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GLOBAL SLUM ANALYSIS ACHIEVEMENT AND CHALLENGES

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SUPPORT BY MATERIAL OF CAROLINE GEVAERT, CLAUDIO PERSELLO, DIVYANI KOHLI, KARIN PFEFFER, ELENA RANGUELOVA, JATI PRATOMO, JIONG WANG

ITC FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

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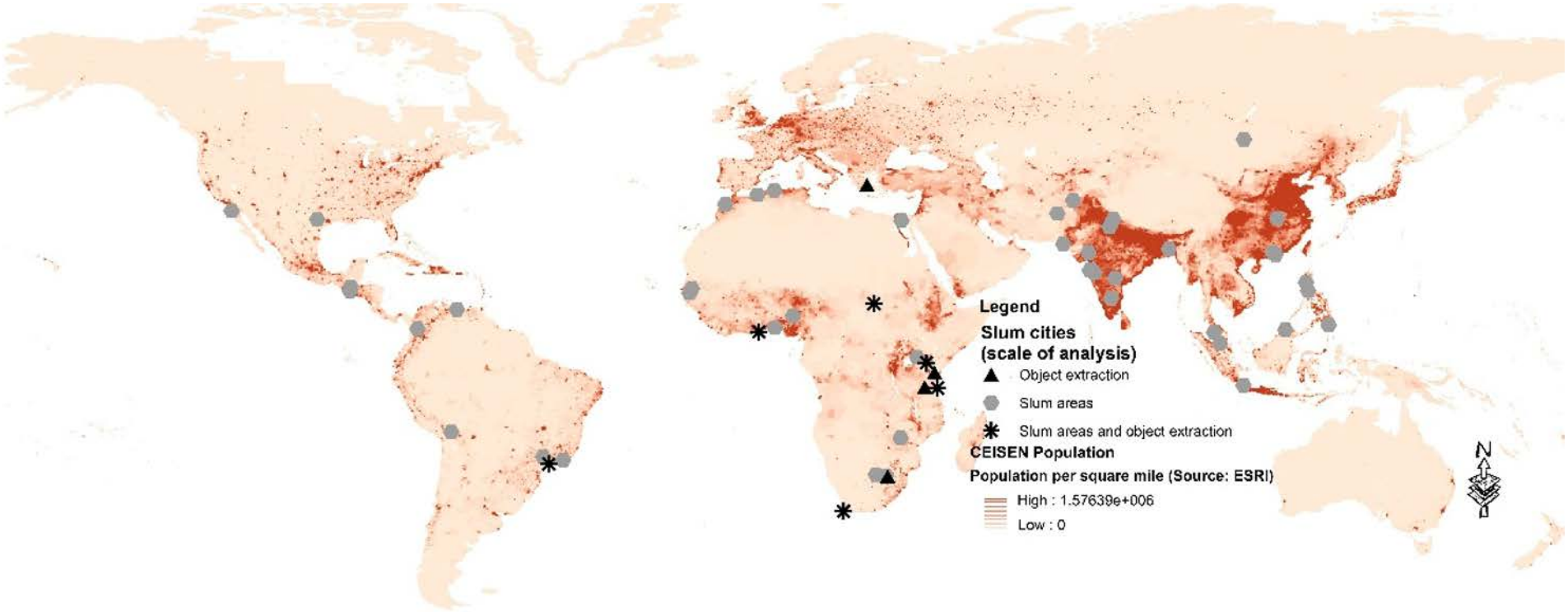
THE URBAN DIVIDE

Source: Johnny Miller - http://unequalscenes.com/nairobi

WHAT DO WE KNOW ABOUT GLOBAL SLUM DEVELOPMENTS



- 15 years of slum mapping using remote sensing
  (Kuffer, Pfeffer and Sliuzas, 2016)
- Based on 87 publications selected and reviewed

WHY DO WE NEED DATA ON SLUMS?

