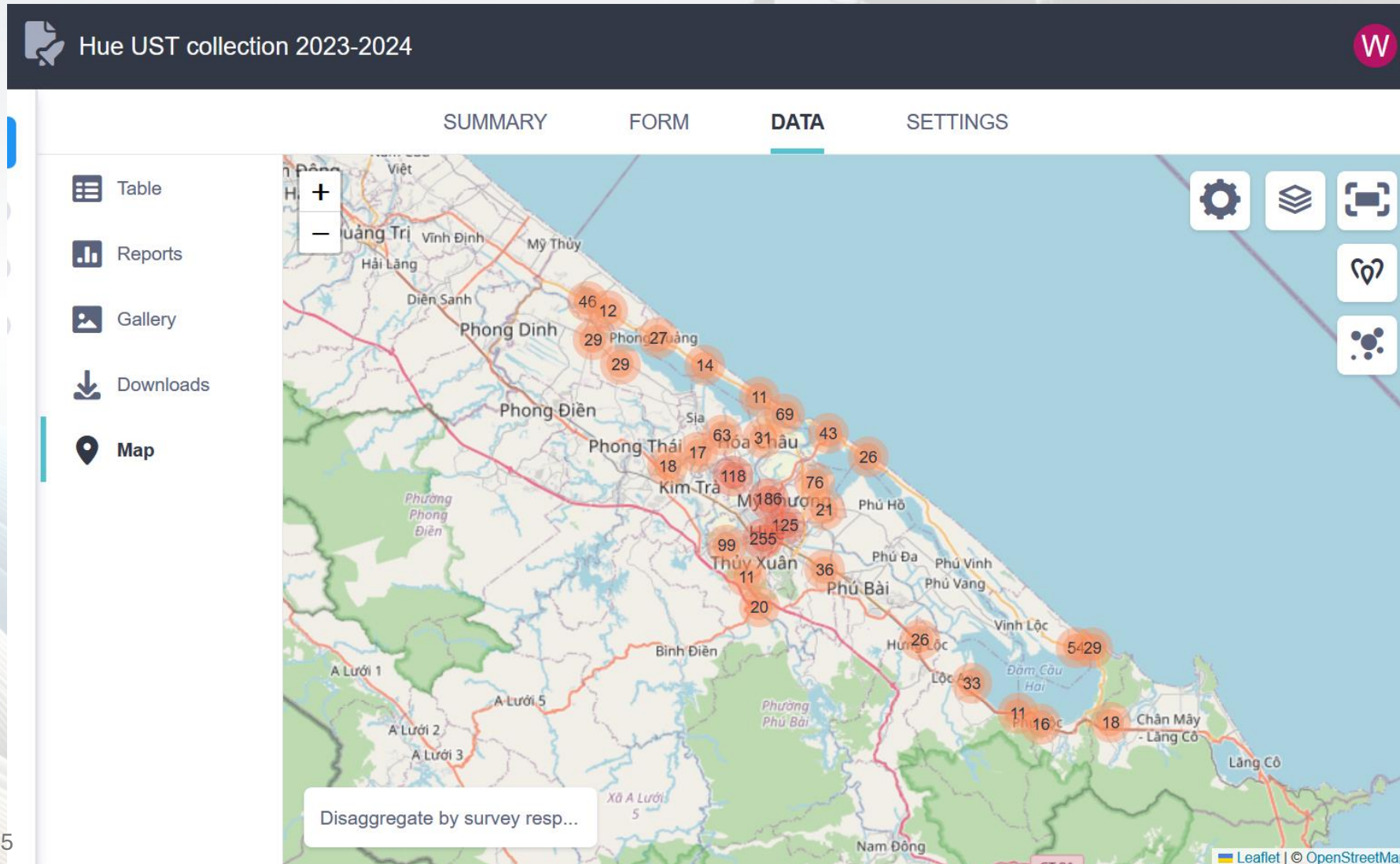


Input training data

- A total of 1572 reference points were collected during two field campaigns in March 2023 and March 2024.
- Each reference point contained information on building categories (for example, urban structure types and building types) sampled across Hue province.
- Trained personnel inspected individual buildings to assign the appropriate building category, yielding a detailed inventory of building types for all reference locations.



Ground truth campaign 2023/24





Ground truth campaign 2023/24

Table
 Reports
 Gallery
 Downloads
 Map

NEW

Deployed 1
 Draft 0
 Archived 0

SUMMARY FORM **DATA** SETTINGS

hide fields

1 - 30 1579 results		Building Types (Moon et al. 2009)	Building under construction	1.0 Number of floors	Roof Type	Roof Material
		Show All	Show All	Search	Show All	Show All
<input type="checkbox"/>	nil...	Rudimental	No	1.0	Gabled Roof	other
<input type="checkbox"/>	nil...	Rudimental	No	2.0	Gabled Roof	Clay Tiles
<input type="checkbox"/>	nil...	Rudimental	No	1.0	Gabled Roof	Clay Tiles
<input type="checkbox"/>	nil...	Rudimental	No	1.0	Gabled Roof	Clay Tiles
<input type="checkbox"/>	nil...	Rudimental	No	1.0	Gabled Roof	Corrugated Met
<input type="checkbox"/>	nil...	Rudimental	No	1.0	Gabled Roof	Clay Tiles
<input type="checkbox"/>	nil...	Rudimental	No	2.0	Gabled Roof	Corrugated Met
<input type="checkbox"/>	nil...	Villa-Individual	No	2.0	Gabled Roof	Clay Tiles

PREV

Page 1 of 53

30 rows

NEXT



Ground truth campaign 2023/24

← → ↻ kf.kobotoolbox.org/#/forms/aAY7brXZq5urtpvsRTpd9r/data/gallery

KoboToolbox Hue UST collection 2023-2024 W

SUMMARY FORM **DATA** SETTINGS

Image Gallery

From All questions Between mm / dd / yyyy and mm / dd / yyyy

05.12.2025

https://github.com/HeigenhauserD/hue_buildings



← → ↺

github.com/HeigenhauserD/hue_buildings

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☰

HeigenhauserD / hue_buildings

🔍 Type / to search

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<> Code

🕒 Issues

🔗 Pull requests

🔗 Actions

📁 Projects

🛡️ Security

📈 Insights

⚙️ Settings

🏠 hue_buildings

Private

👁️ Watch 1

🍴 Fork 0

☆ Star 0

🔗 master ⌵

👤 1 Branch

🏷️ 0 Tags

🔍 Go to file

⌵ Add file

🔗 Code ⌵

👤 schultzhedelberg Update AssetValues_bCopernicusFormat_makeReady_v1.r 3d477ca · 3 months ago 81 Commits

📁 .idea	3rd	last year
📁 eric	updated pipeline for spatial join of polygons and points usin...	4 months ago
📁 preprocessing	Update AssetValues_bCopernicusFormat_makeReady_v1.r	3 months ago
📁 res	2nd	last year
📁 src	updated with changes using the input scaler, preprocessing...	last year
📄 README.md	Update README.md	3 months ago
📄 requirements.txt	added requirements.txt	last year

📖 README

updated pipeline 06/06/25: (1) spatial_join.py to combine building polygons and points with USD classification. get polygons_joined.shp (2) calculate_centroids.py to calculate centroids from polygons_joined.shp. get buildings_centroids.shp (3) generic_data_preprocessing.py enriches buildings_centroids.shp with data from *.tif. get enriched_centroids.shp (4) split_data.py splits data into train.csv and test.csv (5) randomForest_cat.py Random Forest classification

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No description, website, or topics provided.

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