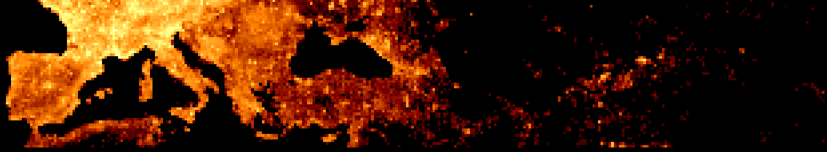


GLOBAL DYNAMIC EXPOSURE AND THE OPENBUILDINGMAP

A BIG-DATA AND CROWD-SOURCING APPROACH TO EXPOSURE MODELING

DANIJEL SCHORLEMMER (GFZ)

THOMAS BEUTIN, FABRICE COTTON, NICOLAS GARCIA OSPINA GFZ), NAOSHI HIRATA (U TOKYO/NIED), KUO-FONG MA (NCU TAIWAN), CECILIA NIEVAS, KARSTEN PREHN (GFZ), AND MAX WYSS (ICES)

KNOWING EVERY BUILDING

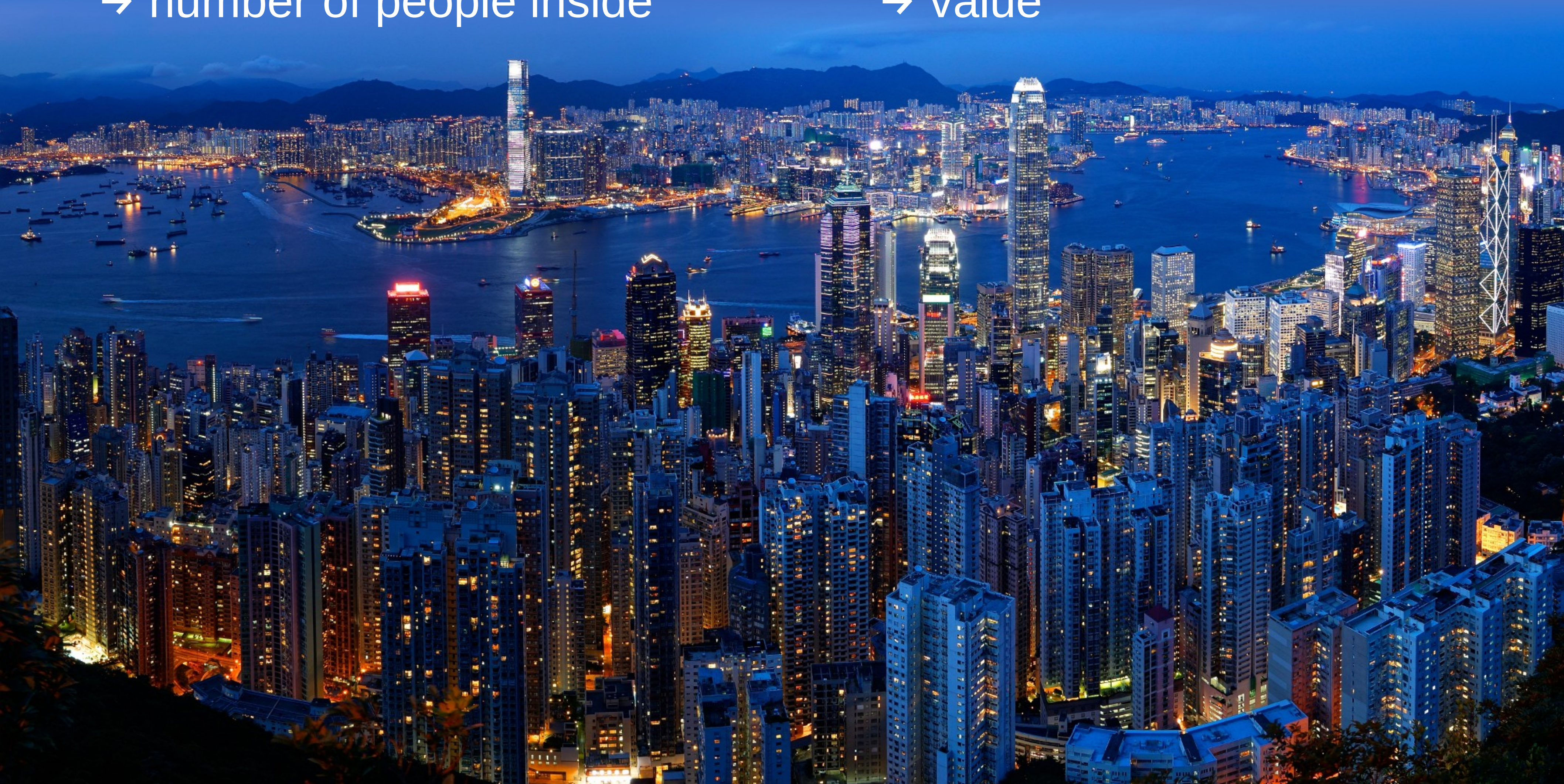
Imagine we know every building worldwide

→ exact location & size

→ number of people inside

→ type and vulnerability

→ value



THE CHALLENGE

– **DYNAMIC** exposure model for monitoring risk based on open data
→ capturing urbanization

– **HIGH-RESOLUTION** exposure data globally
→ on the building-by-building level

[SAN]

UNDERSTANDING THE DYNAMICS

From static to dynamic risk

- → Cities are growing and reshaping
- → Building stock and values are changing
- → Smaller earthquakes can weaken structures

[BAN]

THE STRATEGY

– **CROWD-SOURCED APPROACH FOR DATA COLLECTION**
→ Developing a platform around the OpenStreetMap ecosystem

– **INTEGRATING STANDARDS**
→ From GEM/USGS building taxonomy to EMS98 classification

– **PROVIDING DYNAMIC EXPOSURE**
→ Deriving exposure indicators with SERA/GEM exposure models

DATA COLLECTION

OpenStreetMap data
Open data
Expert knowledge

DATA PROCESSING

Real-time updating
Data integration
Infrastructure classification

DATA DISSEMINATION

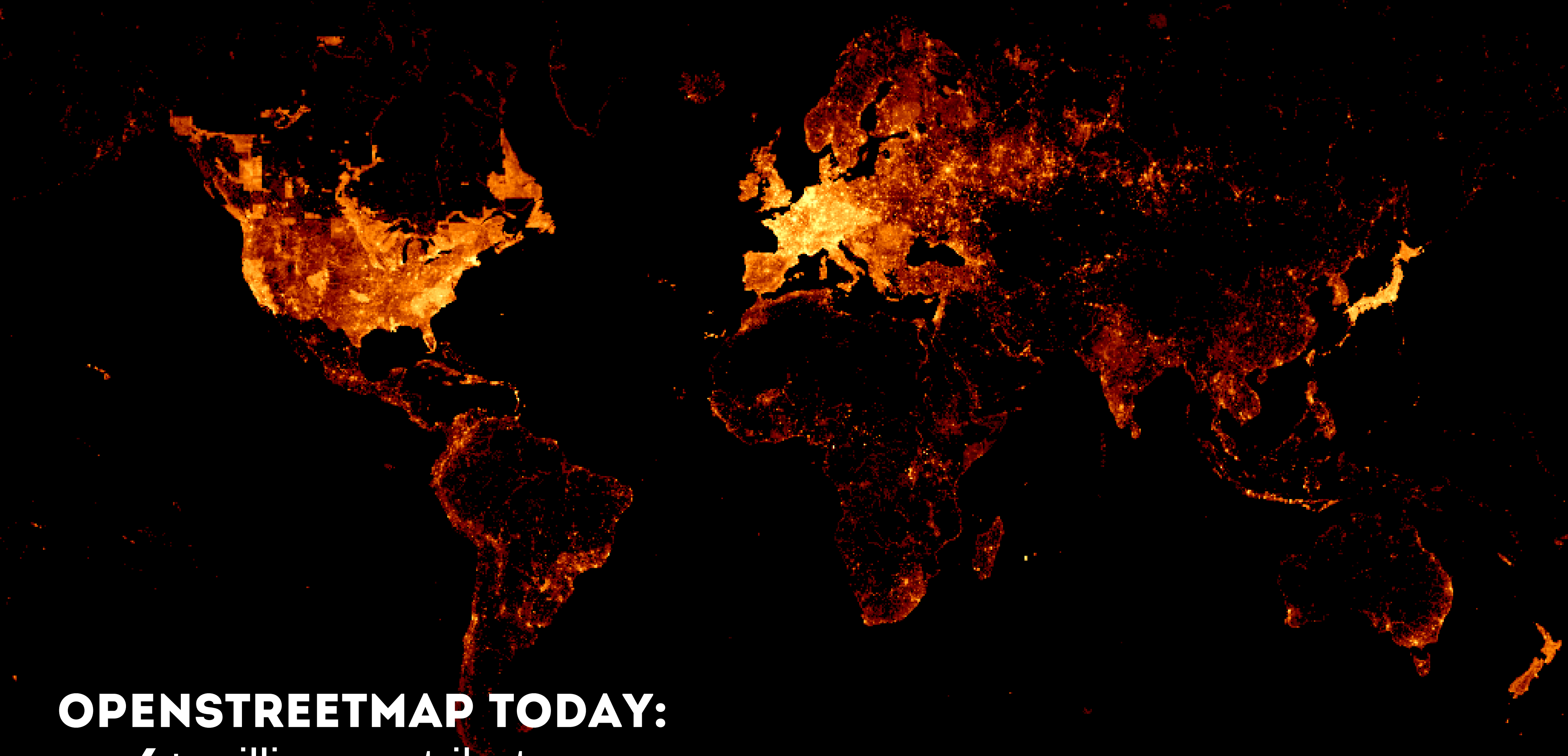
Dynamic exposure
GEM/USGS taxonomy - EMS98
Open web service

