→ 6th ESA ADVANCED TRAINING COURSE ON LAND REMOTE SENSING

Urban Mapping & Change Detection

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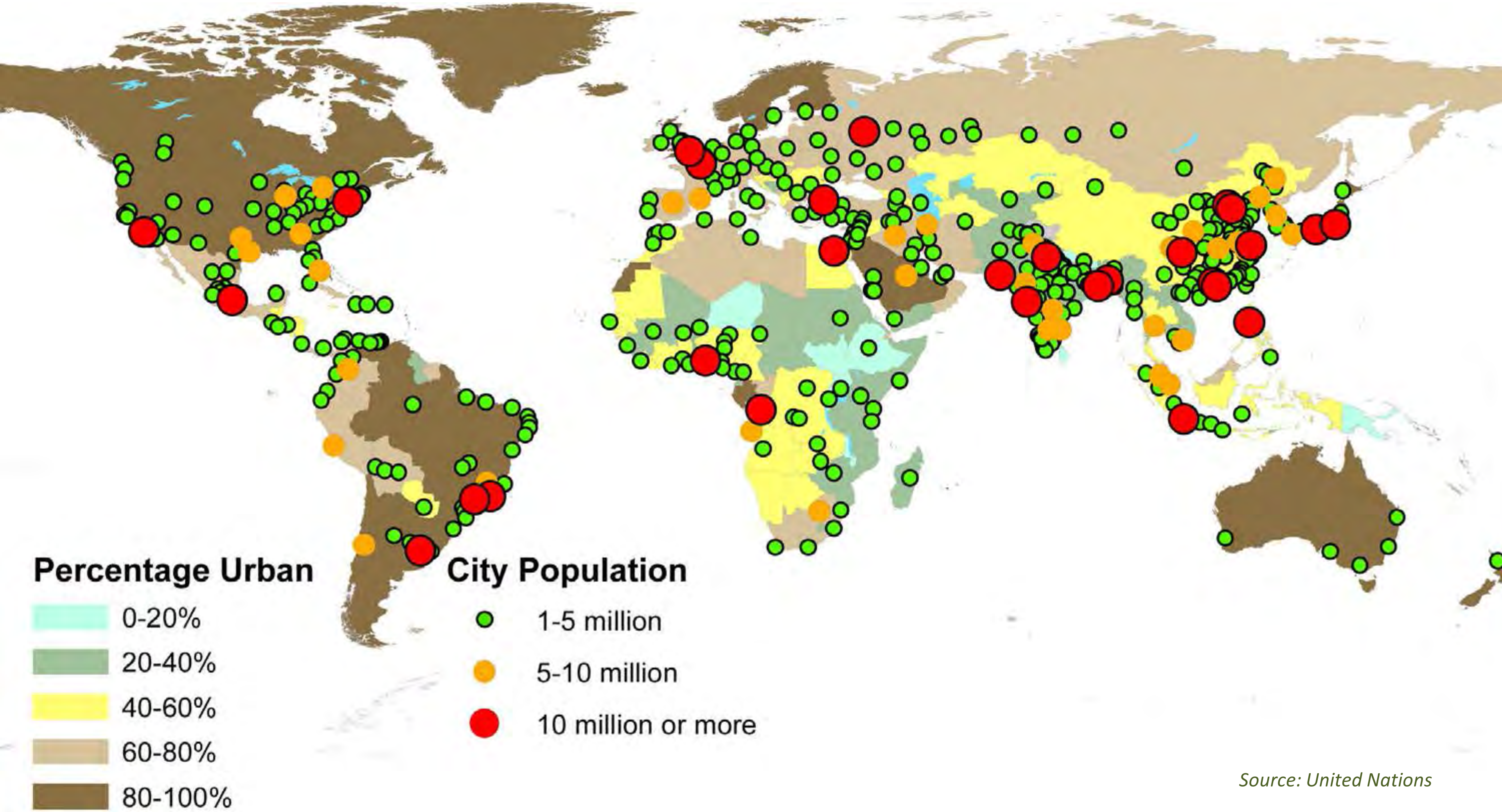
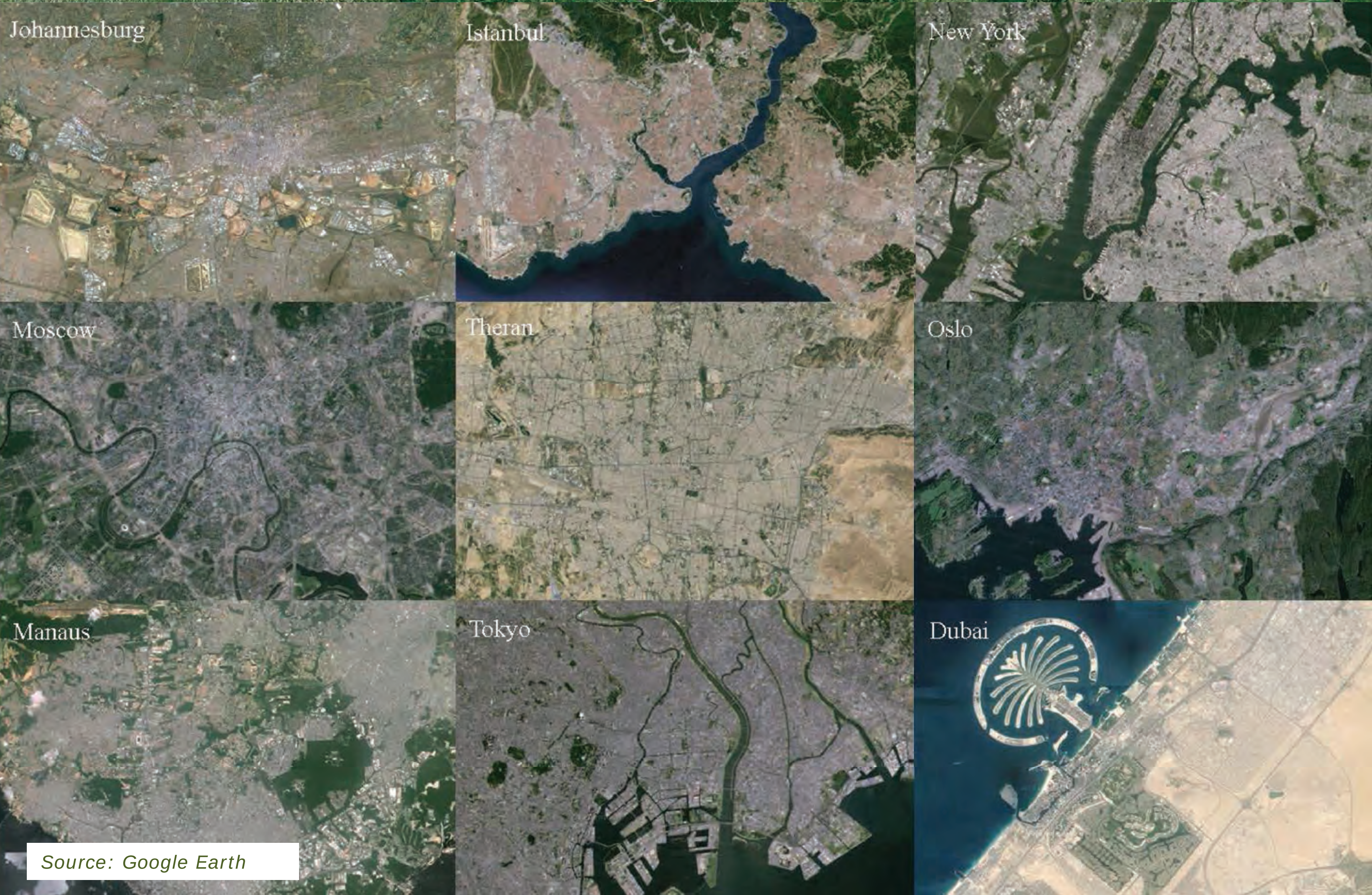
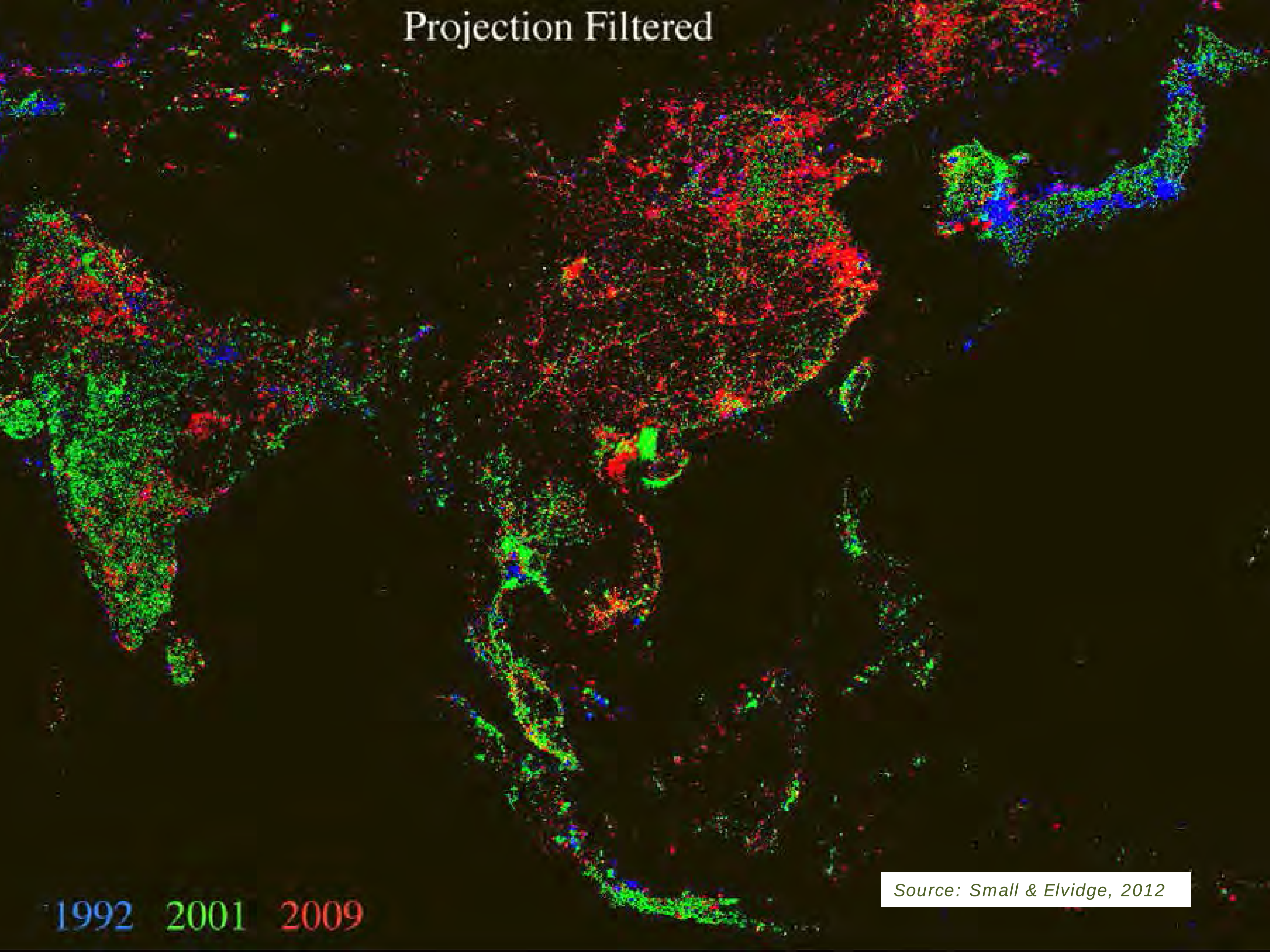
Introduction - The urban millennium



