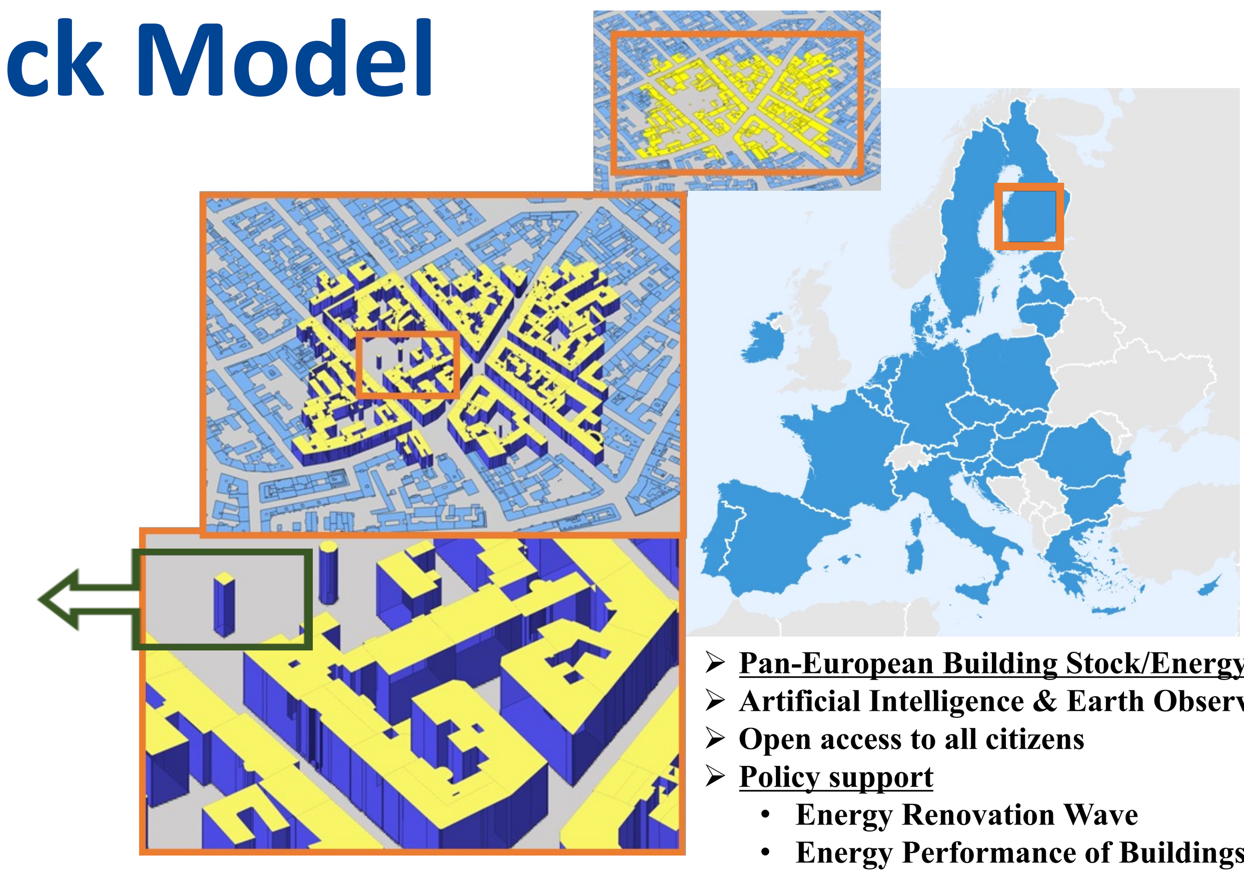
European Commission

Digital Building Stock Model

Link to the JRC Data Catalogue

Building attributes

Attributes	Source / Reliability	
Footprint	Conflation of sources (OSM/Microsoft/ESM)	Available **DBSM v1**
Height	GHSL-based (LoD1)	Coming soon **DBSM v2**
Compactness	Compactness formula	
Function (res/non-res)	GHSL+	
PV potential	PVGIS+	
Age	Machine Learning	Under research
Rooftop type	Machine Learning	
Energy demand	Simplified physical Model	