GLOBAL DYNAMIC EXPOSURE

NATURAL HAZARD RESILIENCE FOR A RAPIDLY CHANGING SOCIETY

OPENSTREETMAP

THE WIKIPEDIA OF GEO DATA



OPENSTREETMAP TODAY:

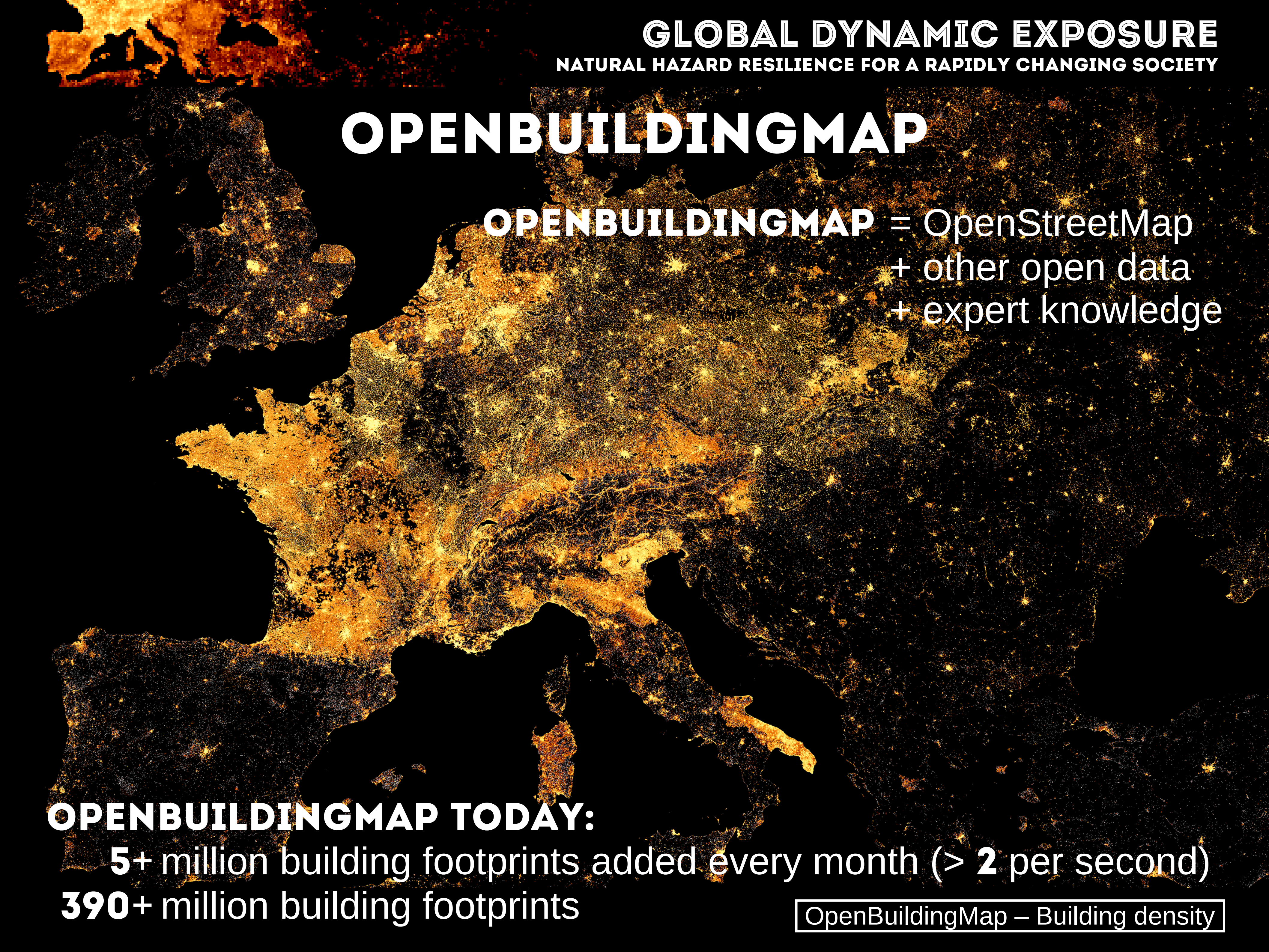
6+ million contributors

6+ billion elements

OpenStreetMap node density

OPENBUILDINGMAP

OPENBUILDINGMAP = OpenStreetMap
+ other open data
+ expert knowledge



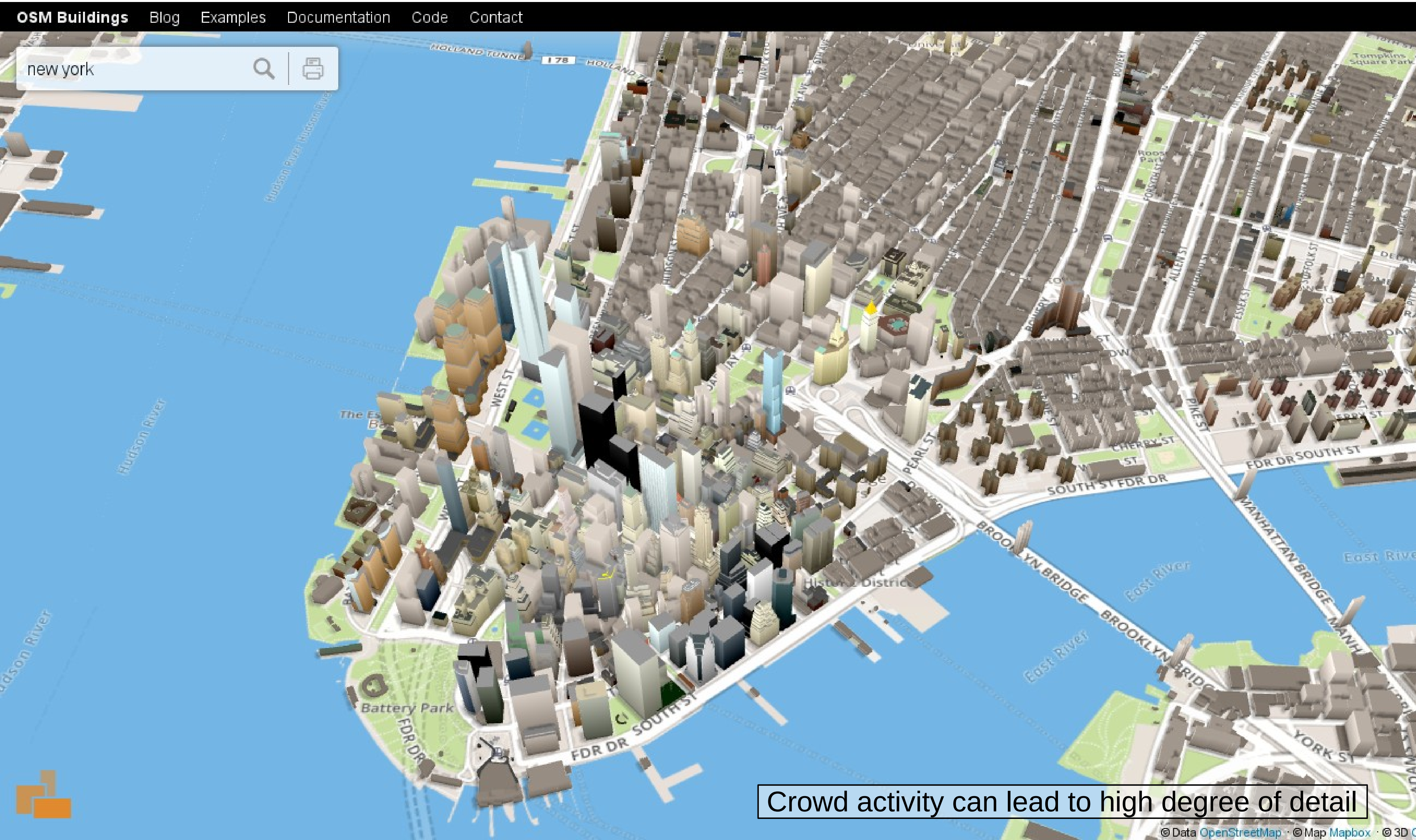
OPENBUILDINGMAP TODAY:

5+ million building footprints added every month (> **2** per second)

390+ million building footprints

OpenBuildingMap – Building density

CROWD ACTIVITY



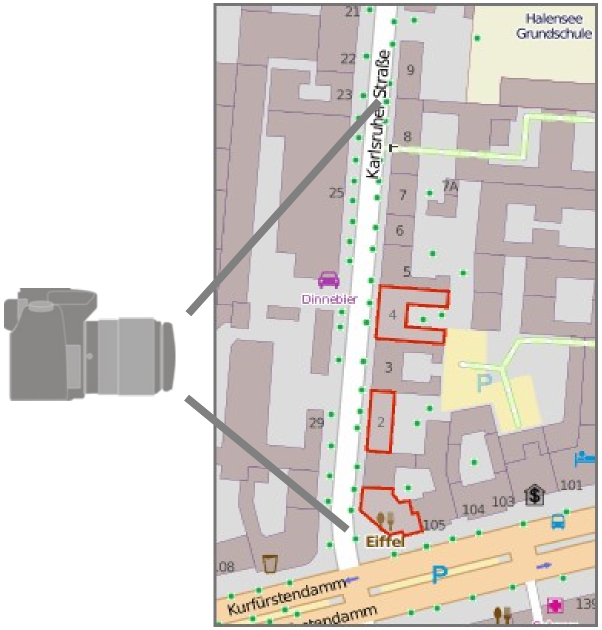
Crowd activity can lead to high degree of detail

DYNAMICS – PROCESSING

→ Updating from OpenStreetmap every 60 seconds
→ Processing all changes
→ Algorithmically assessing all possible building properties

DERIVING TAXONOMY VALUES

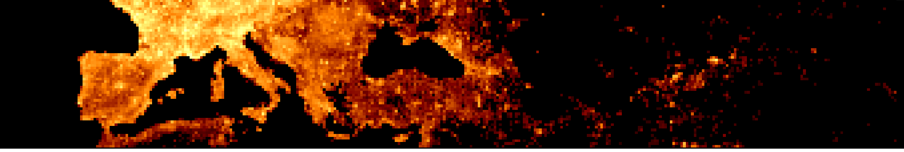
	Corner building	Building #2	Building #4
Land use	residential	residential	residential
Shops etc.	restaurant		
→ Occupancy	mixed	residential	residential
Position			
Direction			
Shape			
Footprint area			
Stories			
→ Inhabitants			
→ Date			
→ Exterior walls			
→ Floor			
→ Roof			



From predominant land use, building type, and points of interest (shops, cafes, etc.) we derive the occupancy.

OpenStreetMap explicit data
OpenStreetMap implicit data
(Semantically) derived data

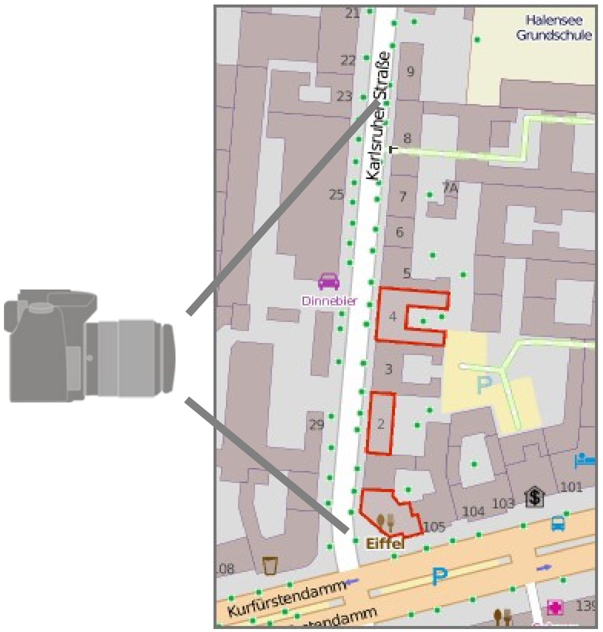
Example from central Berlin, Germany



DERIVING TAXONOMY VALUES

	Corner building	Building #2	Building #4
Land use	residential	residential	residential
Shops etc.	restaurant		
→ Occupancy	mixed	residential	residential
Position	corner	interior of a block	interior of a block
Direction	undefined	along street	along street
Shape	irregular	rectangle	U-shape
Footprint area	~440m²	~325m²	~620m²
Stories	5	7	5
→ Inhabitants	~45	~45	~65
→ Date			
→ Exterior walls			
→ Floor			
→ Roof			

From building footprint area and number of stories we derive the expected number of inhabitants using external statistical data.



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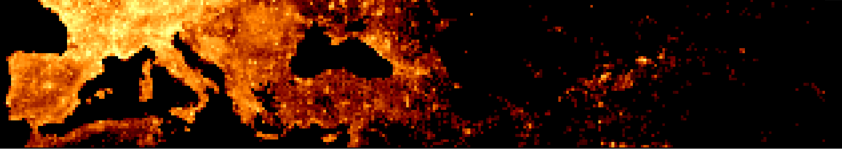
OpenStreetMap implicit data
(Semantically) derived data

Example from central Berlin, Germany



DERIVING TAXONOMY VALUES

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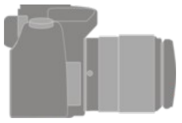
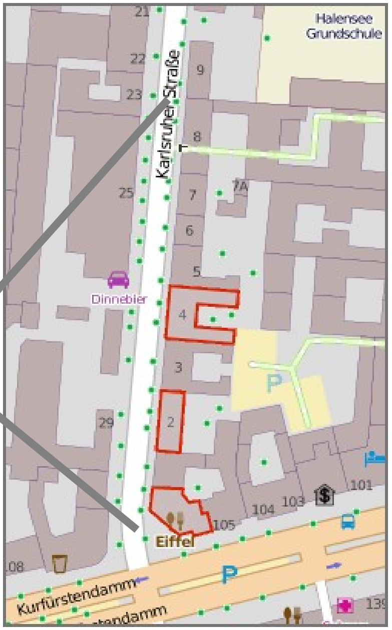
Shape	irregular	rectangle	U-shape
Footprint area	~440m^2	~325m^2	~620m^2
Stories	5	7	5
→ Inhabitants	~45	~45	~65
→ Date	pre-1930	post-1945	pre-1930
→ Exterior walls	masonry	concrete	masonry
→ Floor	wooden beams	concrete	wooden beams
→ Roof	mansard	flat	mansard

From location, position, and number of stories we derive the construction date and subsequently derive information about walls, floors, and roofs from knowledge about local architecture.