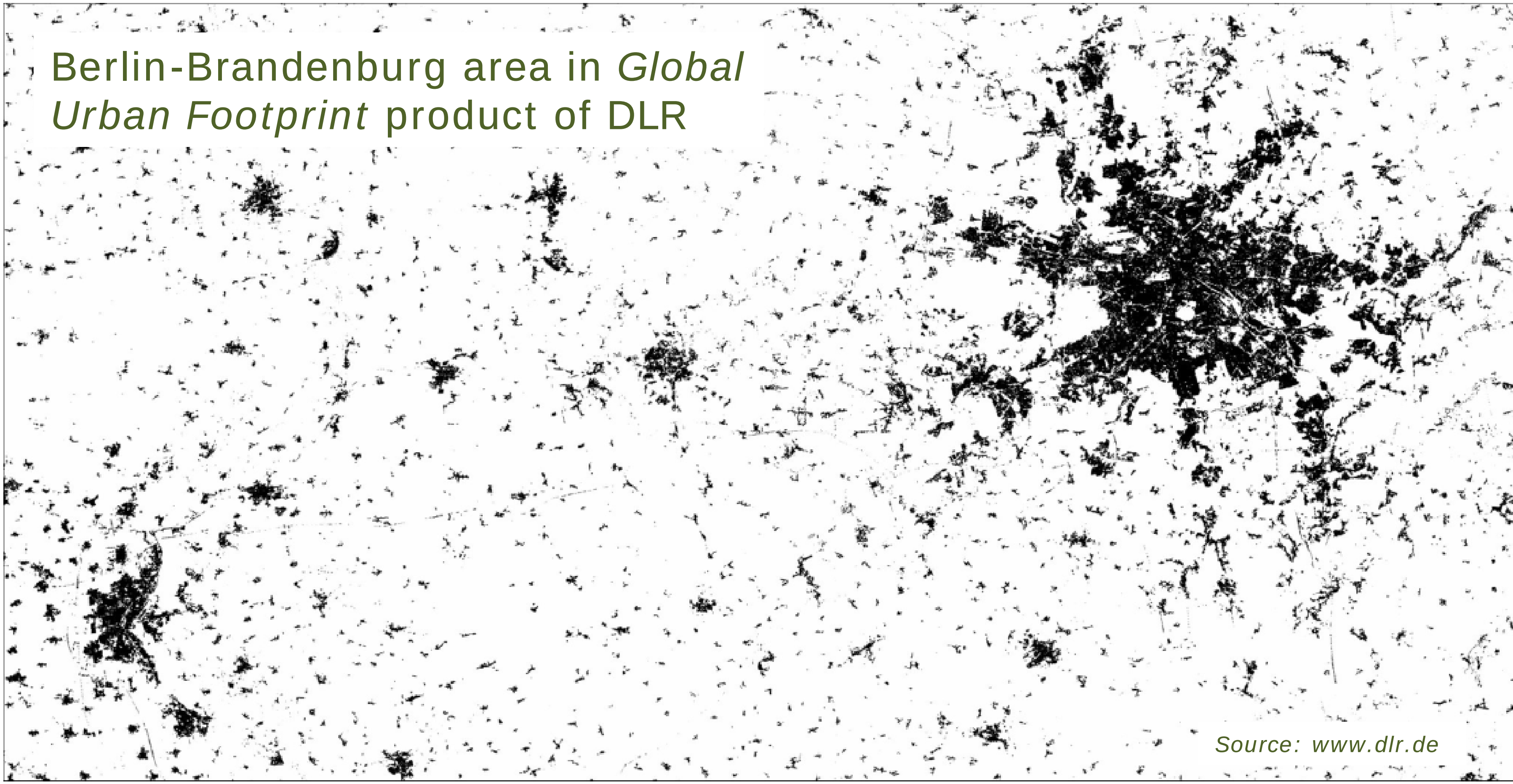
Source: United Nations



Source: Google Earth


Projection Filtered
1992 2001 2009
Source: Small & Elvidge, 2012

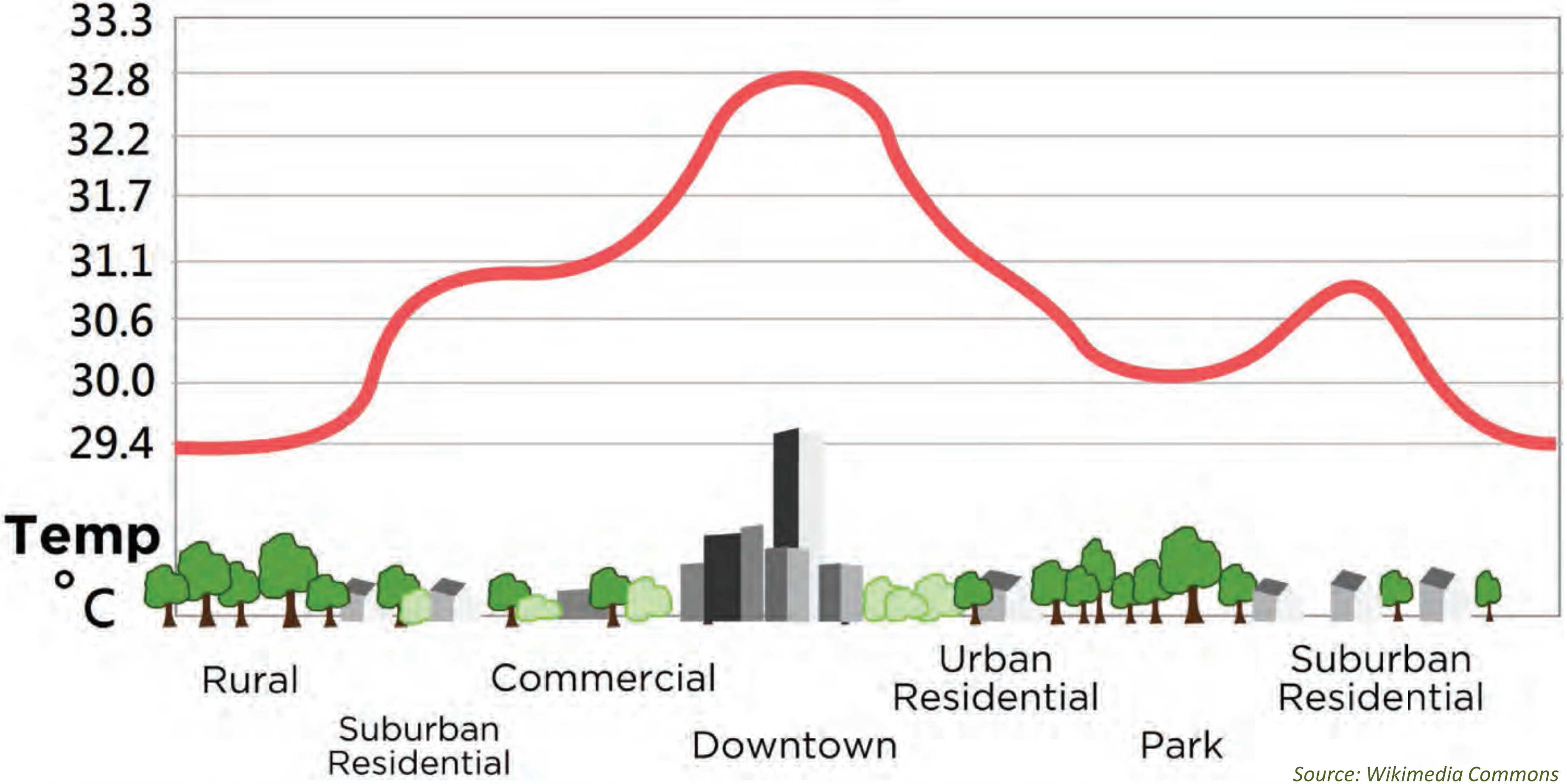
Introduction – Urban remote sensing



Berlin-Brandenburg area in *Global Urban Footprint* product of DLR

Source: www.dlr.de

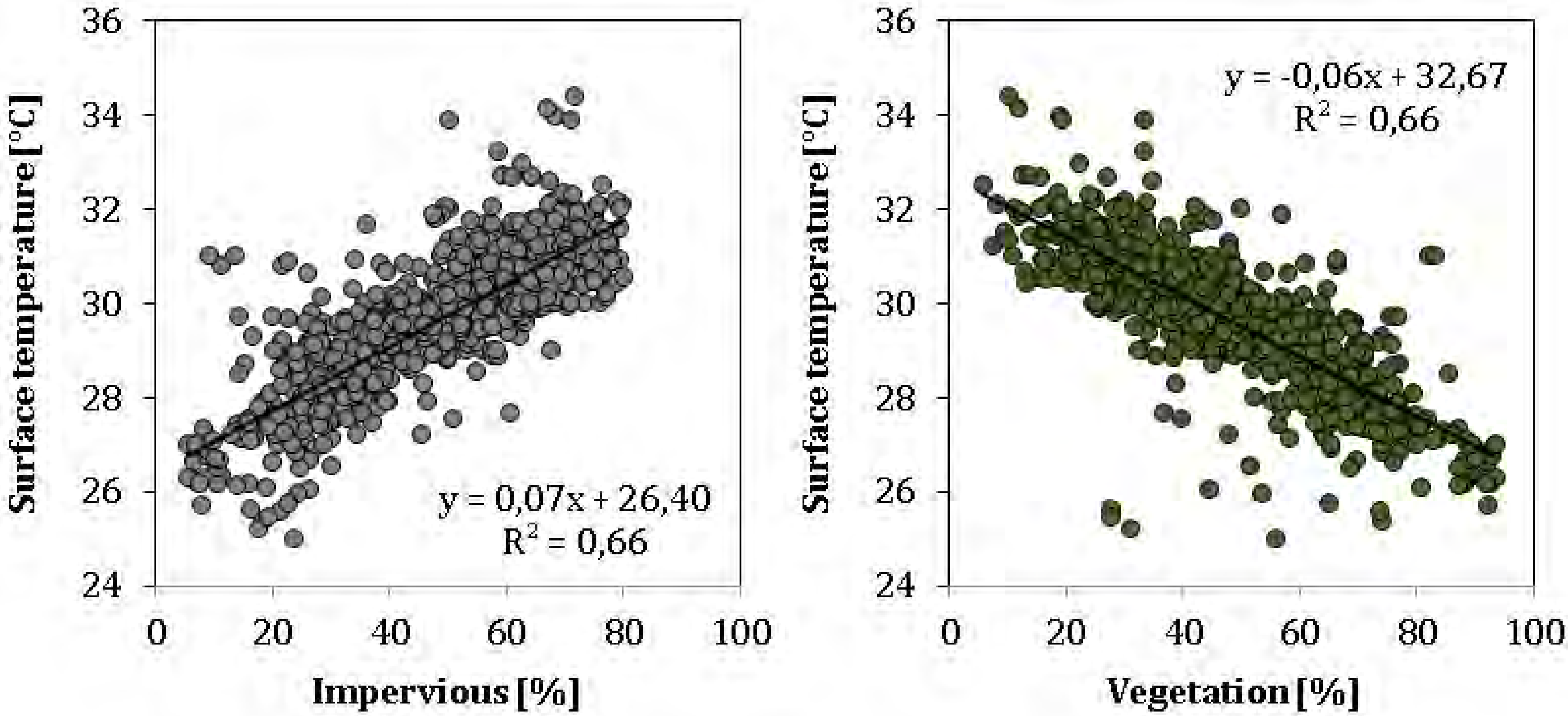
Introduction – Effects of impervious surfaces



Source: Wikimedia Commons

Introduction – Effects of impervious surfaces

Urban surface type influences the micro climate and other environmental variables



Introduction – Urban remote sensing

With more than half of the world's population living in cities and rapid urbanization rates, remote sensing plays a pivotal role in monitoring urban environments.

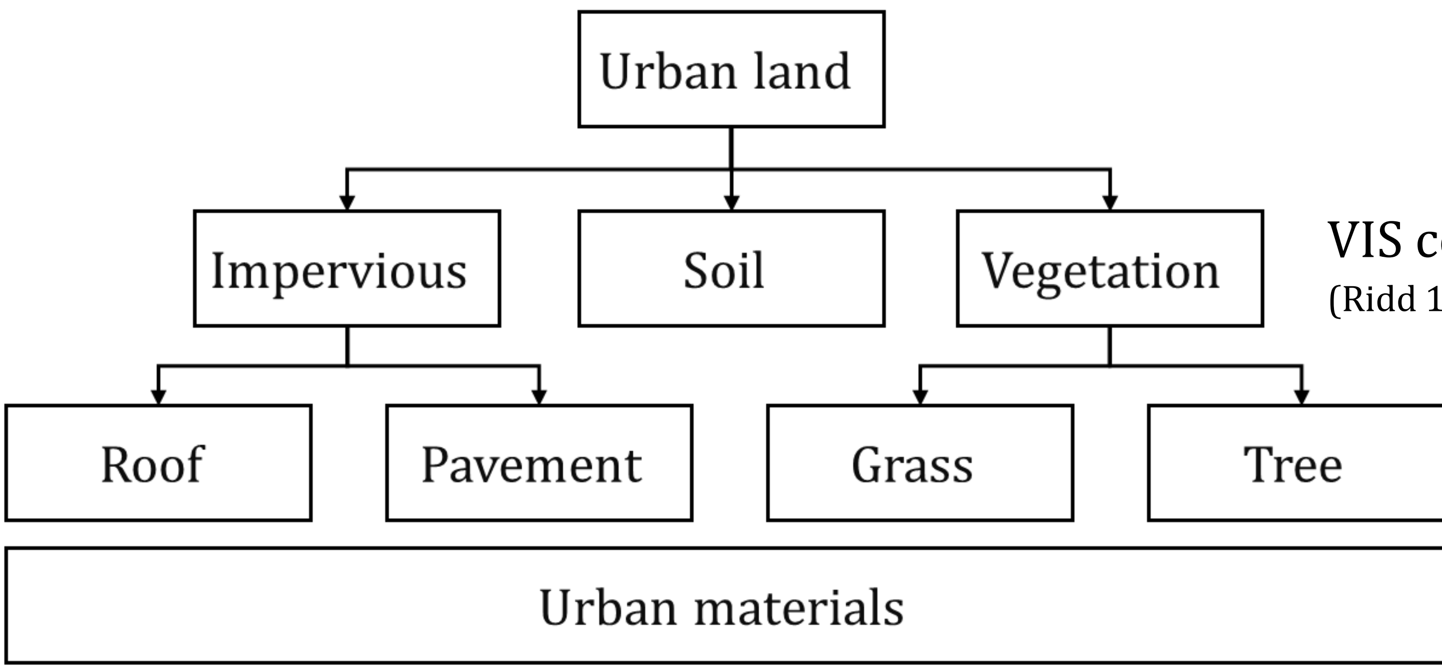
Especially in less developed countries and for fast growing urban agglomerations remote sensing is often the only reliable source of spatial information.

Most urban environmental models use remotely sensed maps as input.