- Pan-European Building Stock/Energy Model
- Artificial Intelligence & Earth Observation data
- Open access to all citizens
- Policy support
  - Energy Renovation Wave
  - Energy Performance of Buildings Directives

Estimating the age of buildings from satellite and morphological features to create a pan-EU digital building stock model

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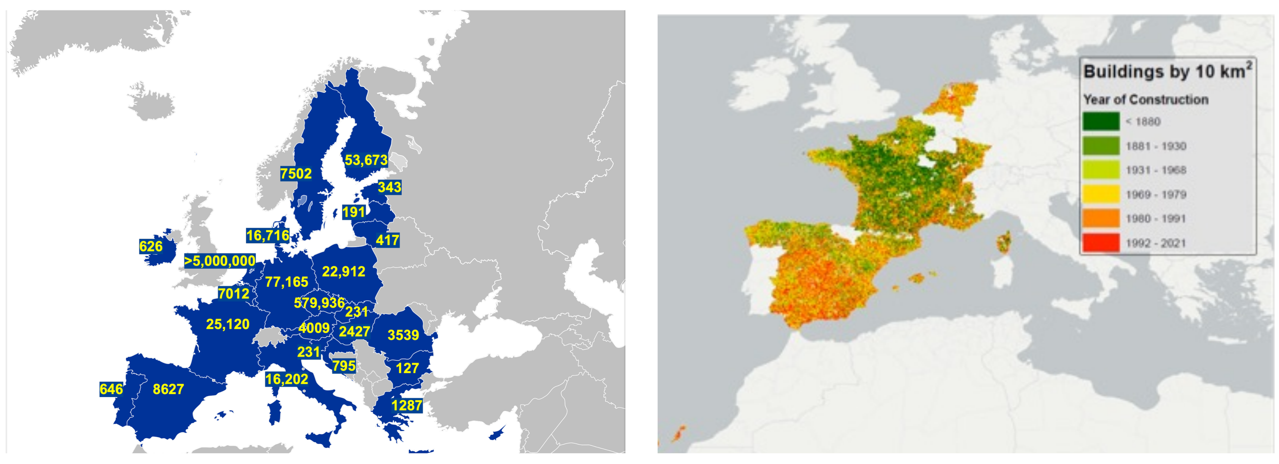
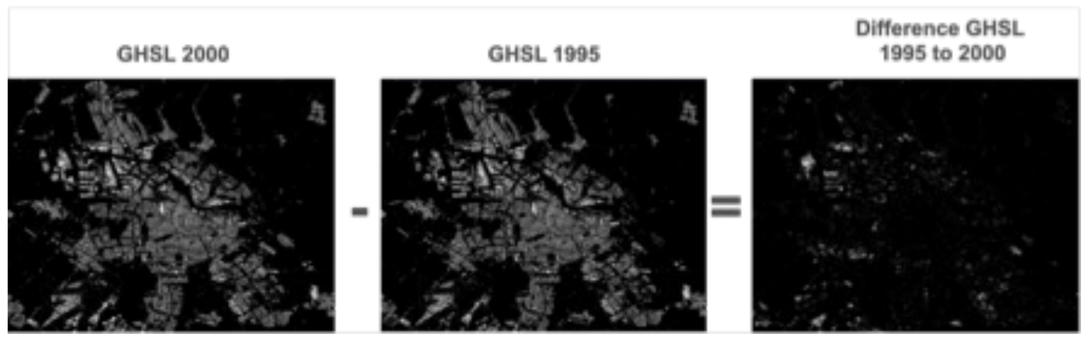
Motivation

- Buildings account for about 40% of the energy consumption in Europe
- it is crucial to have a comprehensive understanding of the building stock to make informed decisions for energy savings.
- Age of buildings only partially available (OpenStreetMap, GISCO and EUBUCCO).