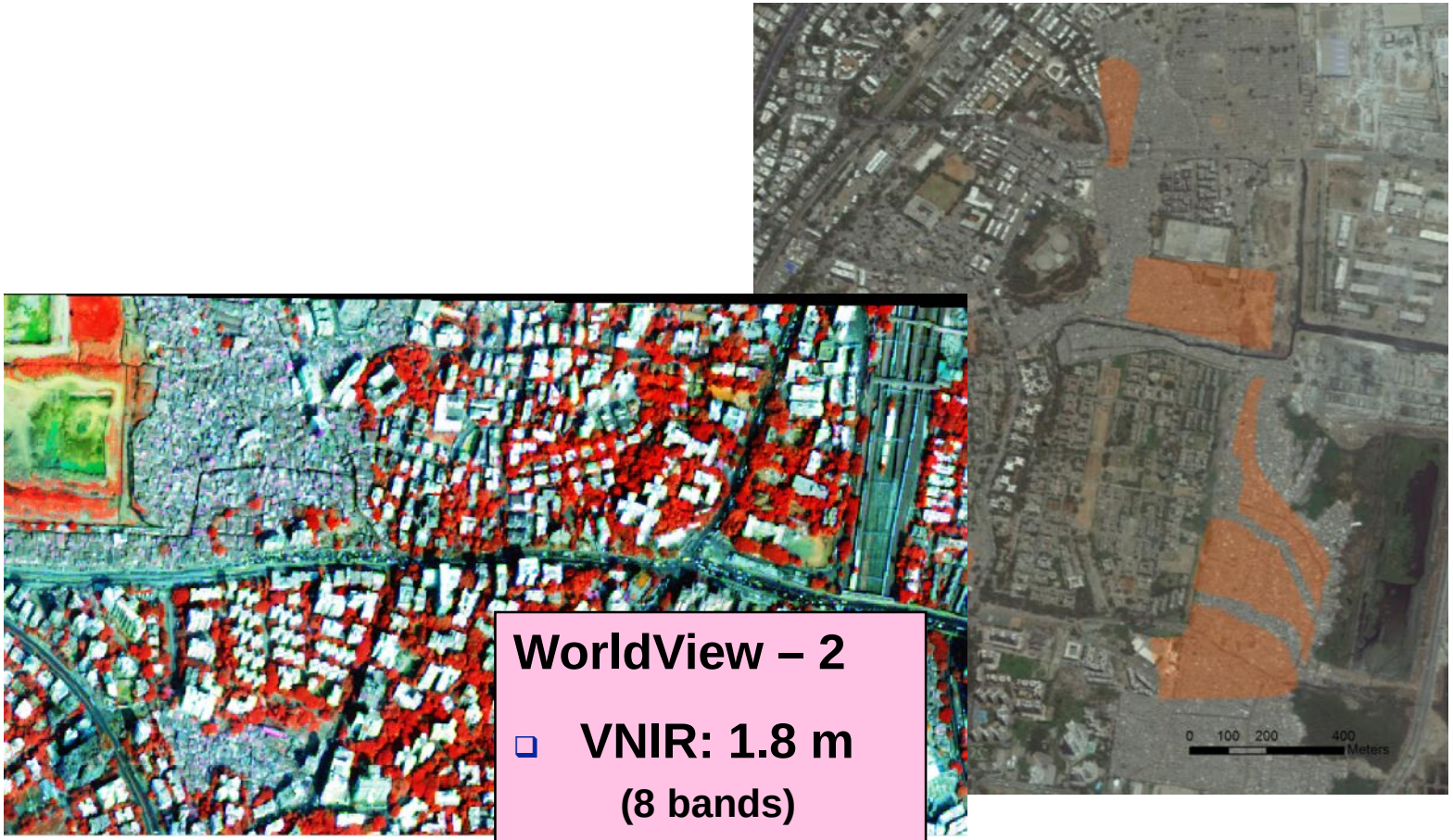
A planned road will bisect Kibera slum in Nairobi, displacing thousands of people.

Source: Johnny Miller - http://unequalscenes.com/nairobi

WHERE ARE THE POOR – DEPRIVED – SLUMS?