Remote sensing analyses usually focus on

- mapping urban extent and growth
- mapping urban composition

Introduction – V-I-S conceptual framework



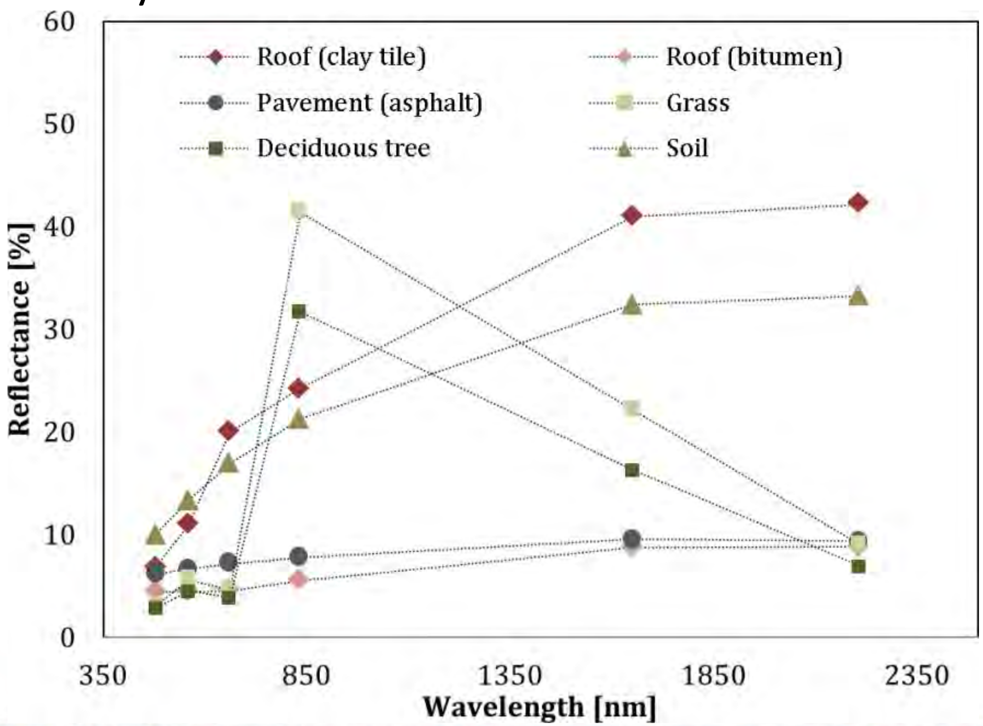
VIS concept
(Ridd 1995)

Challenges of urban remote sensing

Urban areas are composites of many different surface types with greatly varying environmental impacts.

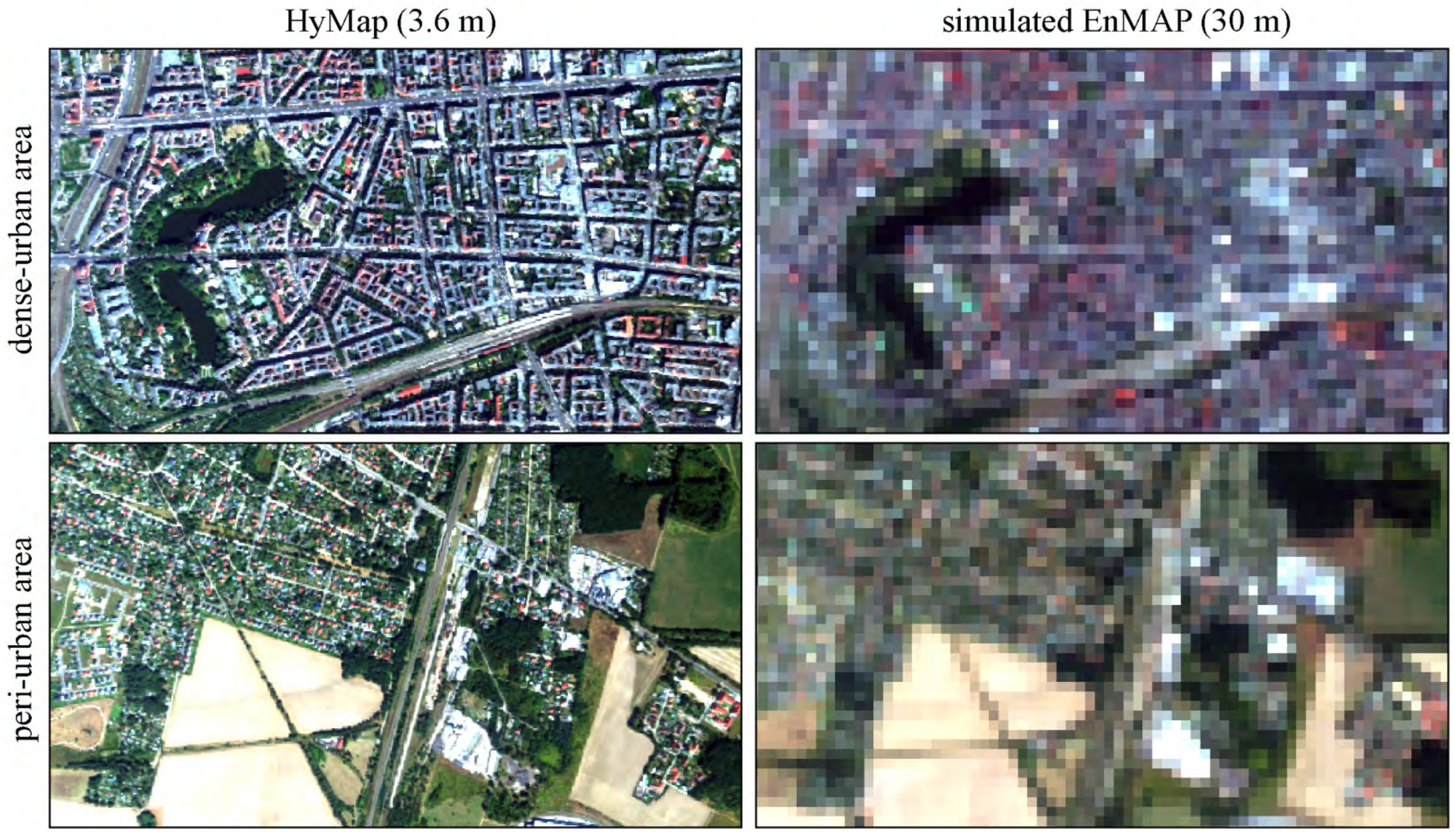
Spectrally complex: high intra-class class variety and often no inter-class differences.

Landsat ETM+ (30 m; 6 spectral bands)



Challenges of urban remote sensing

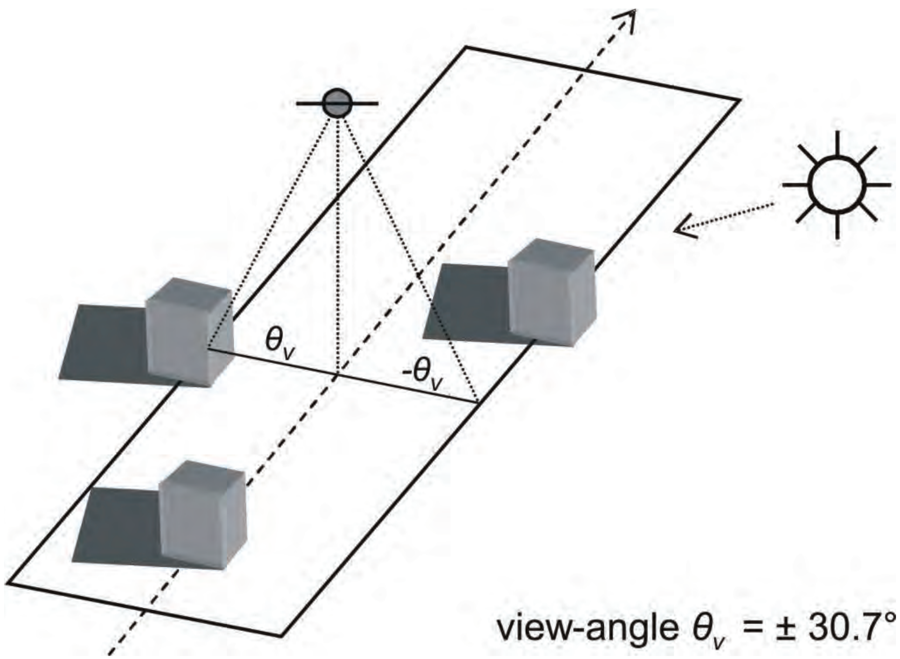
High spatial and temporal dynamics require high spatial resolution

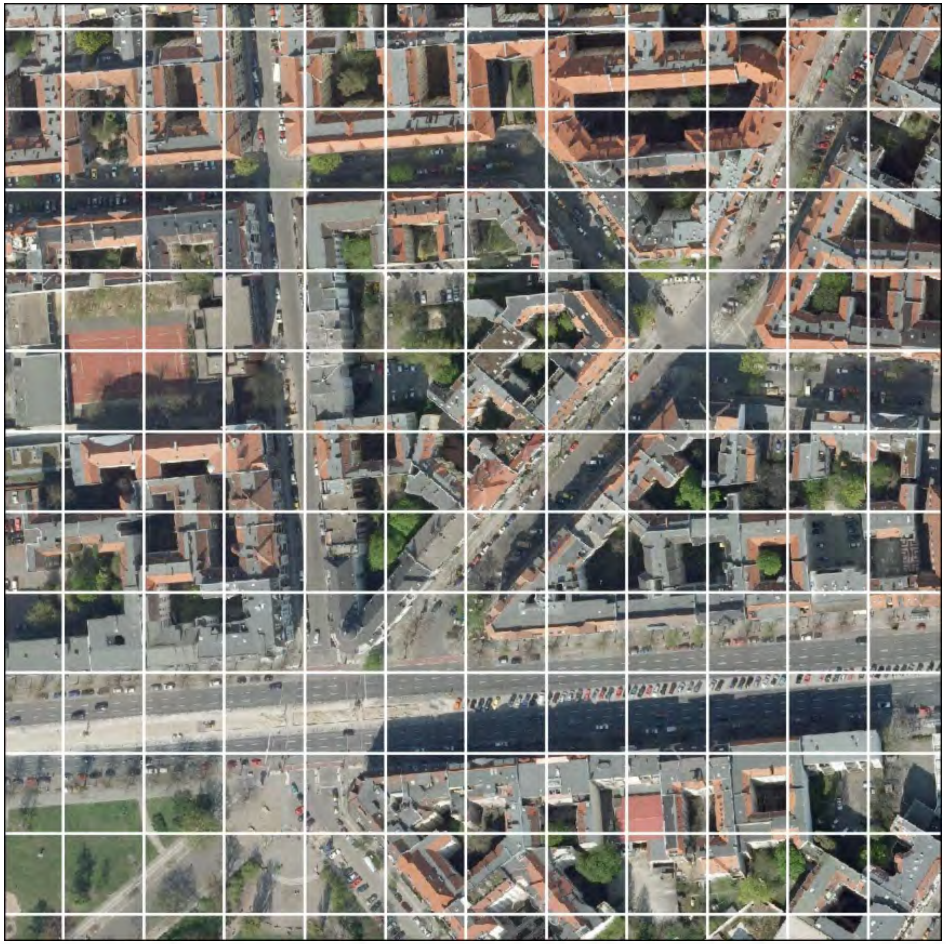


Challenges of urban remote sensing

High number of mixed pixels.

Complex 3-D-geometry and illumination.

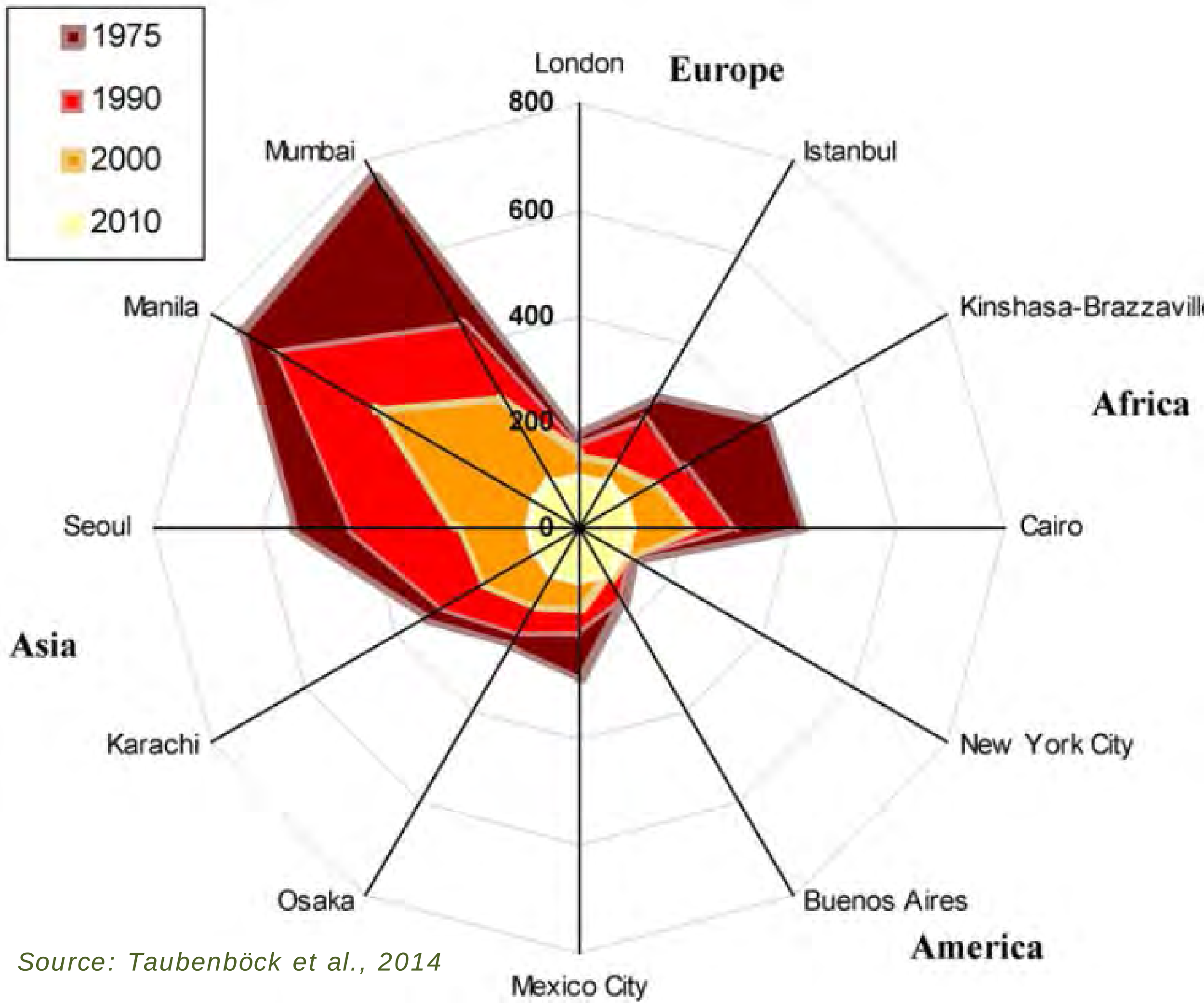




Mapping urban growth from spectral and SAR data

Urban growth can be mapped reliably by means of remote sensing.