Number of buildings in Europe with information on age of construction from left: OpenStreetMap, right: GISCO (EUSTAT)

Age prediction: satellite + morphological features



Time series of Bilt-up satellite data (GSHL)

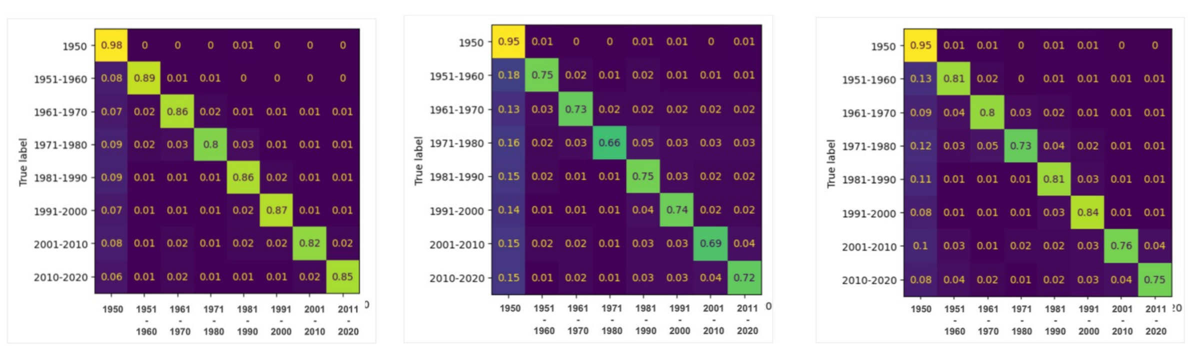
Building features	Neighbourhood features
Shape Complexity	Distance to closest neighbour
House element count	Number of adjoining buildings
House area	Distances to closest street and intersection
	Building count in 20m, 100m and 500 range

Built-up surfaces in period 1995-2000 derived from the multi-temporal built-up surface grid GHS-BUILT-S.

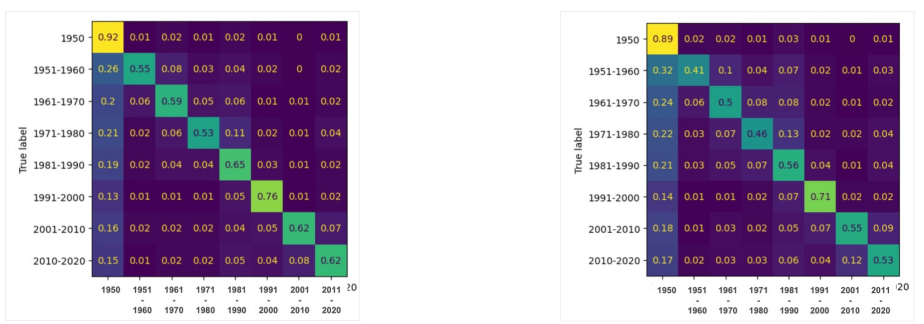
Pre 1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2010	2011-2020
95,693	29,073	18,871	13,992	29,821	27,872	17,301	16,923

Number of buildings per Age Category

Results



(a) Includes GHSL and morphological features (b) Includes only morphological features (c) Includes only GHSL features



(a) Amsterdam predicted using 10% of Amsterdam data on the Rotterdam model (b) Amsterdam predicted using 5% of Amsterdam data on the Rotterdam model

Conclusions

- This study demonstrates the effectiveness of combining satellite and morphological features for predicting the age of buildings using Machine Learning.
- Integrates the multi-temporal built-up surface grid from GHS-BUILT-S and various morphological features from OSM in a Random Forest model.
- As expected, the model exhibited strong local predictability, showing sensitivity to the use of local data, particularly from different cities within the same country.
- Incorporating a small amount of local information could enhance prediction accuracy for a different location.
- For energy-related purposes, it is crucial to have information on the age of renovation, if any. Hence, this data should be combined with information from energy performance certificates in the future.

Cities and buildings for Better lives

Joint Research Centre