MUMBAI

- Municipal data often not up-to-date

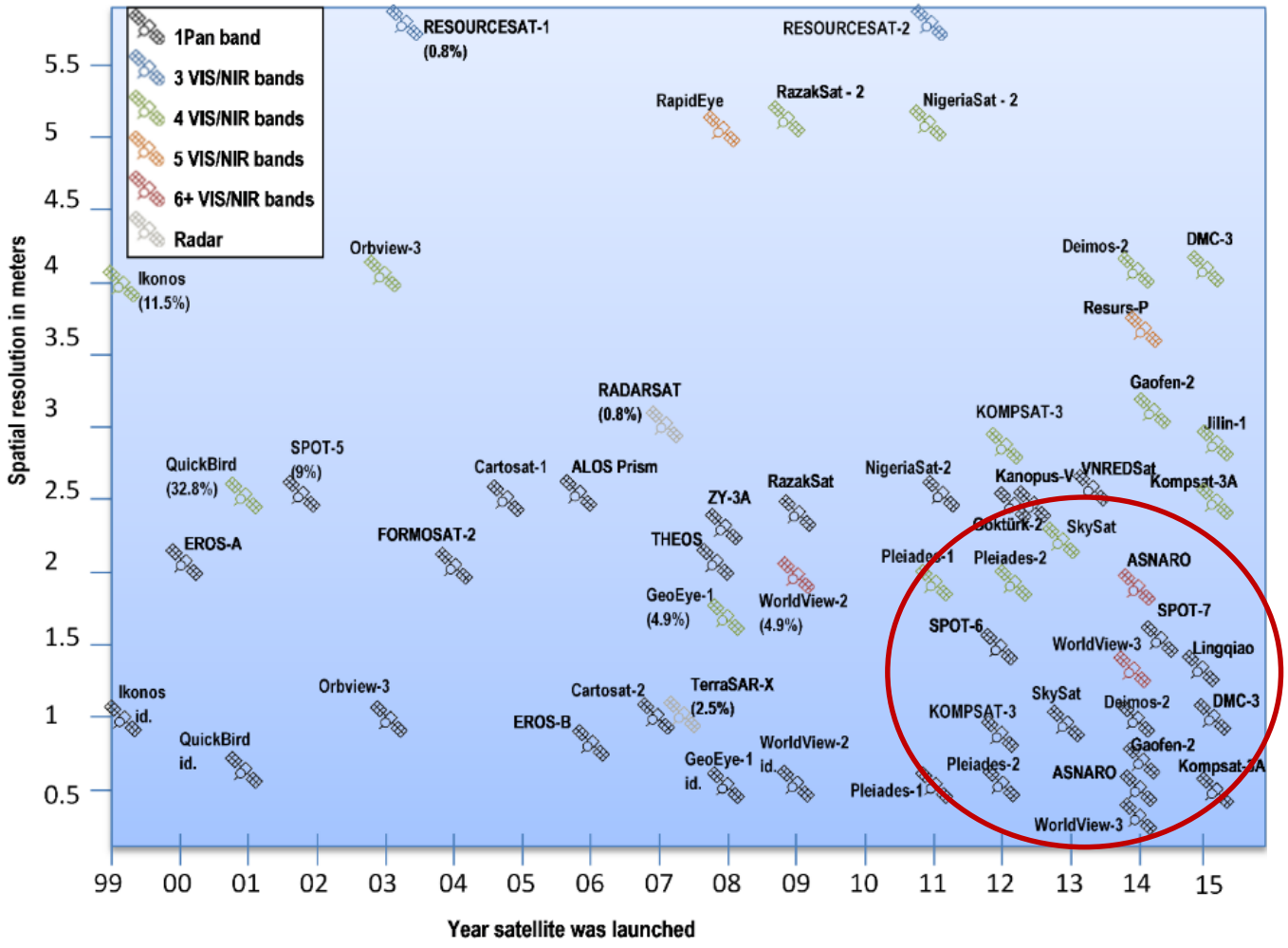


WorldView – 2

- **VNIR: 1.8 m**
  (8 bands)
- **PAN: 0.5 m**

MAPPING SLUMS FROM SPACE

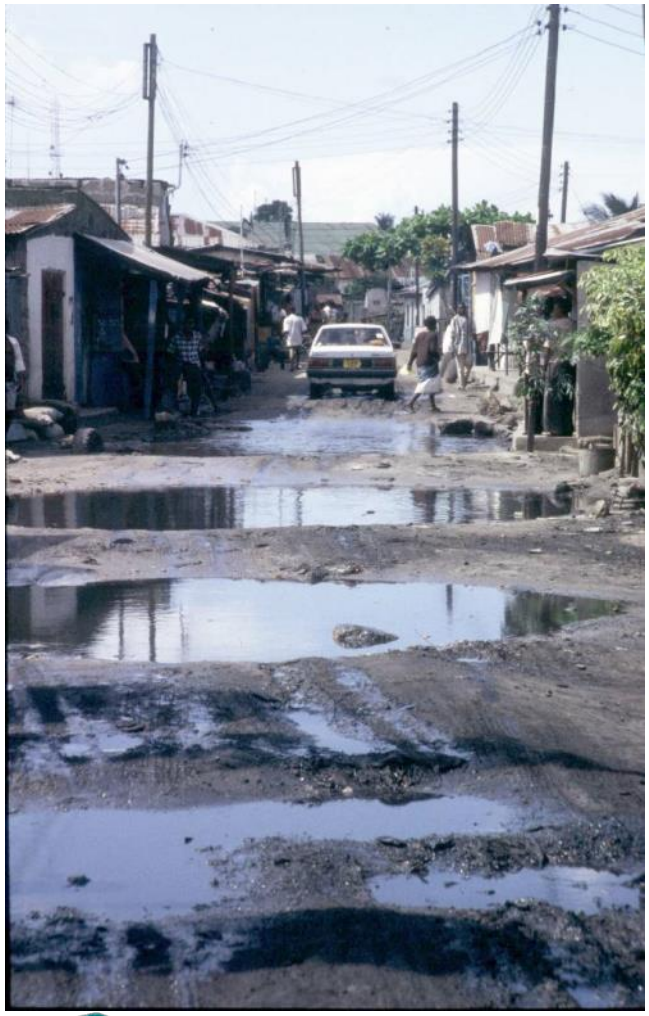
VERY-HIGH-RESOLUTION SENSORS



MORPHOLOGY OF SLUMS – FROM SPACE

Features	Slums	Planned areas
Size	• Small building sizes	• Generally larger building sizes
Density	• High densities (roof coverage) • Lack of public (green) spaces	• Low – moderate density areas • Provision of public (green spaces)
Pattern	• Organic layout structure	• Regular layout pattern
Site Characteristics	• Hazardous locations • Access to livelihood opportunities • Etc…	• Formal development with services and infrastructure provision