Taubenböck et al. use data from Terra-SAR and Landsat to quantify urban growth since 1975 in four time steps.



Source: Taubenböck et al., 2014

Mapping urban growth …

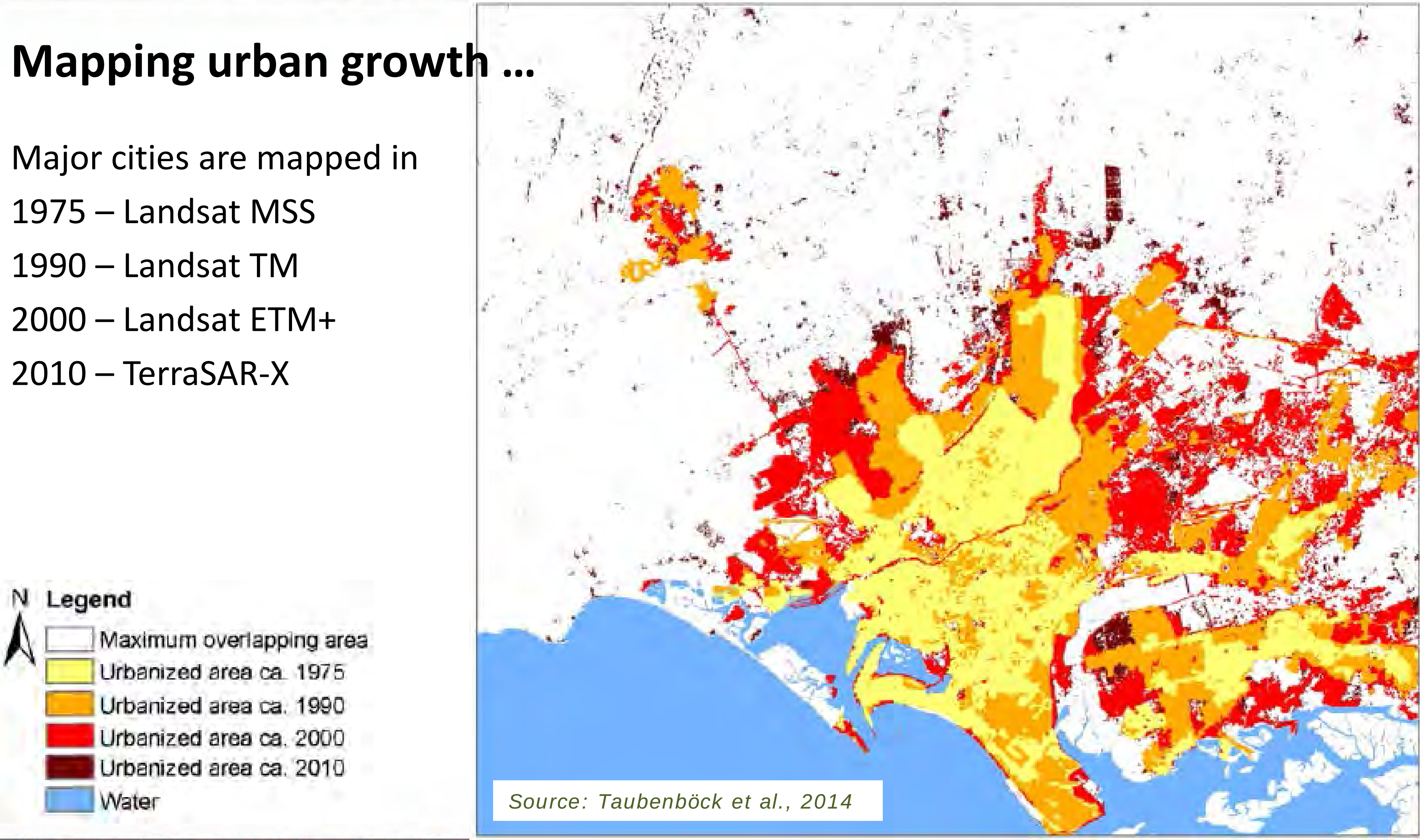
Major cities are mapped in

1975 – Landsat MSS

1990 – Landsat TM

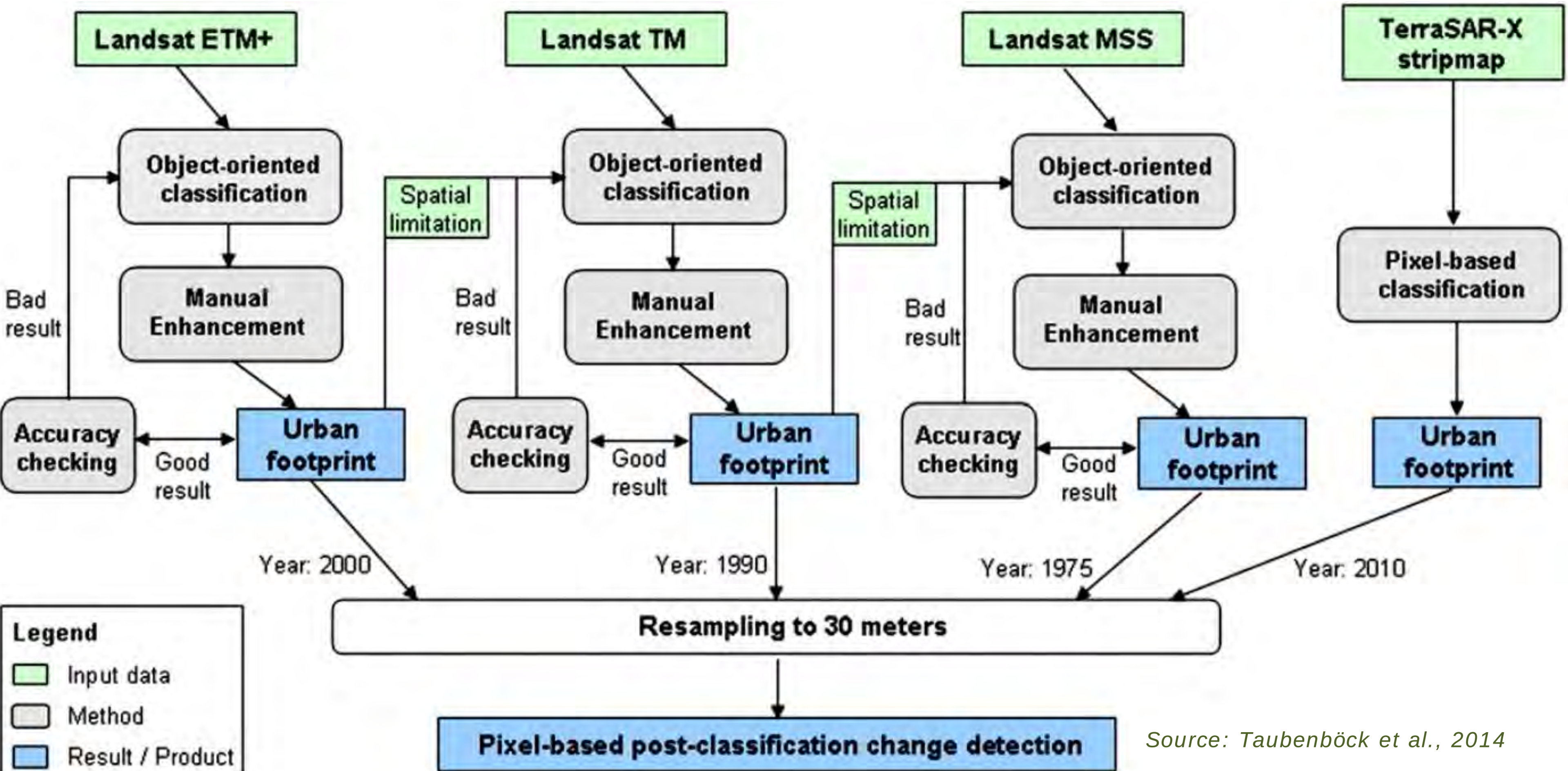
2000 – Landsat ETM+

2010 – TerraSAR-X



Mapping urban growth from spectral and SAR data

Landsat and TerraSAR data are classified with different approaches.

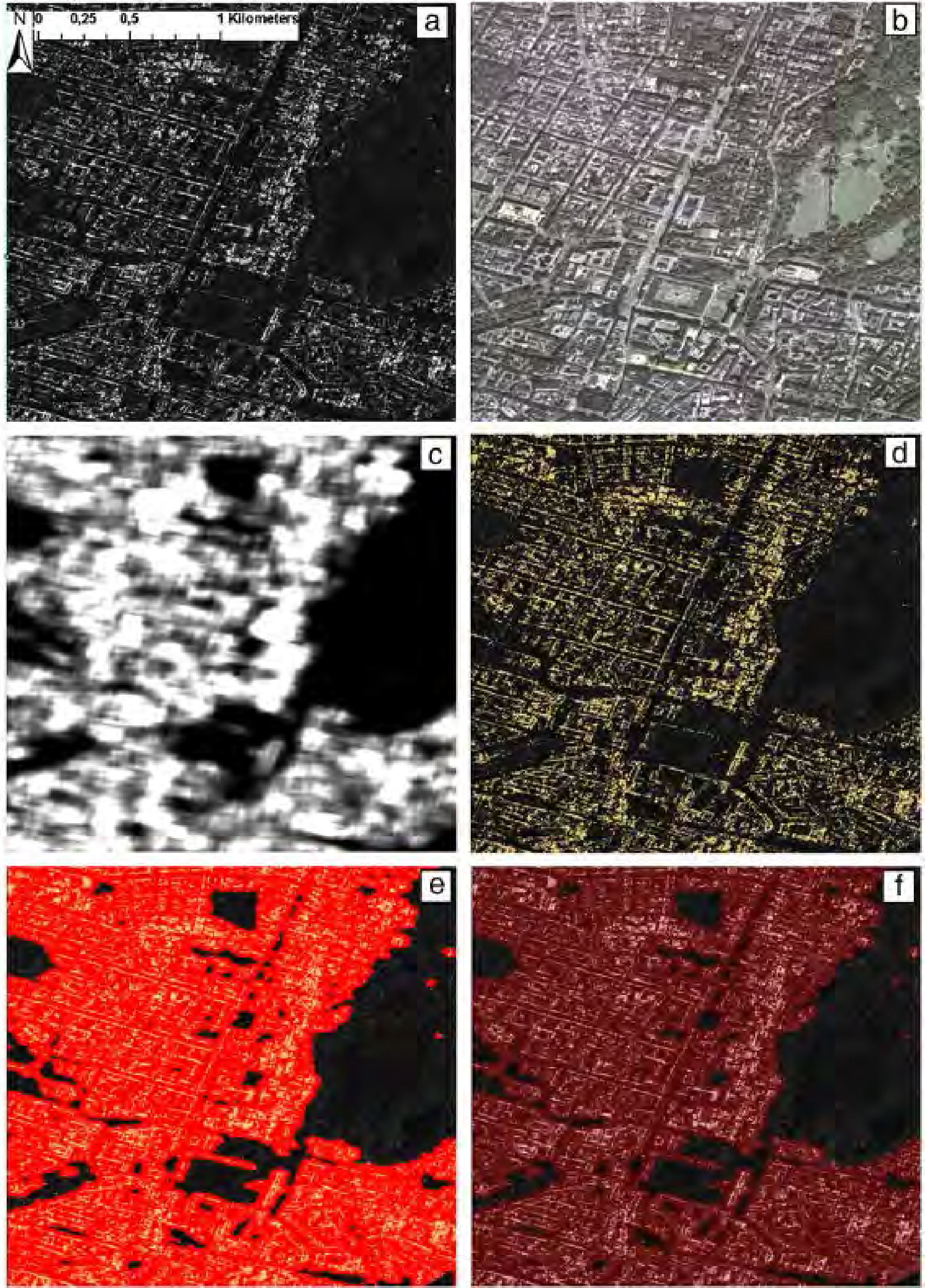


Source: Taubenböck et al., 2014

Mapping urban growth …

For the 2010 TerraSar-X classification the speckle divergence (c) is used to identify areas with high vertical structures.