OpenStreetMap explicit data
OpenStreetMap implicit data
(Semantically) derived data

Example from central Berlin, Germany

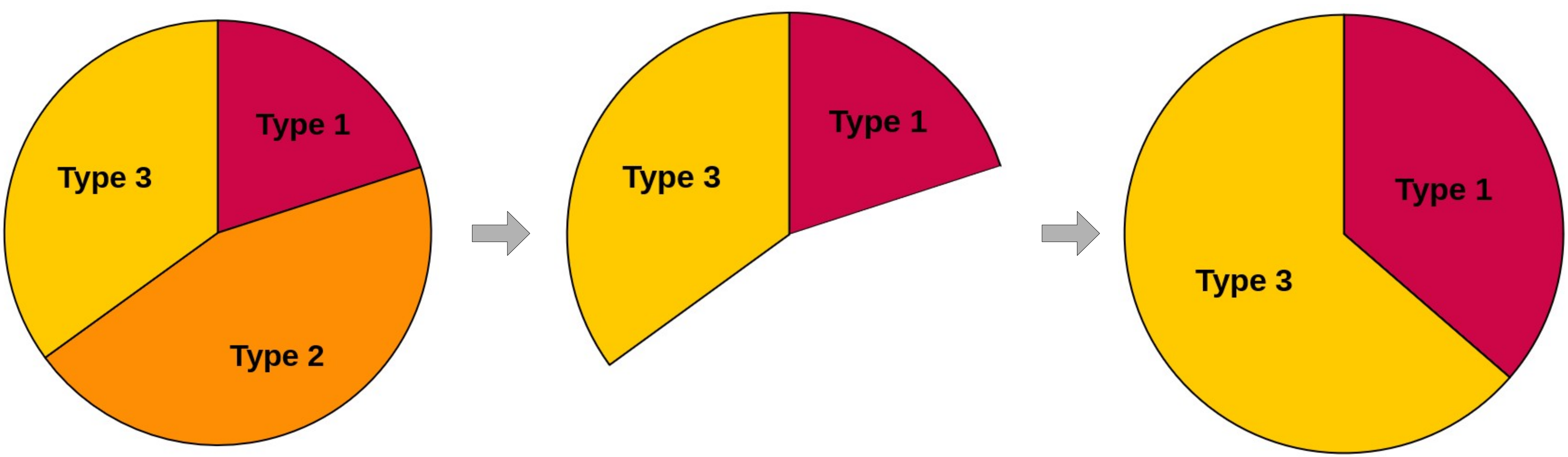
NARROWING DOWN…

If for a building the available information is not sufficient for an unambiguous classification, we use all available information to narrow down the classical building-type distribution (for the region) to the possible subset of types that match the available building data

All building types

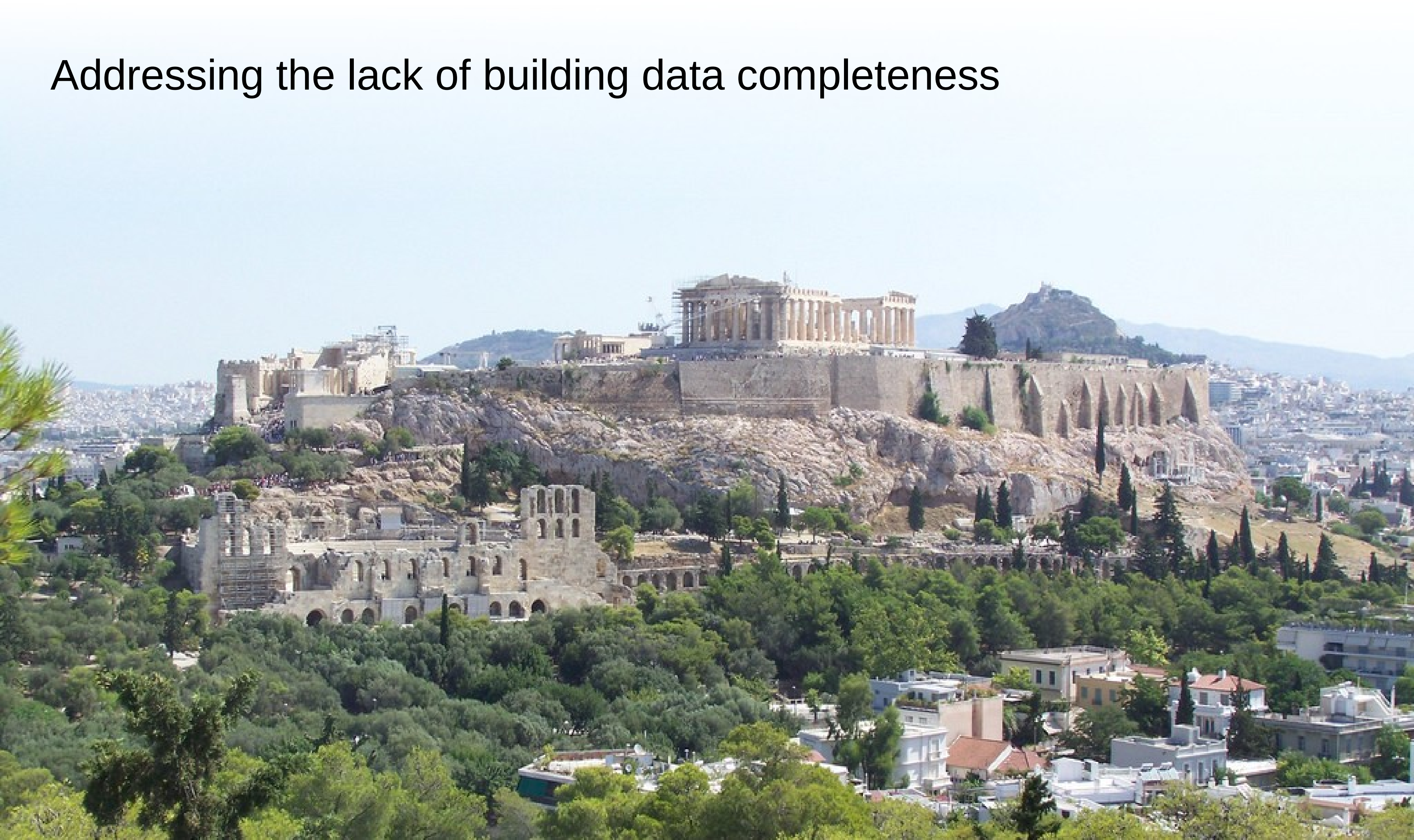
Eliminate those that do not match with the available information