WHAT IS SPECIFIC TO SLUMS – AN HOW MUCH DO THEY DIFFER?



Dar es Salaam
Tanzania

Cairo, Egypt

Vizag, India

Size, shape, height, type, maintenance and material of dwelling

Object Types

TYPOLOGY OF DEPRIVED AREAS

Temporal Dynamics

History, development process (e.g., collective/organized occupations) permanency, segregation

Land / Site Characteristics

Land tenure, land cover/use, topography, size, density, services, location, and proximity to hazards

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DYNAMICS OF SLUMS – BANGALORE (DYNASLUM PROJECT)

Decision Support System for policy makers and urban planners to understand how, when and where slums grow in developing countries.

Emergence and Growth of a slum in Huidi, Bangalore (red polygon).

a) Slums emerge near a construction Site in 2008.

b) Slum grows near the same site.

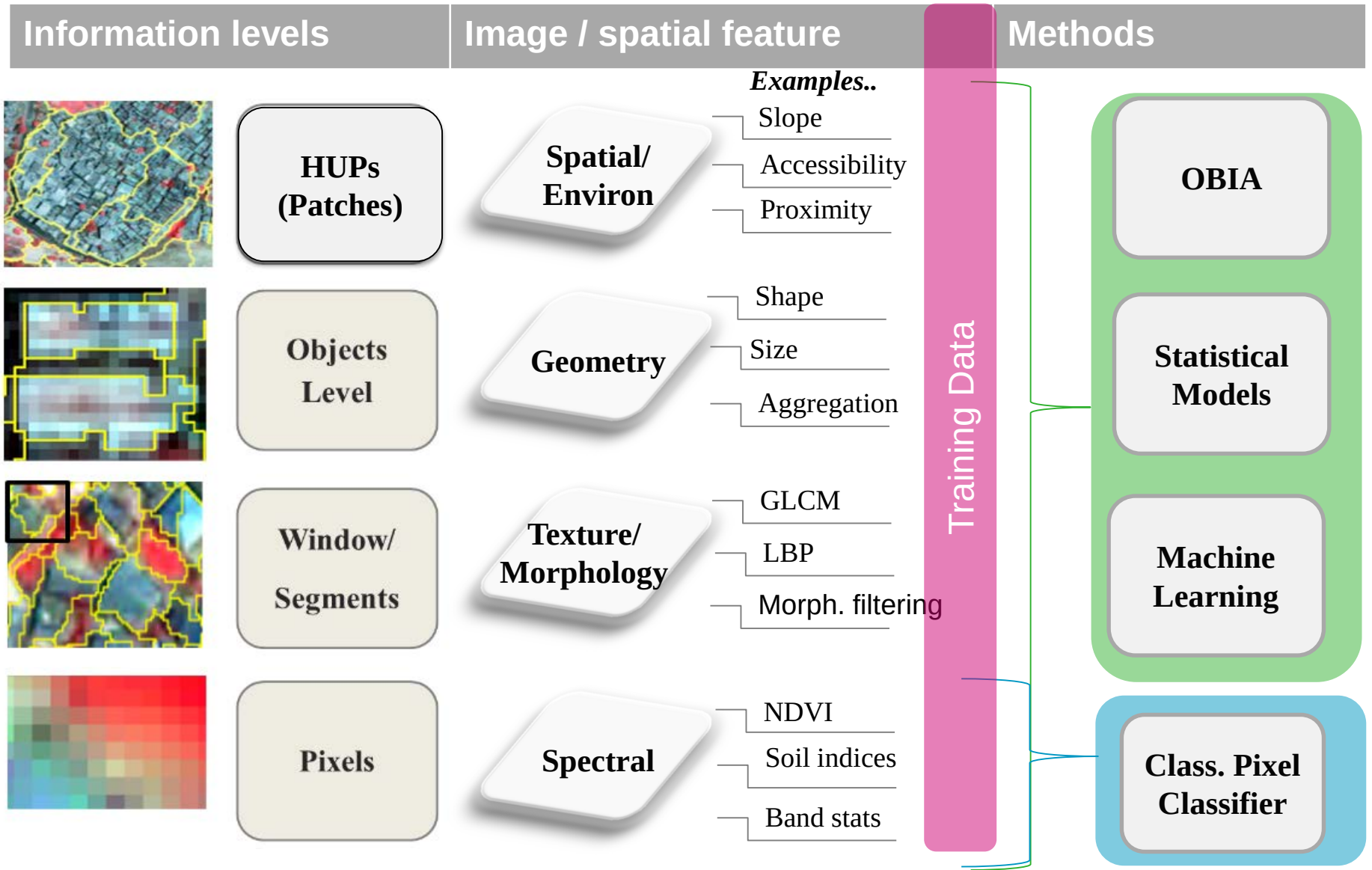
c) Slum disappear when construction is complete in 2013.