These are transferred into urban seeds (d), which are then generalized to delineate the urban footprint.



Source: Taubenböck et al., 2014

Mapping urban growth from spectral and SAR data

Griffiths et al. monitor the growth of Dhaka, Bangladesh, for 1990, 2000 and 2006 based on Landsat TM/ETM+ and ERS-1/ASAR data.

By fusing the multispectral optical and the SAR data they can map urban extent reliably in this heavily monsoon influenced area of rapid urbanization.

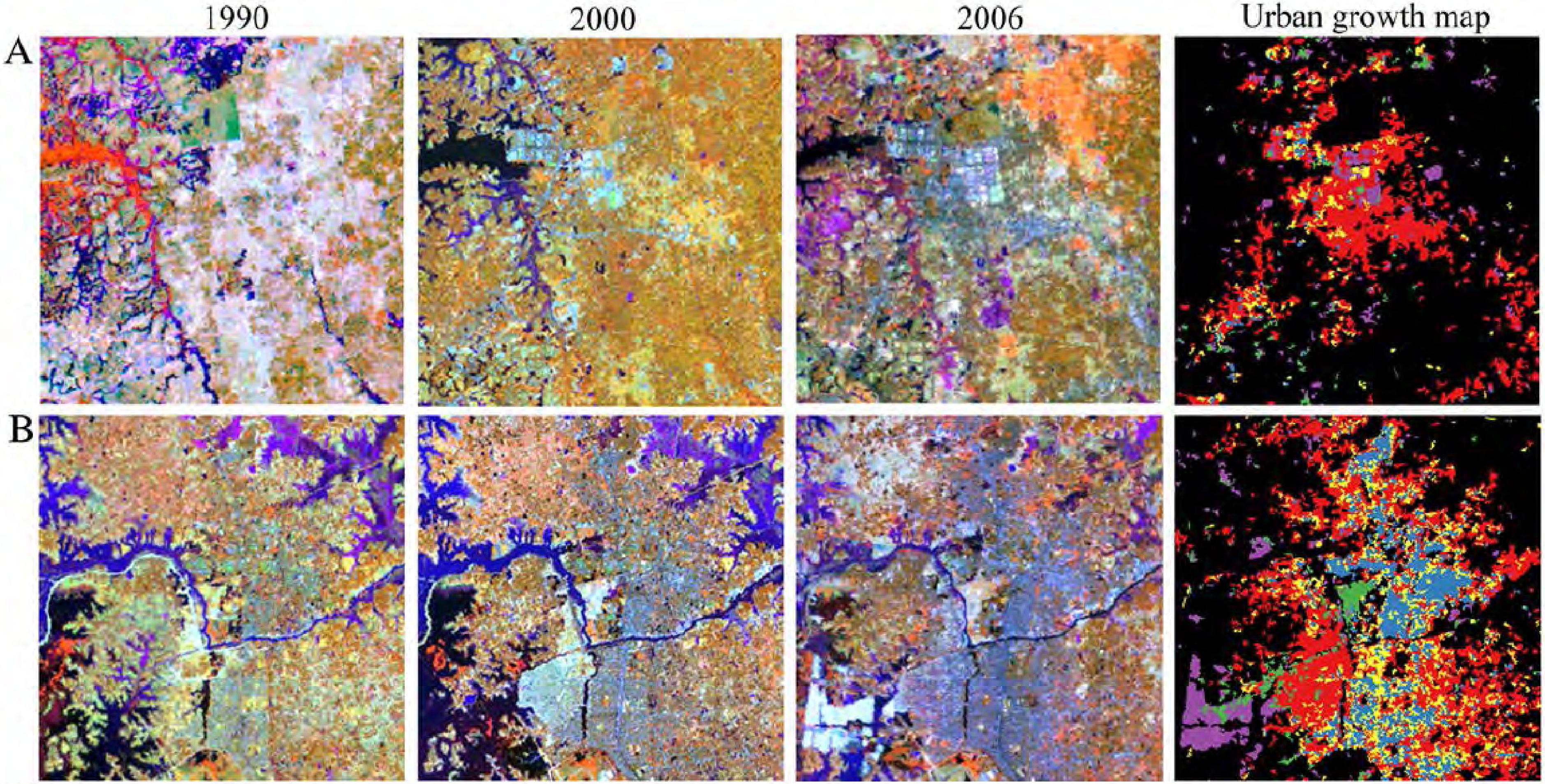
Both sensor types contribute to the high overall accuracy

2006 – Results of feature selection – 2 classes		
#1	ETM+(27.01.06) b6	72.3
#2	SAR (02.12.07) HH	90.1
#3	ETM+(27.01.06) b4	92.1
#4	SAR (31.10.07) HH	93.0
#5	ETM+(13.12.2006) b3	93.4
#6	ETM+(27.01.06) b5	93.6
#7	ETM+(13.12.2006) b5	93.8

Source: Griffiths et al., 2010

Mapping urban growth from spectral and SAR data

Source: Griffiths et al., 2010



Mapping urban growth from spectral and SAR data

Leinenkugel et al. map the percent impervious surface for the city of Can Tho, Vietnam using Terra-SAR X and Spot-5 data.

They use the high resolution SAR data to delineate urban surfaces and then use the Spot-5 data and a regression approach to predict impervious surface within the pixels of the delineated area.

The regression model is training using information from high resolution Quickbird data.

Mapping urban growth …

Object-based delineation of settlement footprints from TerraSAR-X data starting with the identification of

(a) distinct backscattering centres (DBC) and

(b) (b) potential urban structures (PUS)

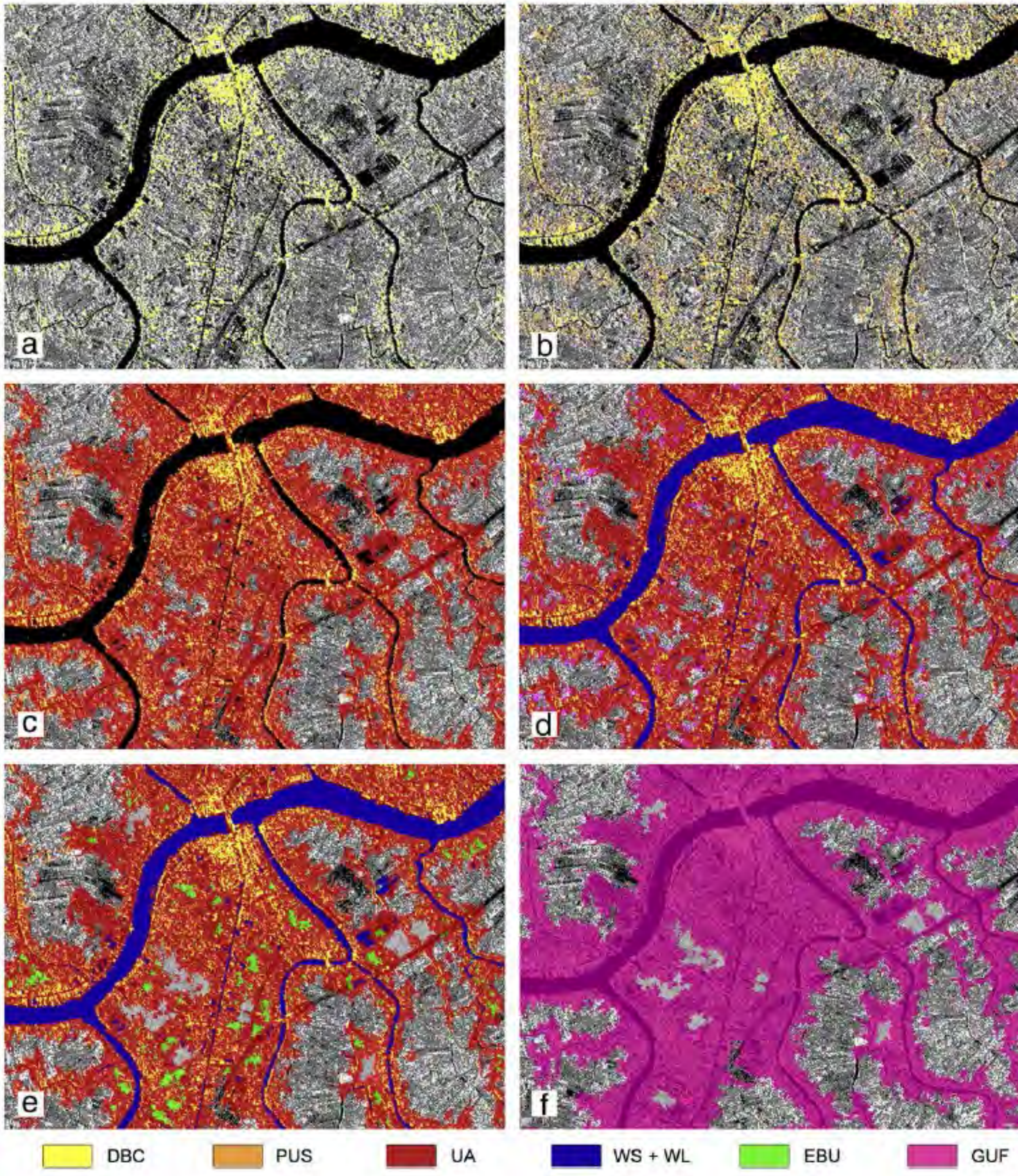
(c) urban areas (UA),

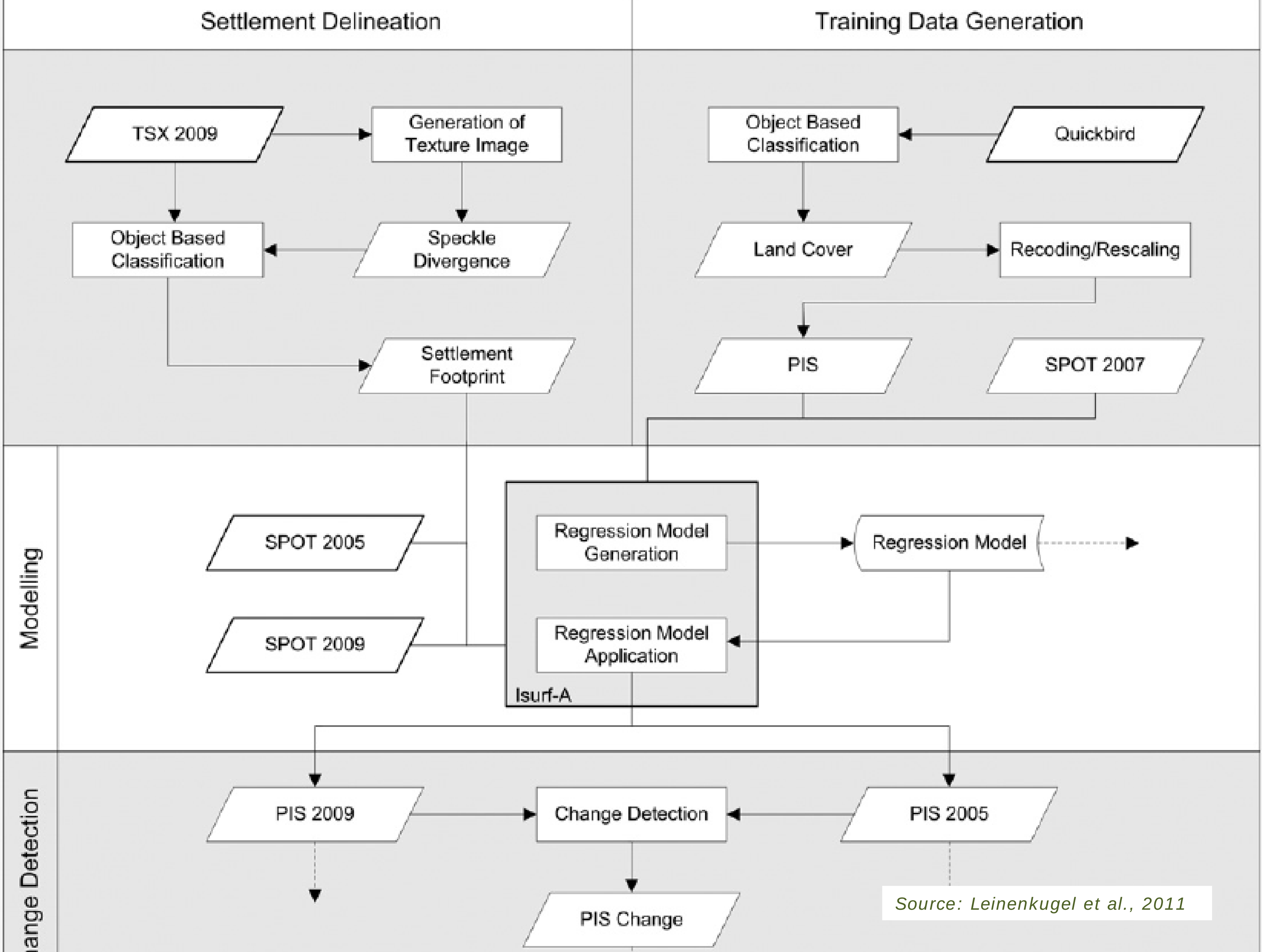
(d) water surfaces (WS, WL)

(e) regions completely enclosed by urban objects (EBU)

(f) of the urban footprint (GUF).