Remaining building types that comply with known constraints

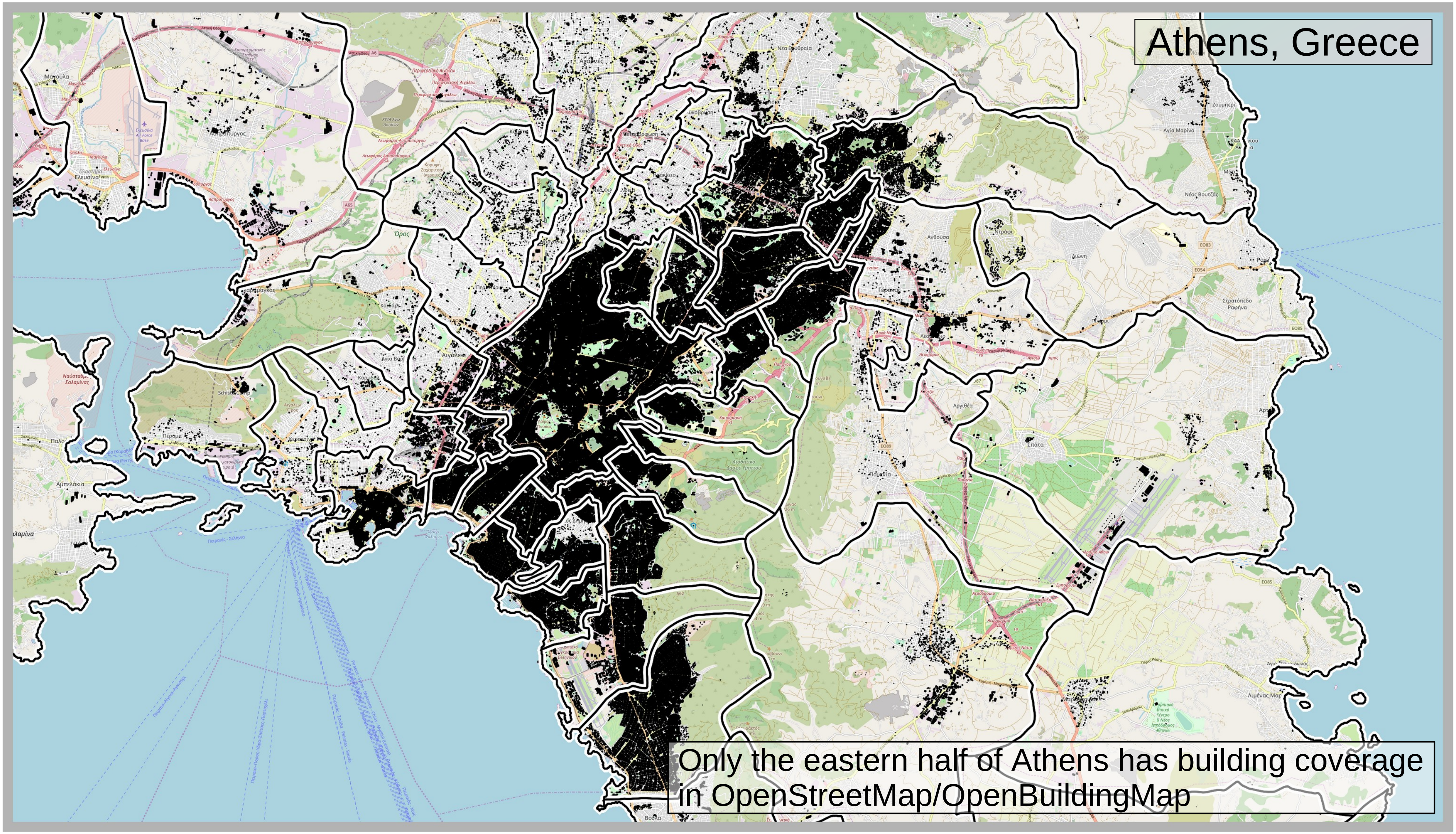


ATHENS, GREECE

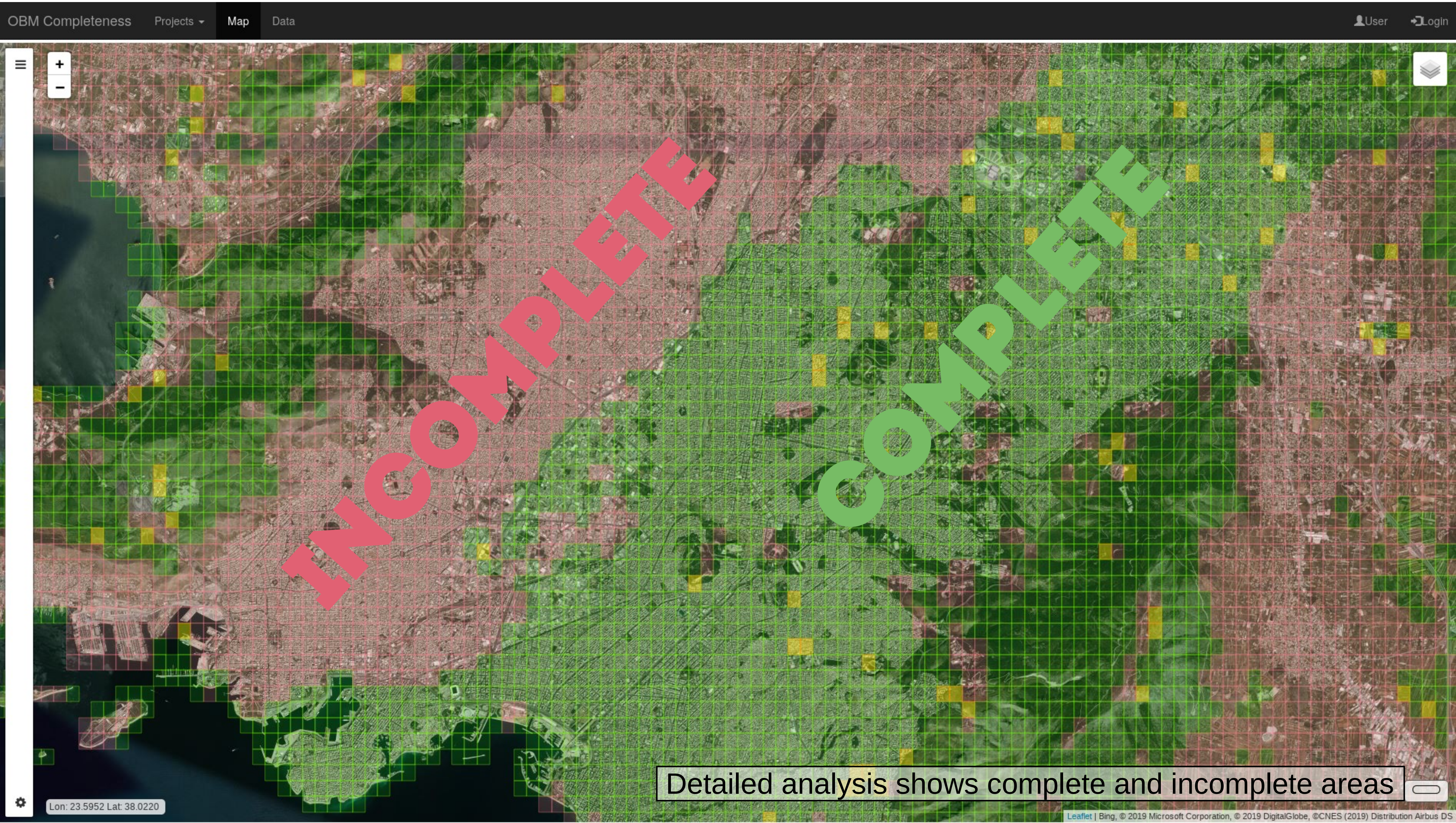
Addressing the lack of building data completeness



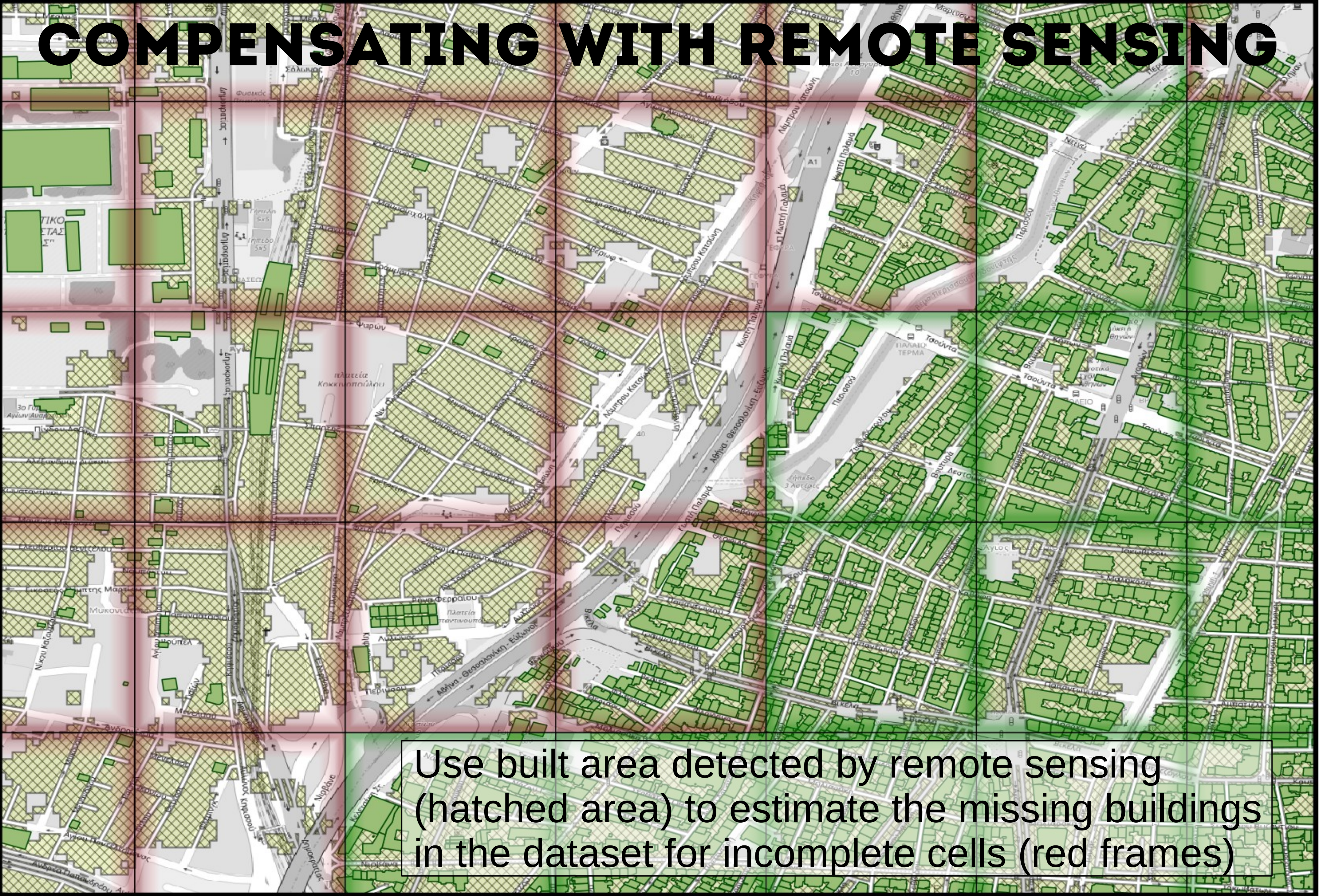
LACK OF COMPLETENESS



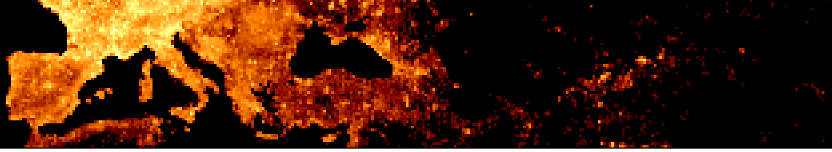
LACK OF COMPLETENESS



COMPENSATING WITH REMOTE SENSING



Use built area detected by remote sensing (hatched area) to estimate the missing buildings in the dataset for incomplete cells (red frames)



KINDS OF EXPOSURE OUTPUTS

INCOMPLETE

AGGREGATION LEVEL

- → Number of buildings in a cell
- → Number of people per building type in a cell
- → Proportion of building types in a cell
- → Replacement cost of all buildings of the same type in a cell

COMPLETE

BUILDING-BY-BUILDING LEVEL

- → Building type
- → Number of people in the building
- → Replacement cost of the building

INCREASING THE RESOLUTION

FROM AGGREGATION LEVEL

Aggregated exposure on a 1x1km grid from the upcoming GEM Global Exposure Database.