d) A slum re-emerge at the same site in 2014 (Images– Google Earth).

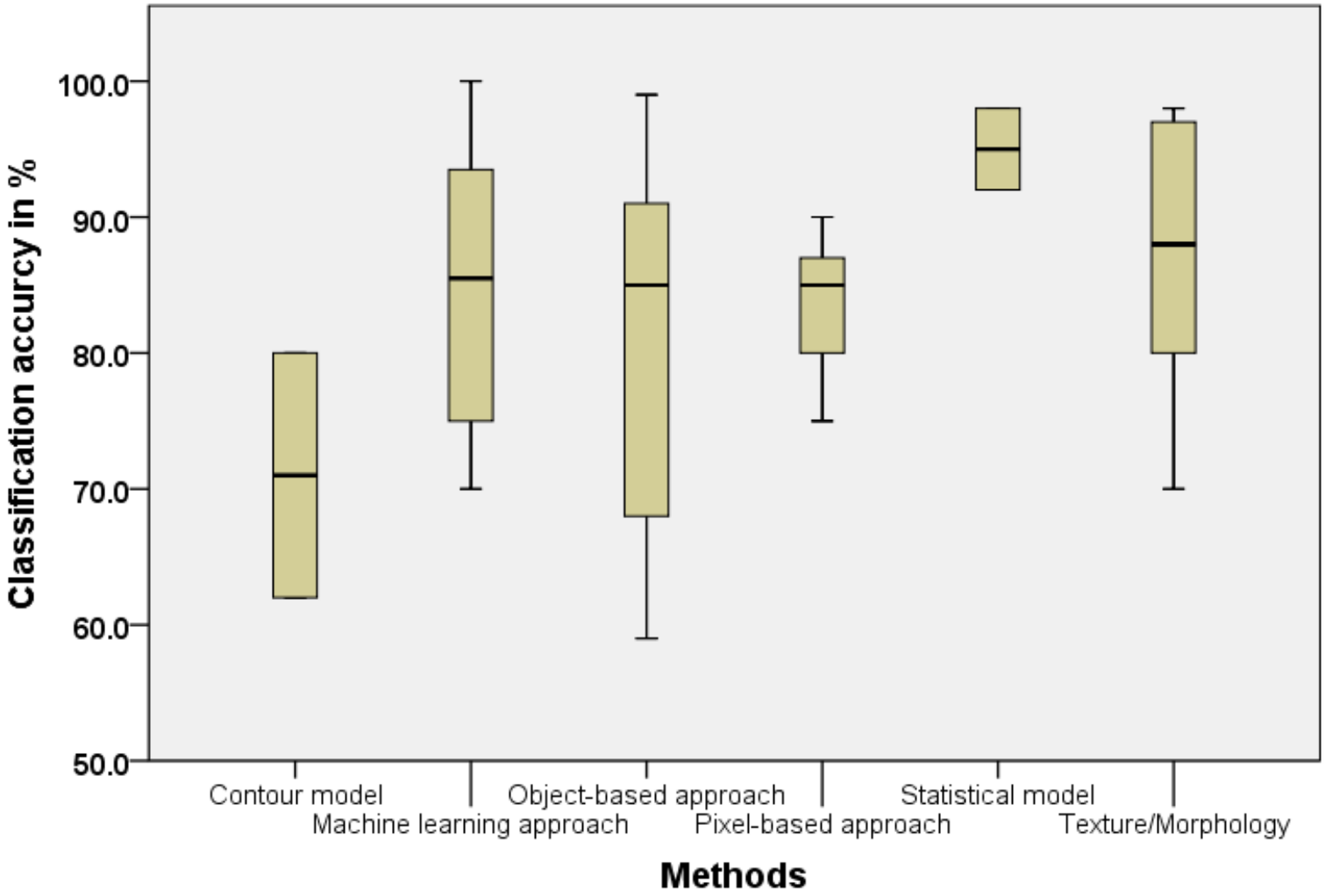
1. Ranguelova, E.; Kuffer, M.; Pfeffer, K.R., R.; Lees, M.H. Image based classification of slums, built-up and non-built-up areas in Kalyan, India. In *EARSeL Symposium*, Prague, 2017.