Source: Leinenkugel et al., 2011



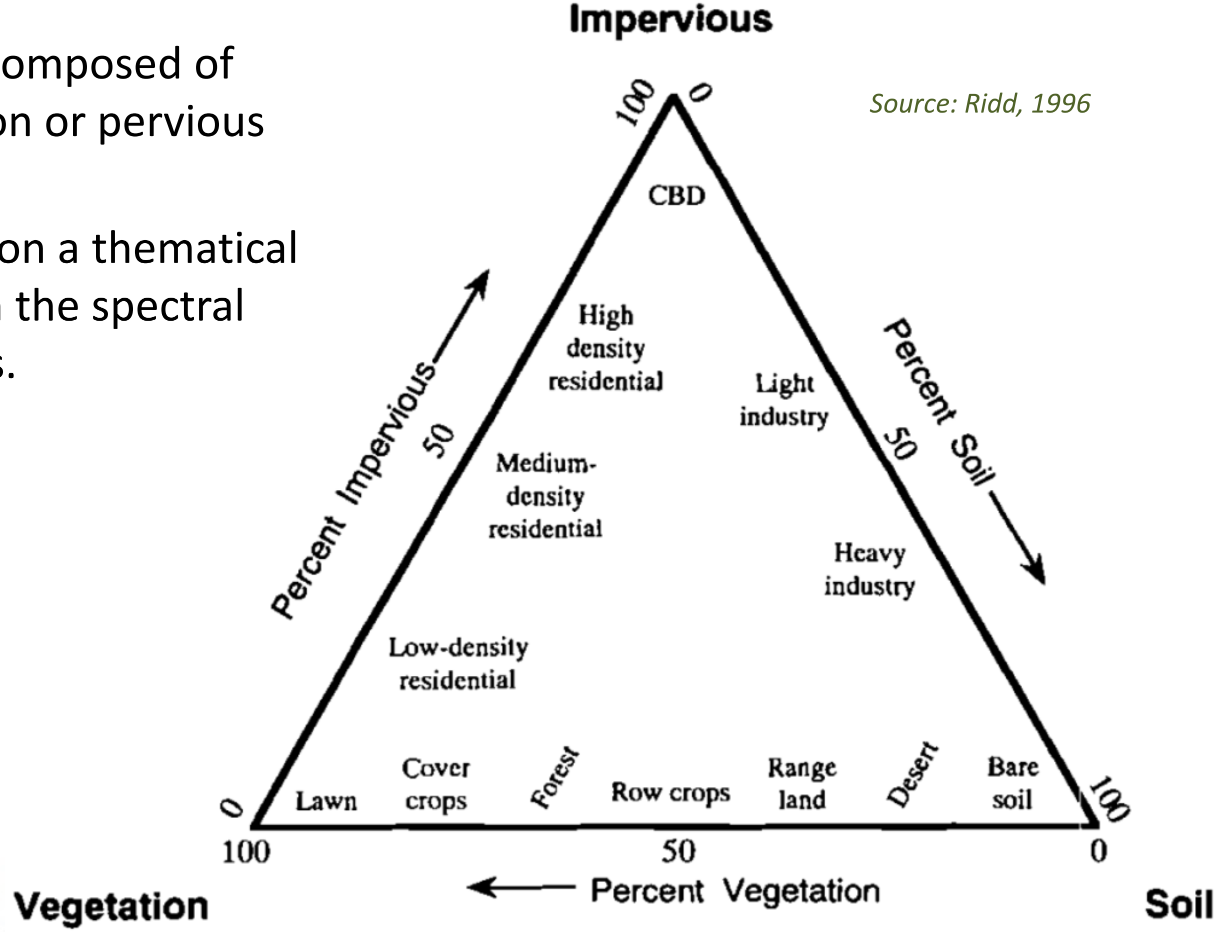


Source: Leinenkugel et al., 2011

Mapping urban composition from spectral data

Ridd assumes, every pixel is composed of impervious surface, vegetation or pervious land cover.

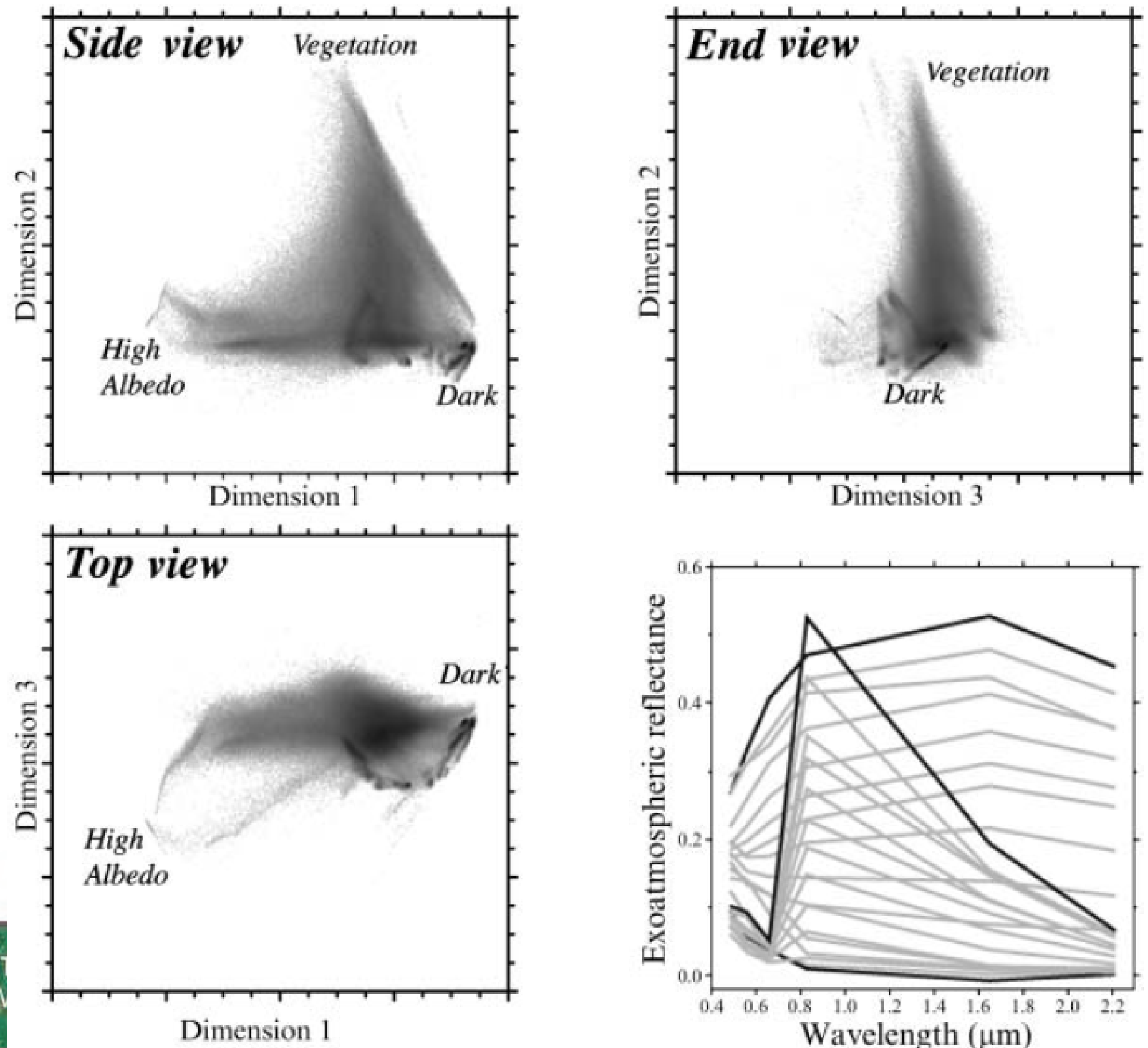
Ridd's V-I-S concept is based on a thematical framework. It is not based on the spectral characteristics of urban areas.



Source: Ridd, 1996

Mapping urban composition from spectral data

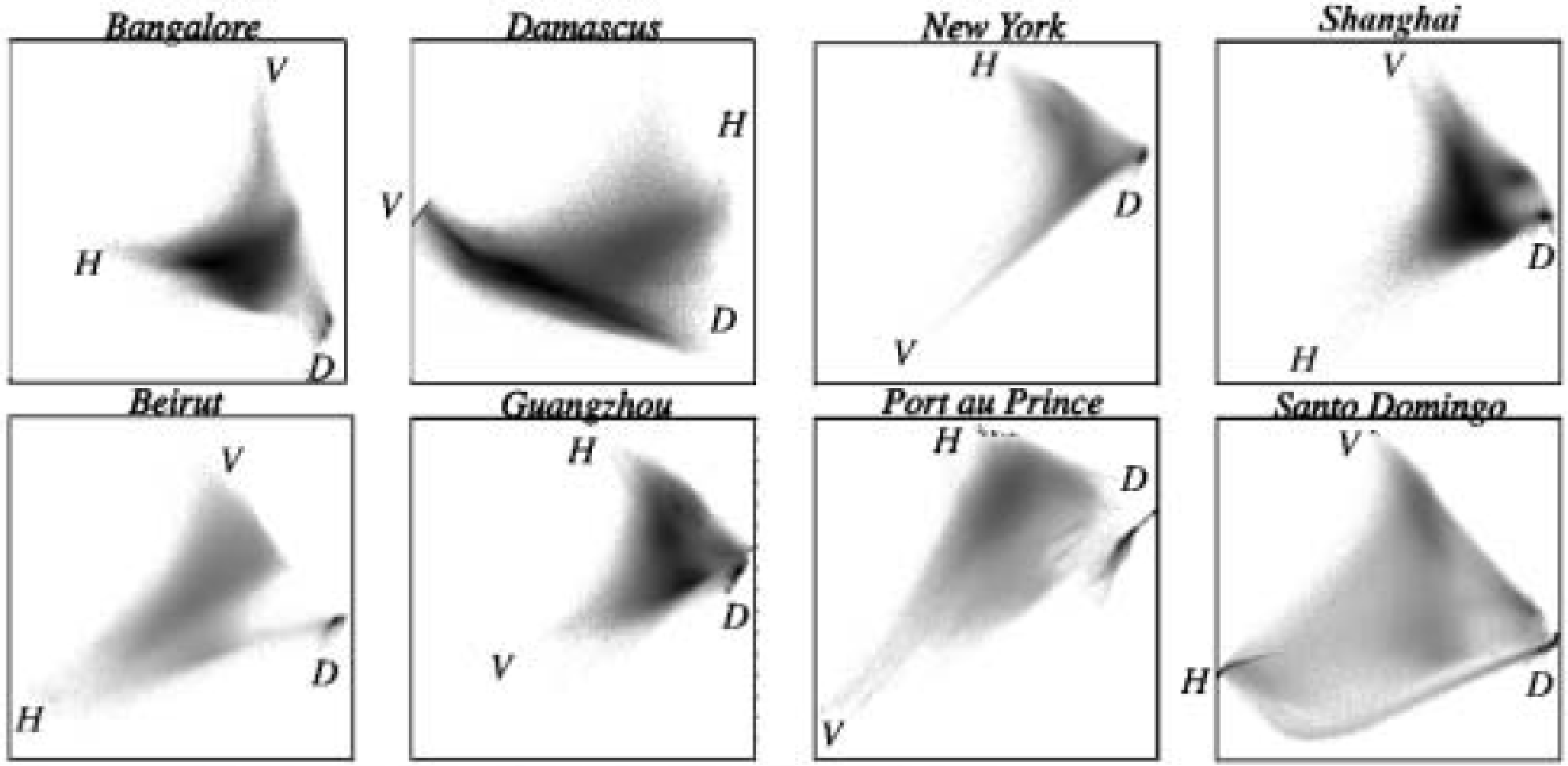
Small analyses more than 24 urban cities and concludes that the spectral properties working with Landsat ETM+ always relate to the degree of brightness and the portion of vegetation. This results in a mixing triangle in the first two PC components.