Derived from data on population, households, land cover, building inventory, living standard, topography, ...

VIA BLOCK-BY-BLOCK LEVEL

Exposure data on street block or multi-block resolution.

Highlights critical infrastructure such as power facilities and bridges but also hospitals and school.

TO BUILDING-BY-BUILDING LEVEL

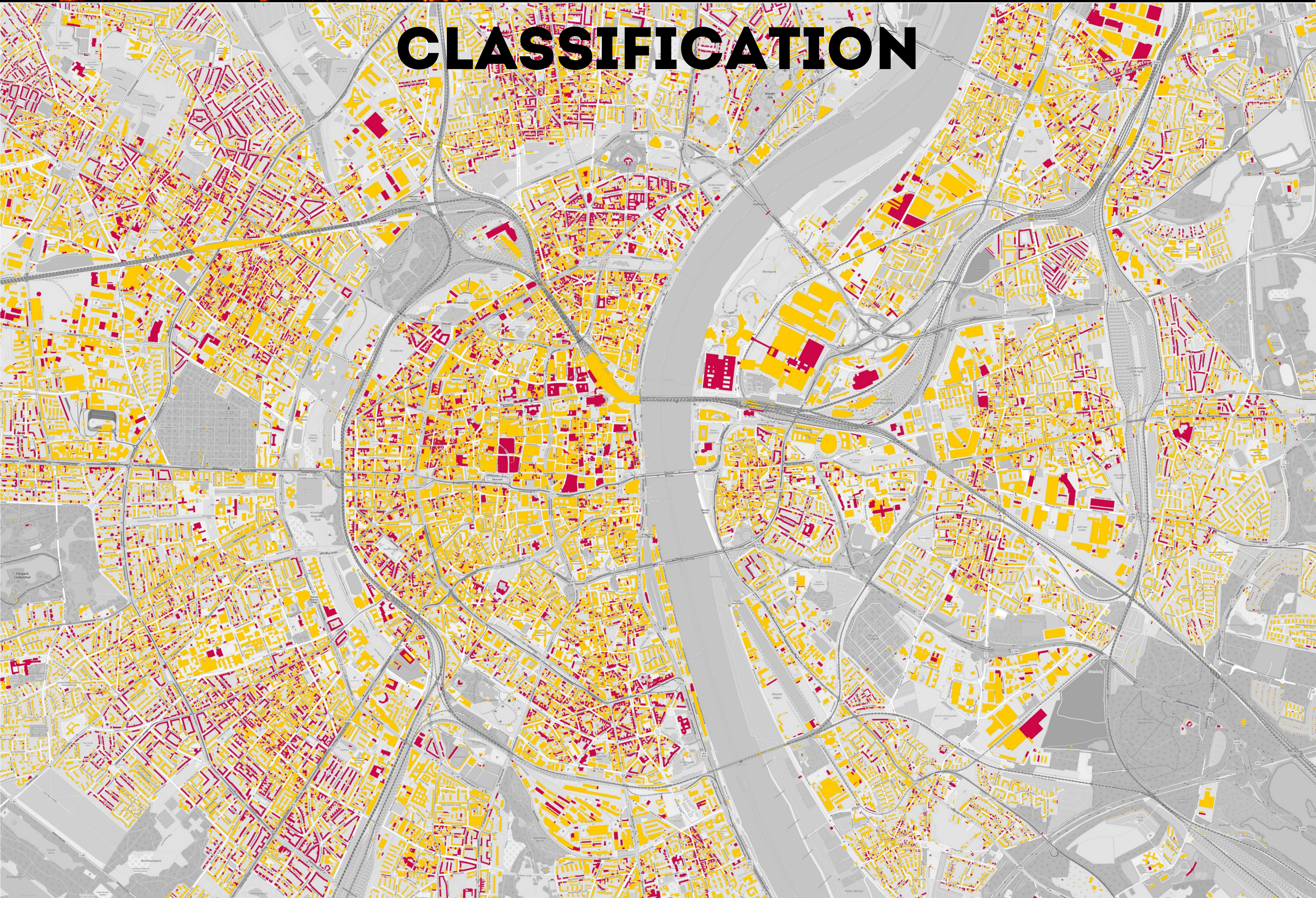
Exposure on a building-by-building resolution.

Depends on availability of detailed building data, covering building footprints, occupancy type, amenities, and structural information.

COLOGNE

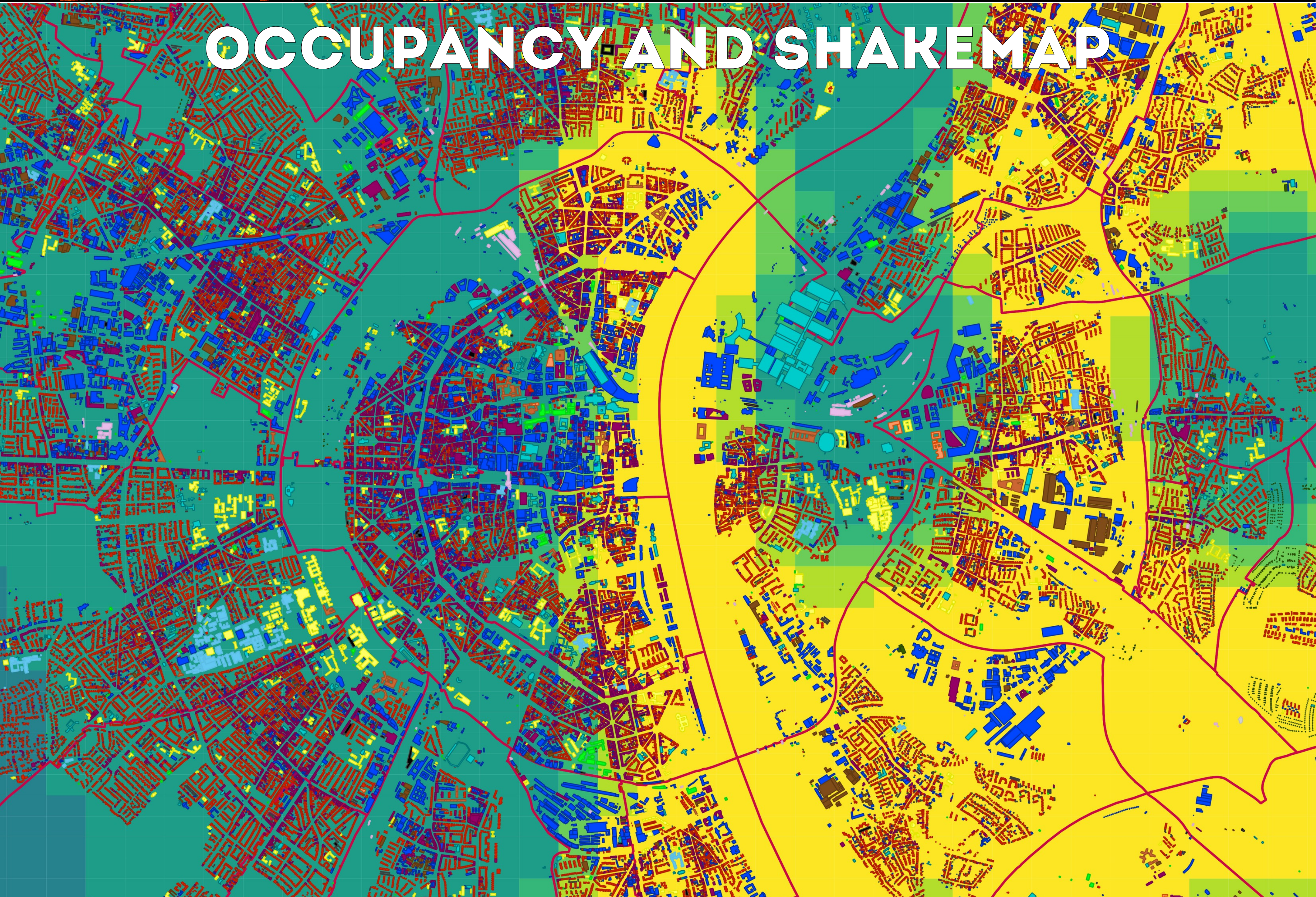
- Example earthquake risk model for the city
- Full building coverage in OpenBuildingMap
- Additional open-data sources available