https://www.esciencecenter.nl/project/dynaslum

ACHIEVEMENTS AND CHALLENGES

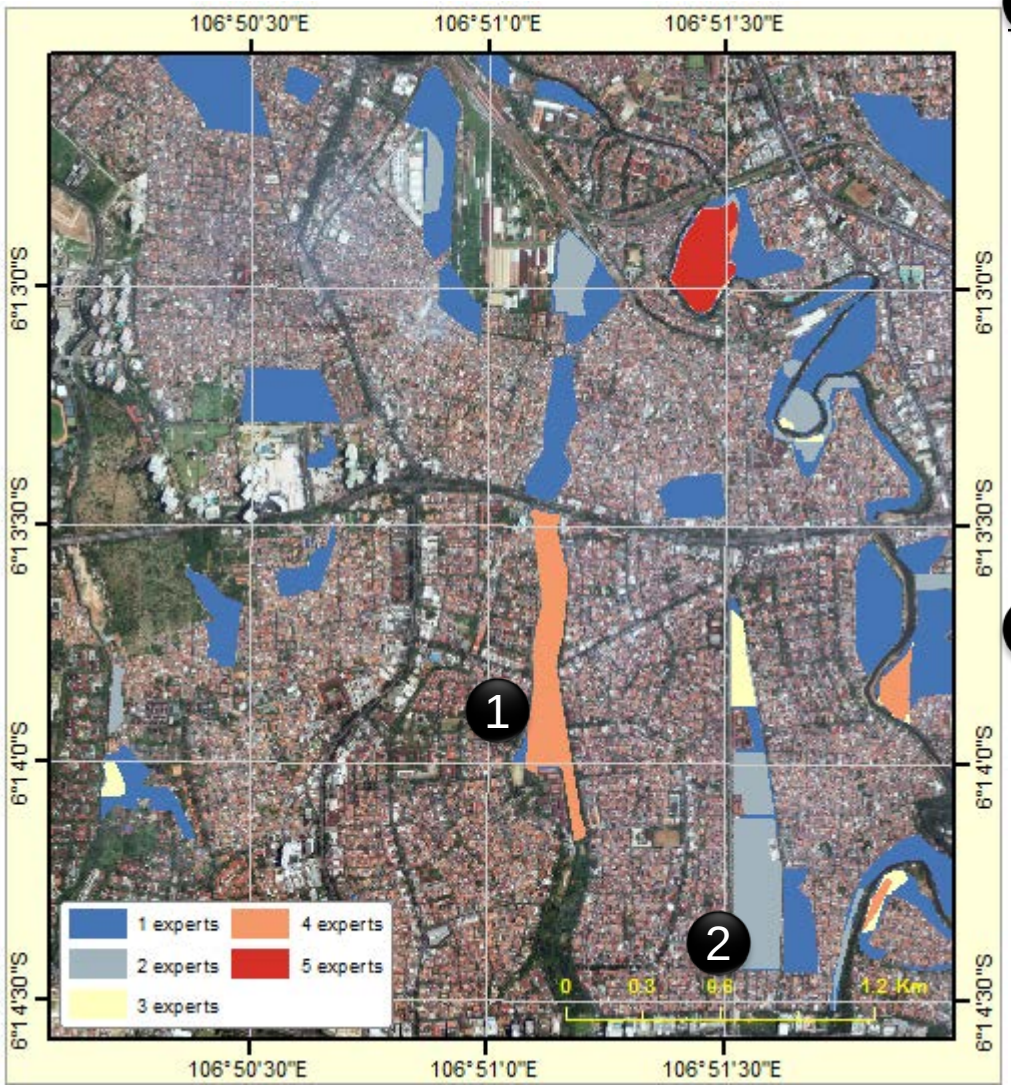


REPORTED ACCURACIES OF AUTOMATED SLUM DETECTION METHODS



2. *Kuffer, M.; Pfeffer, K.; Sliuzas, R. Slums from space—15 years of slum mapping using remote sensing. Remote Sens.* ***2016****, 8, 455.*

UNCERTAINTIES IN THE REFERENCE DATA FOR CLASSIFICATION ACCURACIES



1

Higher agreement: poor building material, high density and located in the riverbank

2

Misclassifications: high density and have a roof from asbestos

3. Pratomo, J.; Kuffer, M.; Martínez, J.A.; Kohli, D. Uncertainties in analyzing the transferability of the generic slum ontology. In GEOBIA 2016; Enschede, The Netherlands, 2016.