Source: Small, 2005

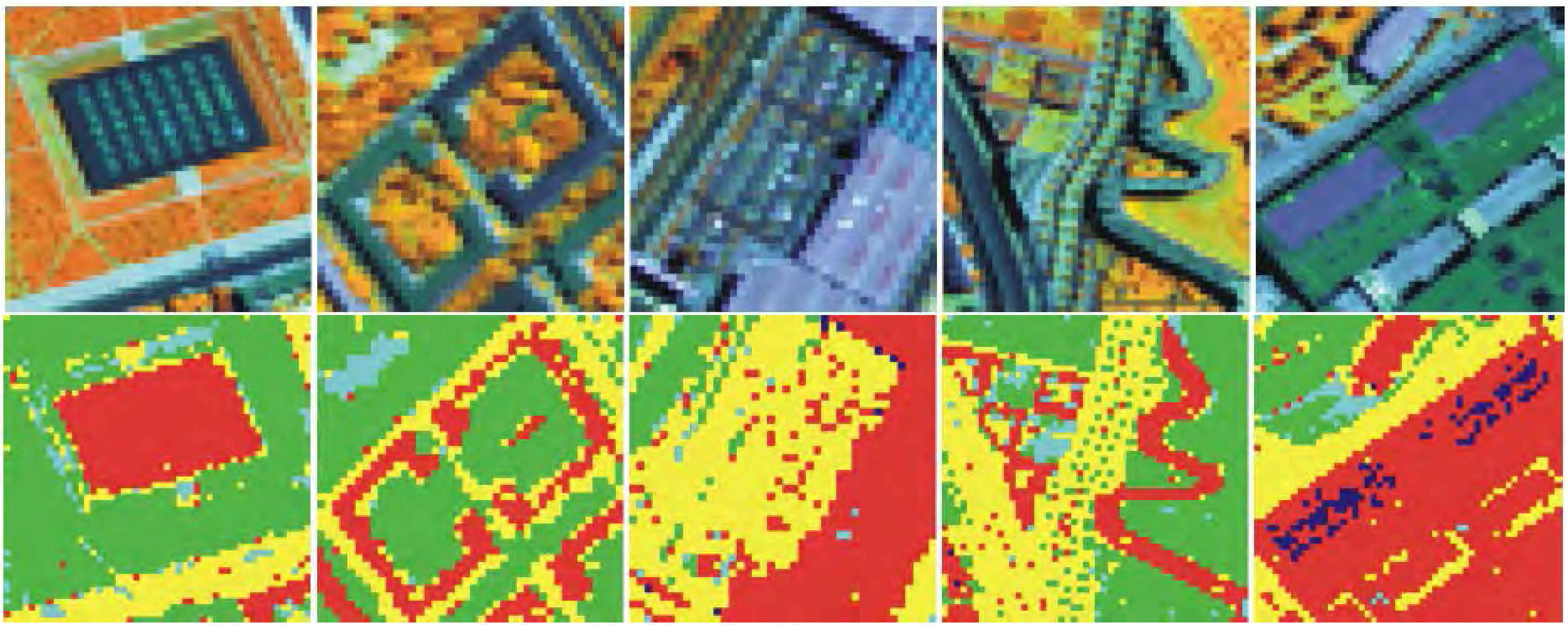
Mapping urban composition from spectral data

Source: Small, 2005



Mapping urban composition from spectral data

Using higher spatial and spectral characteristics together with machine learning, *van der Linden* and colleagues showed that urban more surface types may be mapped.

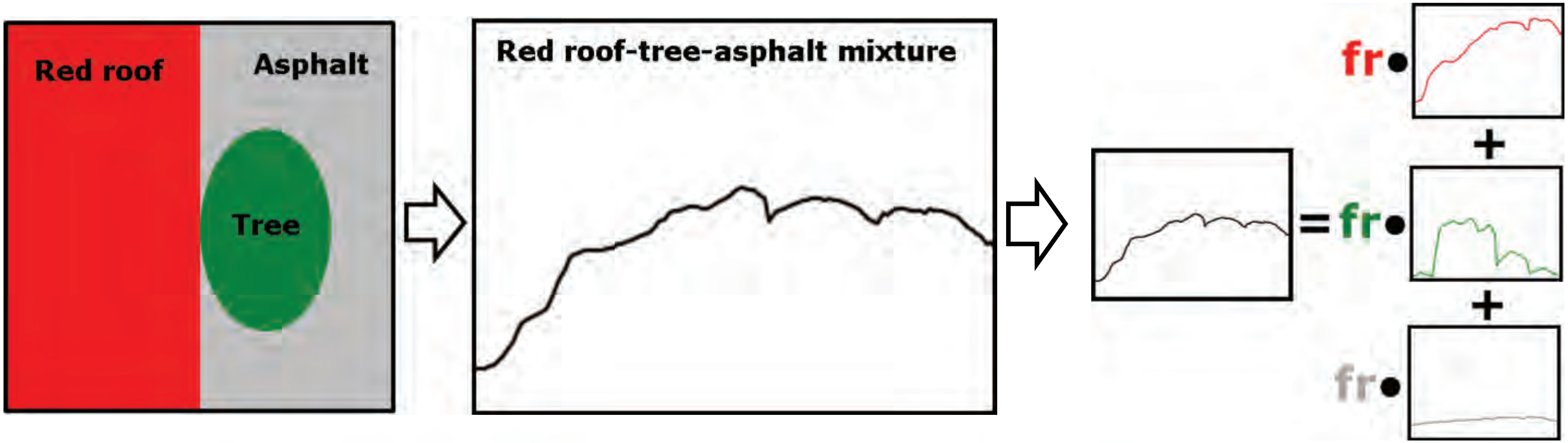


Source: van der Linden et al., 2007

Mapping urban composition from spectral data

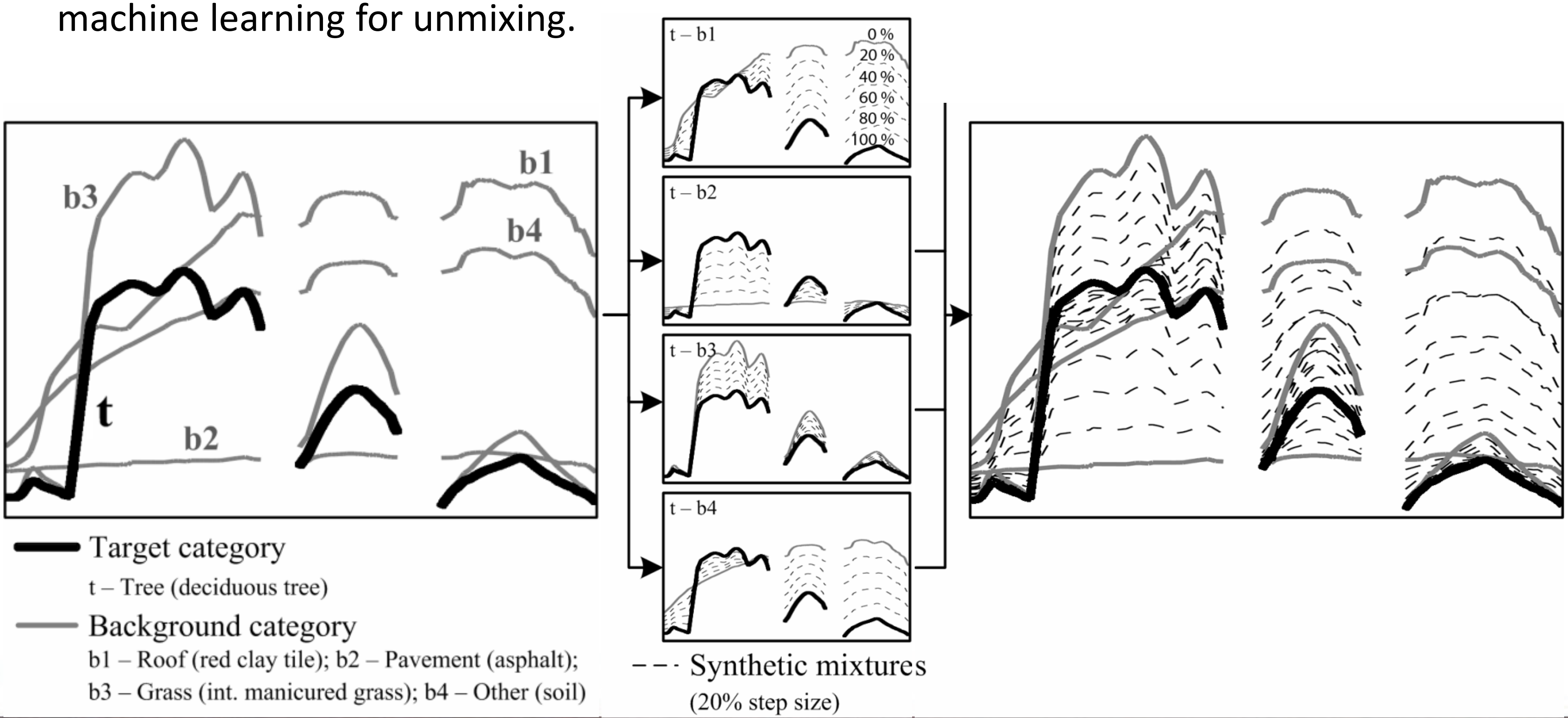
Given the high number of mixed pixels, quantitative mapping appears more useful than traditional classification to describe urban composition.

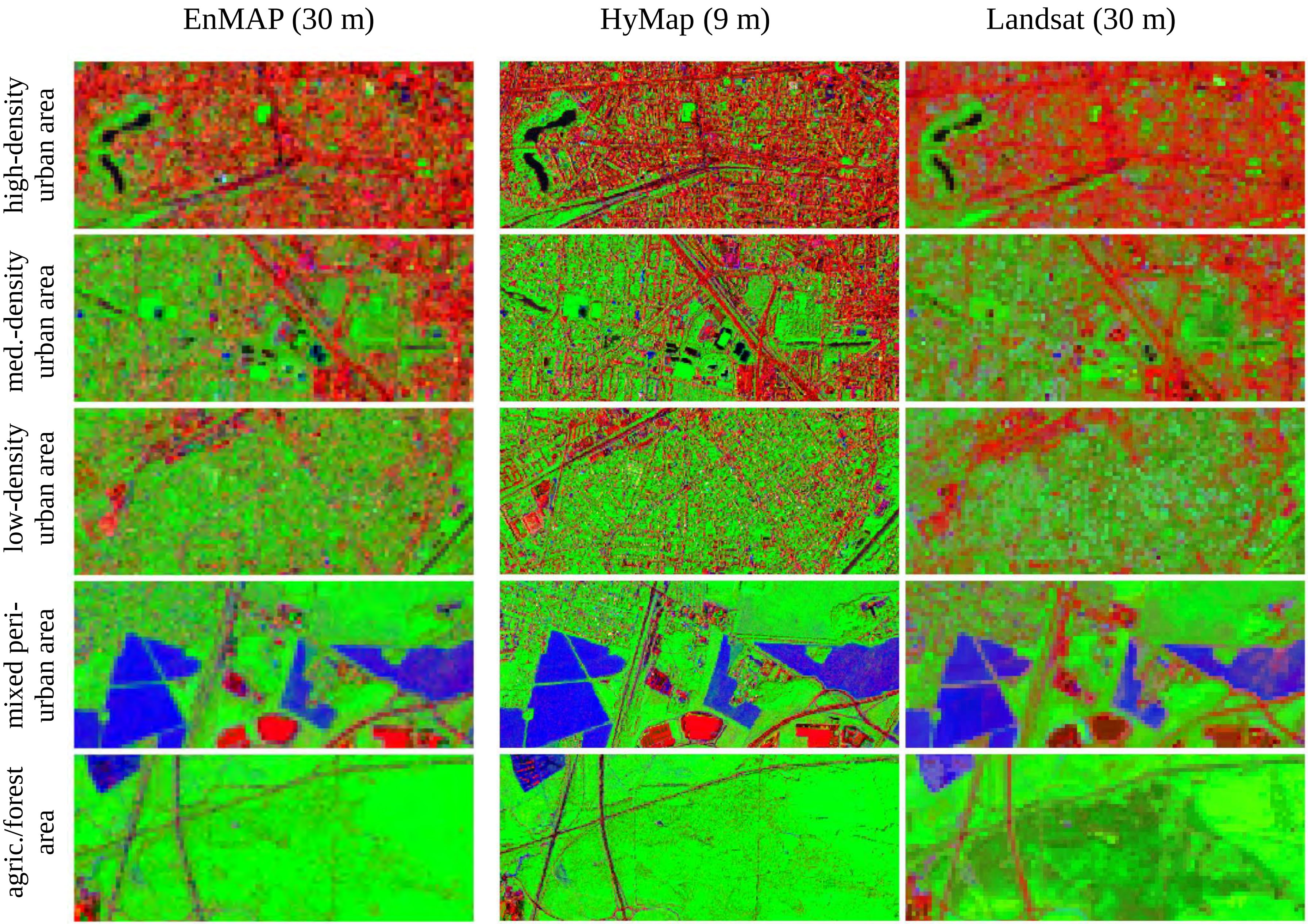
Concepts for quantitative mapping most often assume a linearly mixed spectrum, which can be decomposed into "pure" components, e.g. by spectral mixture analysis



Mapping urban composition from spectral data

Okujeni and van der Linden introduced synthetically mixed training data to use machine learning for unmixing.