CLASSIFICATION



GLOBAL DYNAMIC EXPOSURE

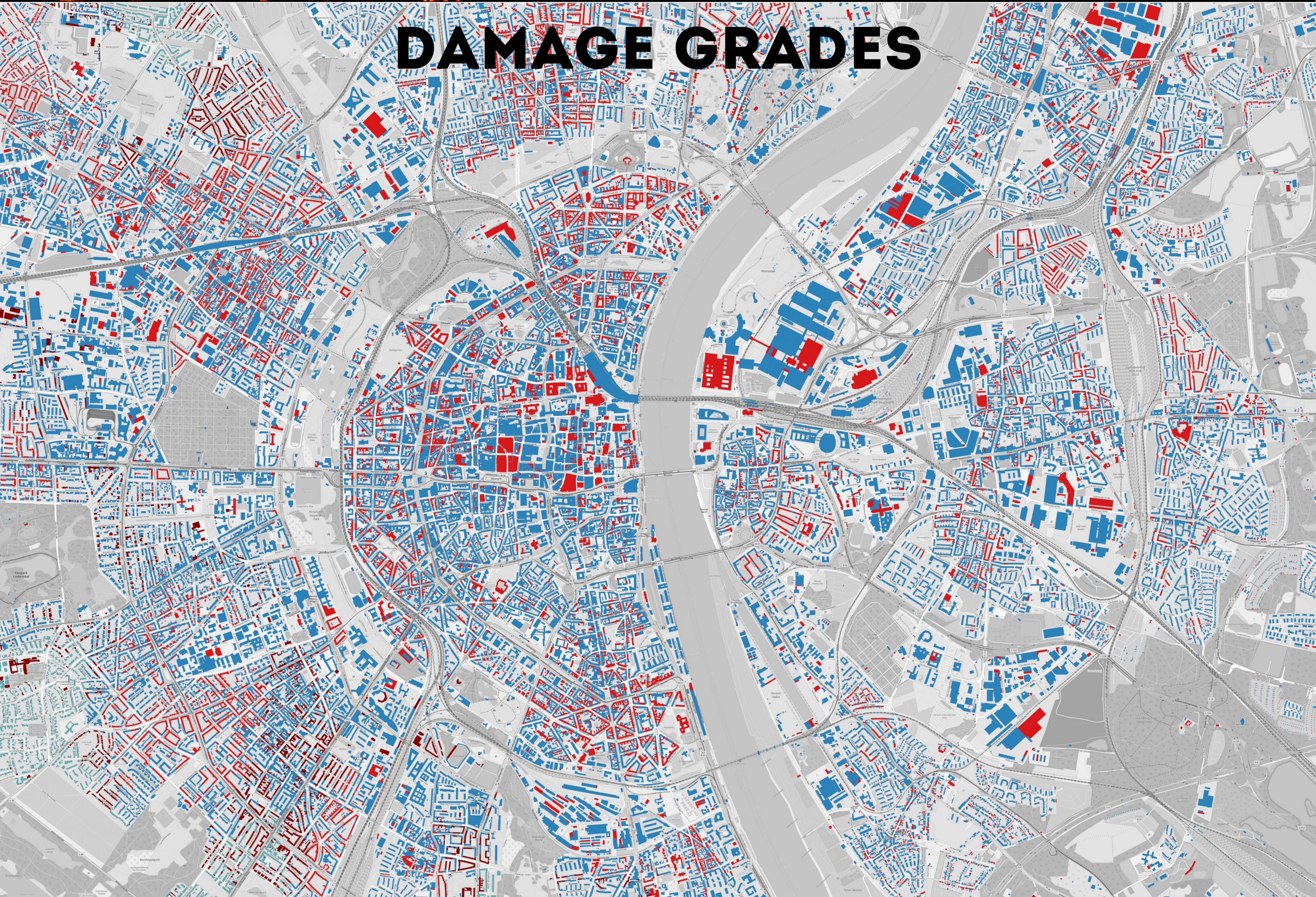
NATURAL HAZARD RESILIENCE FOR A RAPIDLY CHANGING SOCIETY



GLOBAL DYNAMIC EXPOSURE

NATURAL HAZARD RESILIENCE FOR A RAPIDLY CHANGING SOCIETY

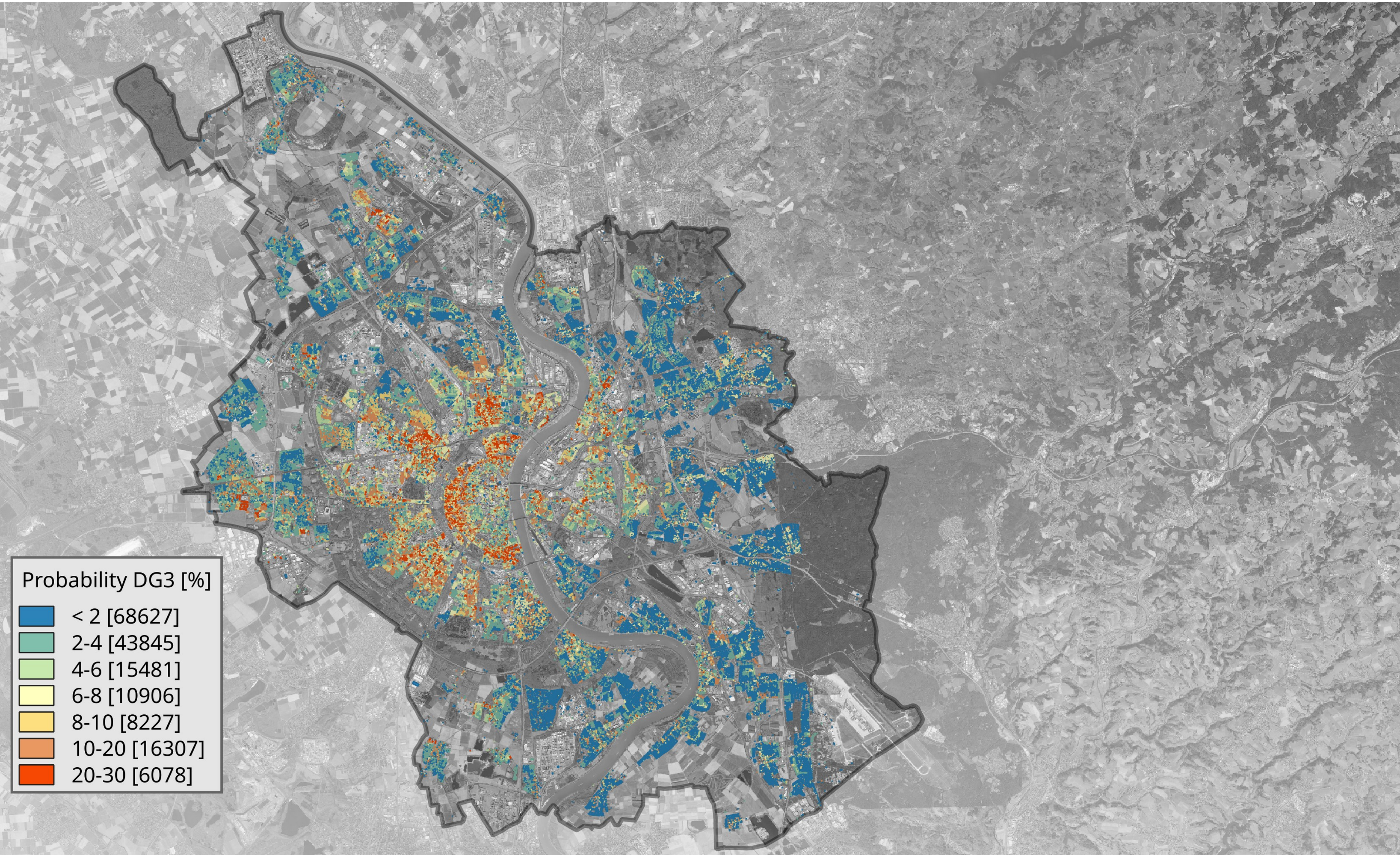
DAMAGE GRADES



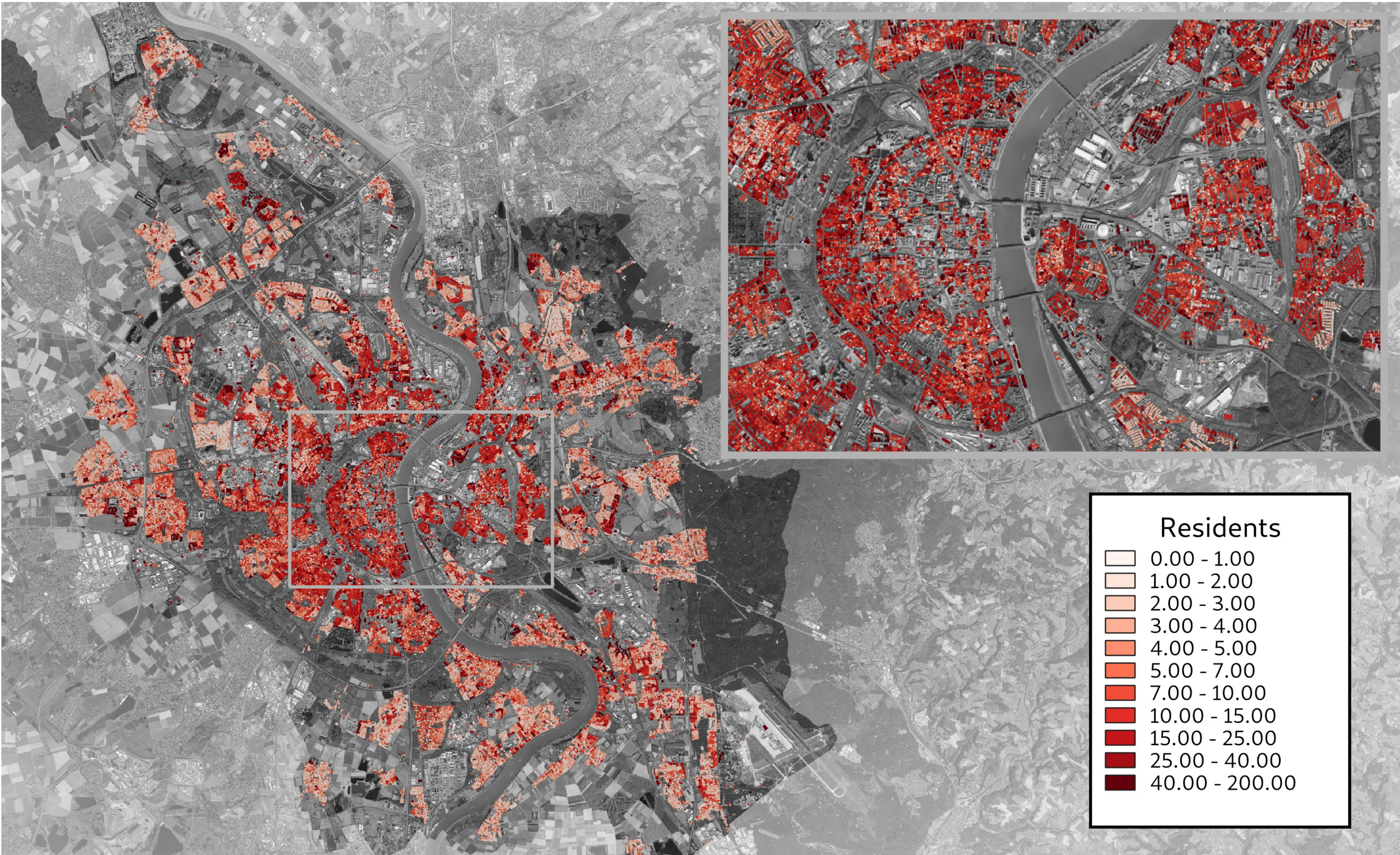
GLOBAL DYNAMIC EXPOSURE

NATURAL HAZARD RESILIENCE FOR A RAPIDLY CHANGING SOCIETY

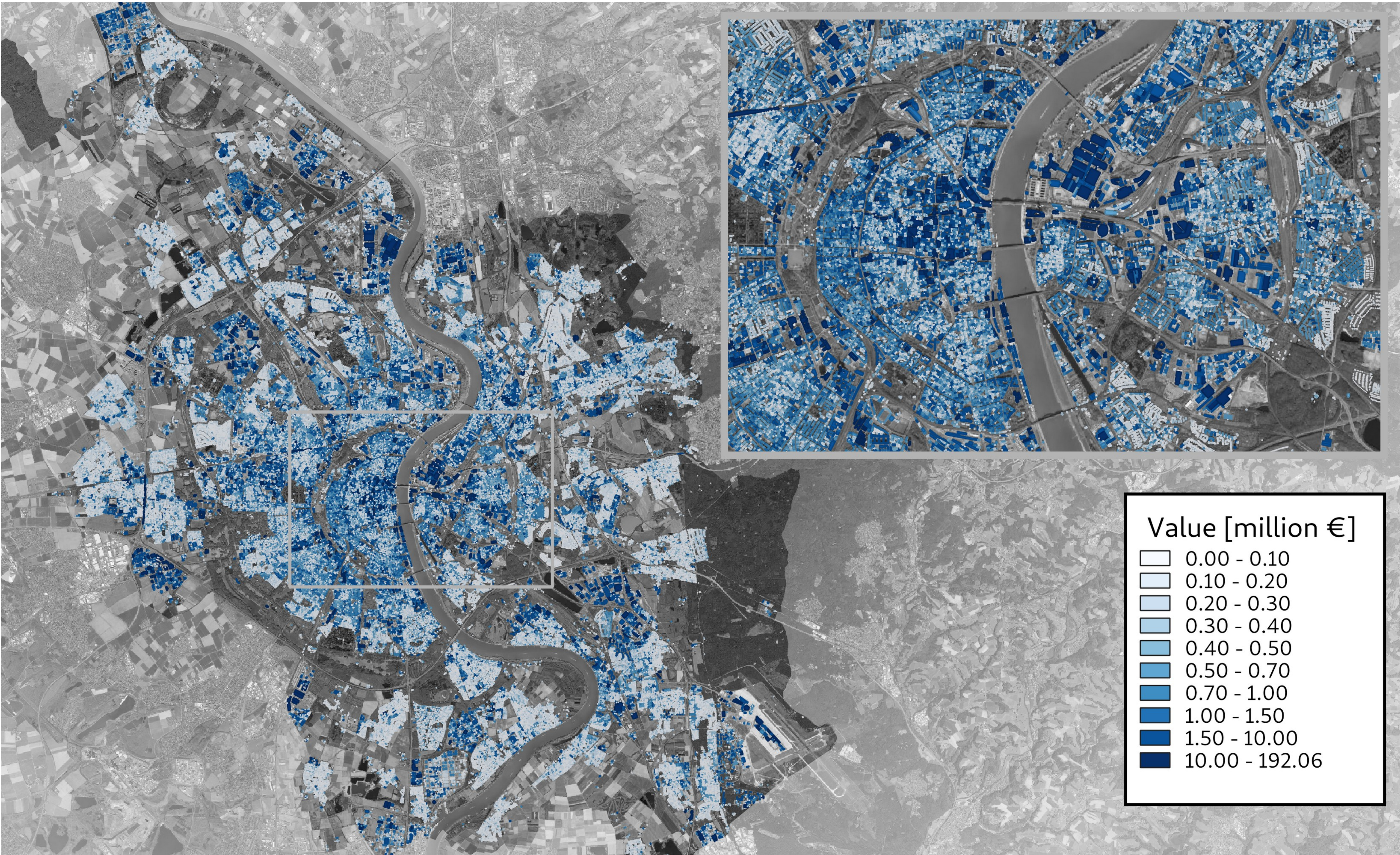
HEAVY DAMAGE



RESIDENTS PER BUILDING



VALUE


Value [million €]
0.00 - 0.10
0.10 - 0.20
0.20 - 0.30
0.30 - 0.40
0.40 - 0.50
0.50 - 0.70
0.70 - 1.00
1.00 - 1.50
1.50 - 10.00
10.00 - 192.06

SUMMARY

GLOBAL DYNAMIC EXPOSURE

→ Open and purely algorithmic (reproducible) model
→ Building on constantly growing databases

CROWD-SOURCING WILL CREATE

→ Amounts of high-quality data never seen before
→ Risk awareness and understanding of mitigation measures

THANK YOU

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