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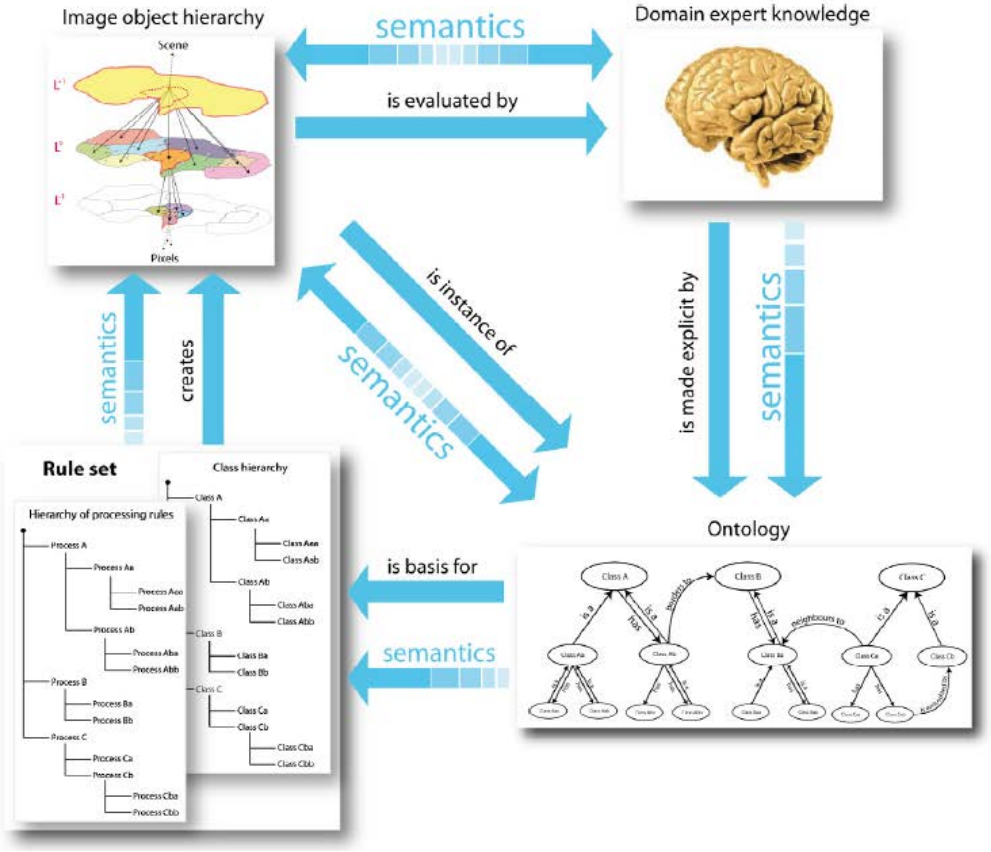
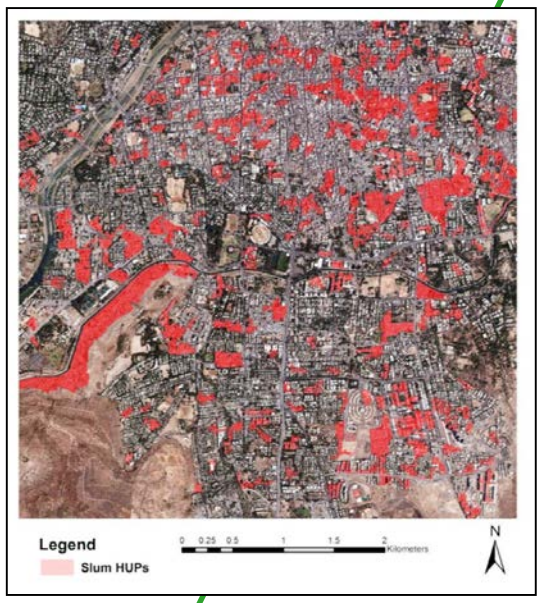
OBIA – OBJECT BASED IMAGE ANALYSIS



4. Blaschke, T. et al. Geographic object-based image analysis—Towards a new paradigm. ISPRS J. Photogramm. Remote Sens. ***2014***, 87, 180-191.