Impervious-Vegetation-Soil: RGB

Source: Okujeni et al., 2015

Mapping urban composition from spectral data

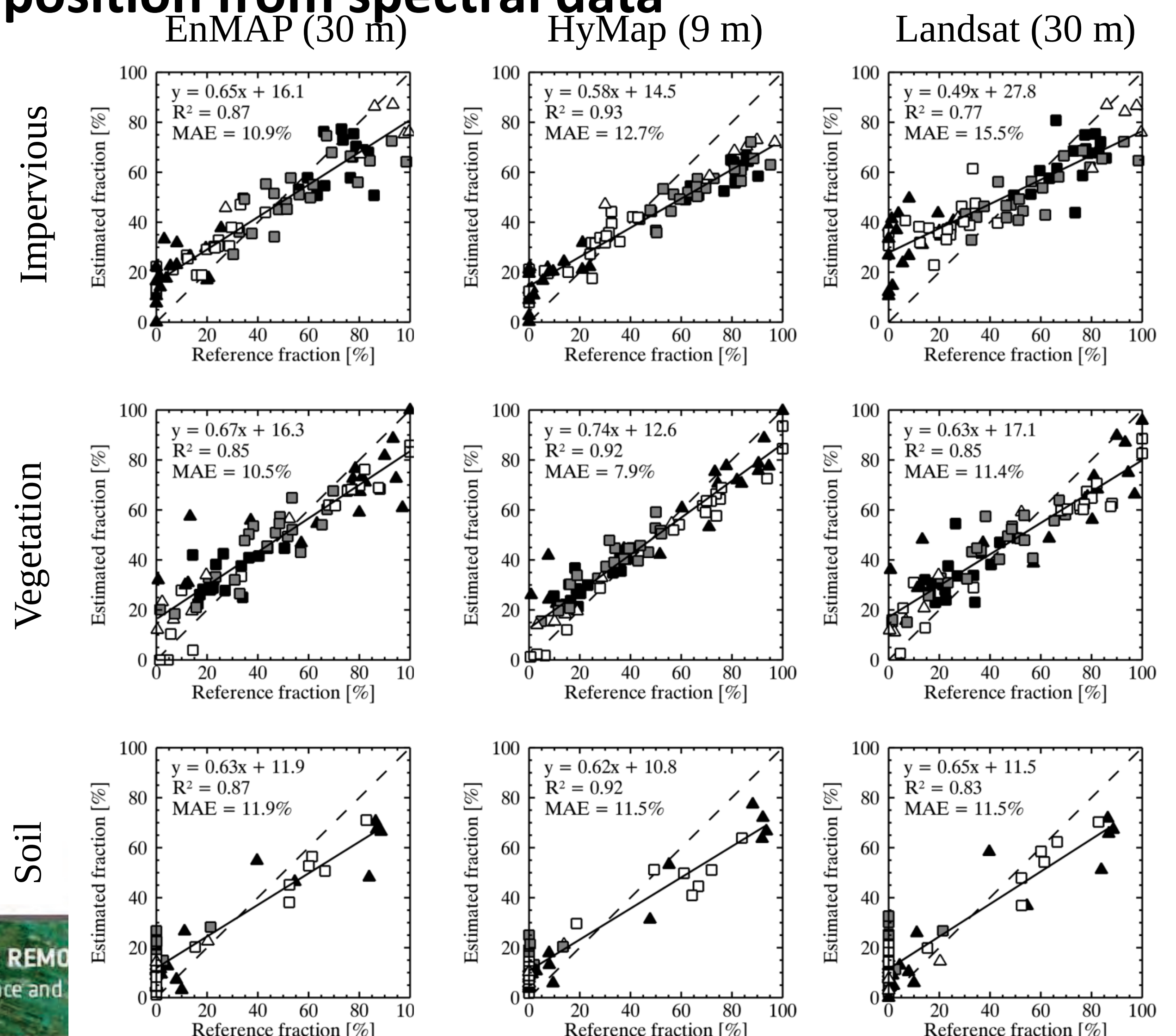
All VIS components can be modelled at high accuracy using SVR with synthetic mixtures.

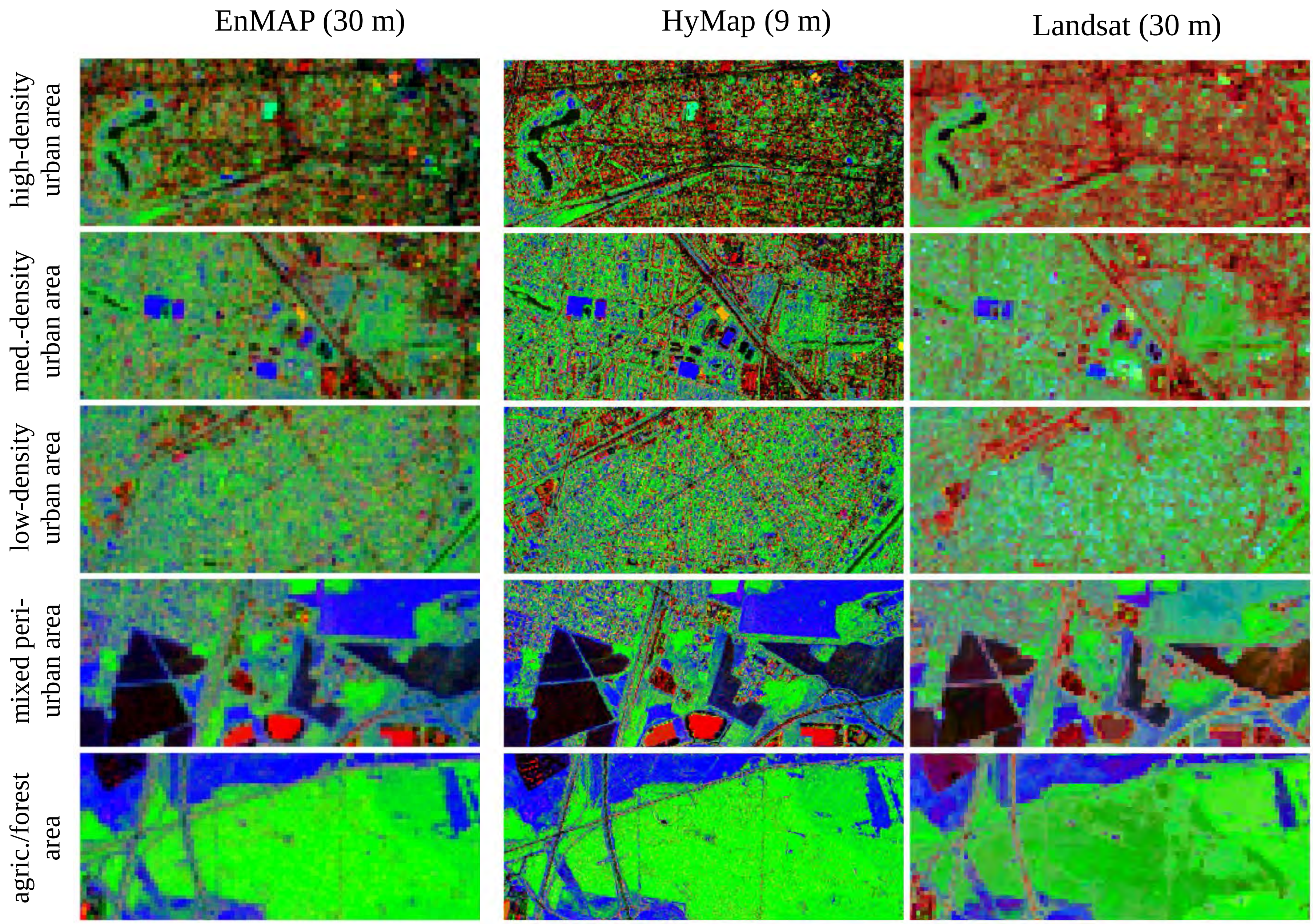
The decrease in accuracy from 9 m to 30 m is relatively low.

EnMAP data leads to slightly better results than Landsat data.

Results for soils are comparable.

Source: Okujeni et al., 2015





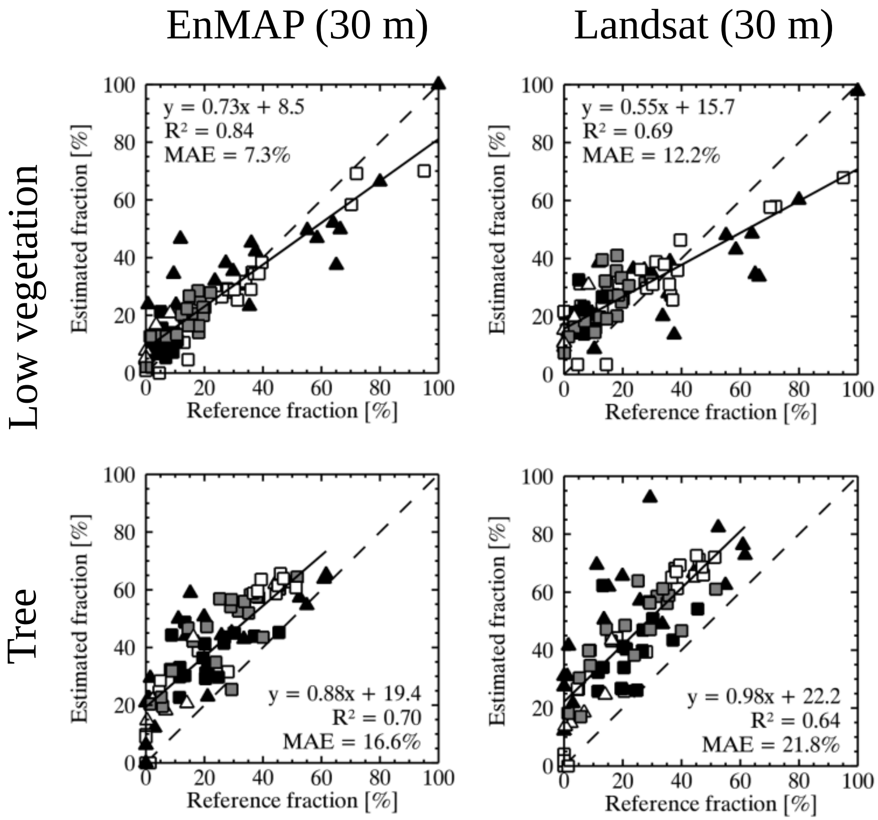
Roof-Tree-Low vegetation: RGB

Source: Okujeni et al., 2015

Mapping urban composition from spectral data

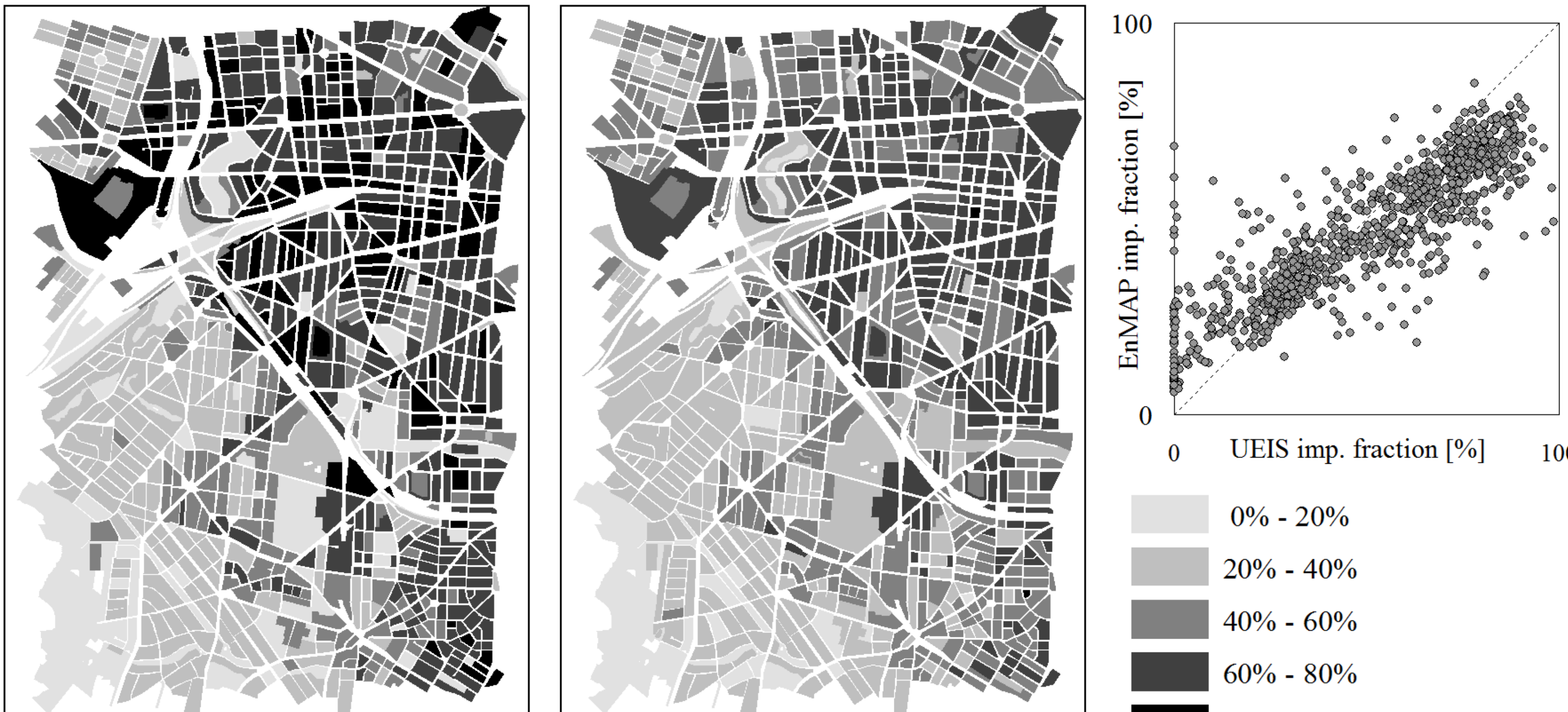
The SVR with synthetic mixtures allows extending the VIS framework for two vegetation and impervious types, although a clear decrease in accuracies can be observed for tree cover.

This time, the accuracy from EnMAP is clearly better than for Landsat.



Source: Okujeni et al., 2015

Mapping urban composition from spectral data



UEIS Impervious map

EnMAP Impervious map

References

Griffiths *et al.* (2010). Mapping megacity growth with multi-sensor data. Remote Sensing of Environment, 114, 426-439.

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Taubenböck et al. (2012). Monitoring urbanization in mega cities from space. Remote Sensing of Environment, 117, 162-176.

If not indicated differently, figures are taken from presentations or the dissertations of S. van der Linden and A. Okujeni. See edoc.hu-berlin.de.