SLUM ONTOLOGY



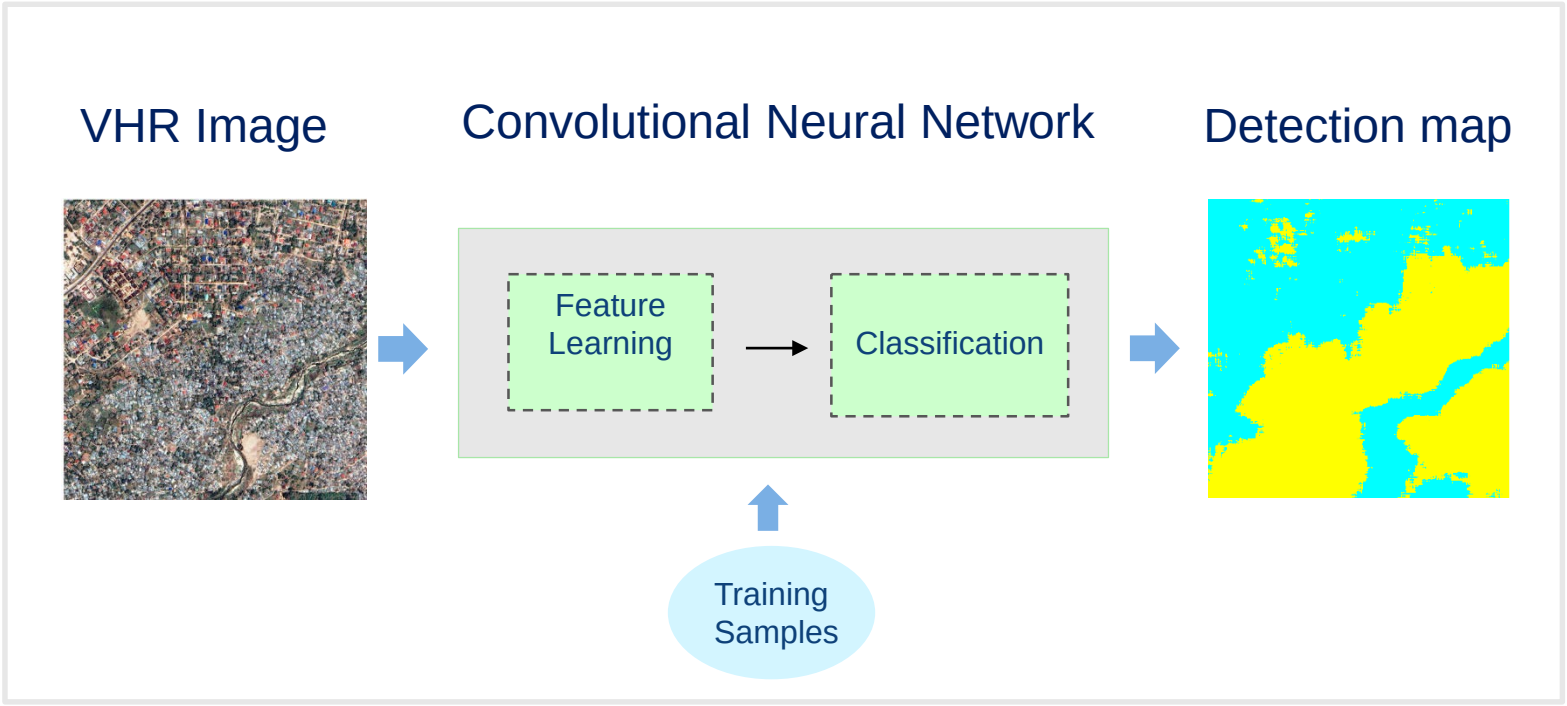
- Object Level
  - Building Characteristics
  - Road Layout
- Settlement Level
  - Shape
  - Density
- Neighborhood Level
  - Connectivity
  - Hazardous Location

5. *Kohli, D.; Sliuzas, R.V.; Kerle, N.; Stein, A. An ontology of slums for image-based classification. Comput. Environ. Urban Syst.* ***2012****, 36, 154–163.*

MACHINE LEARNING

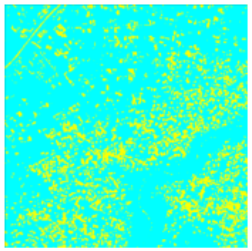
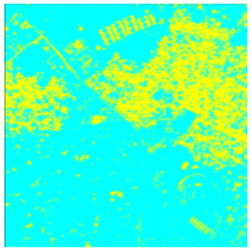
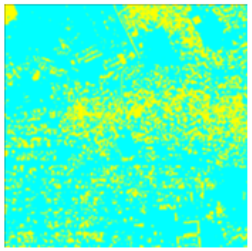
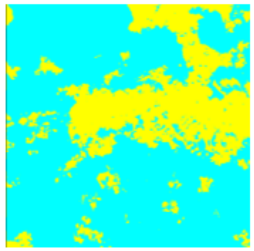
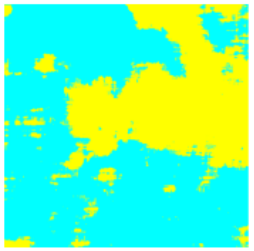
DEEP LEARNING APPROACH

Deep learning methods such as Convolutional Neural Networks can automatically learn spatial features from the input image.



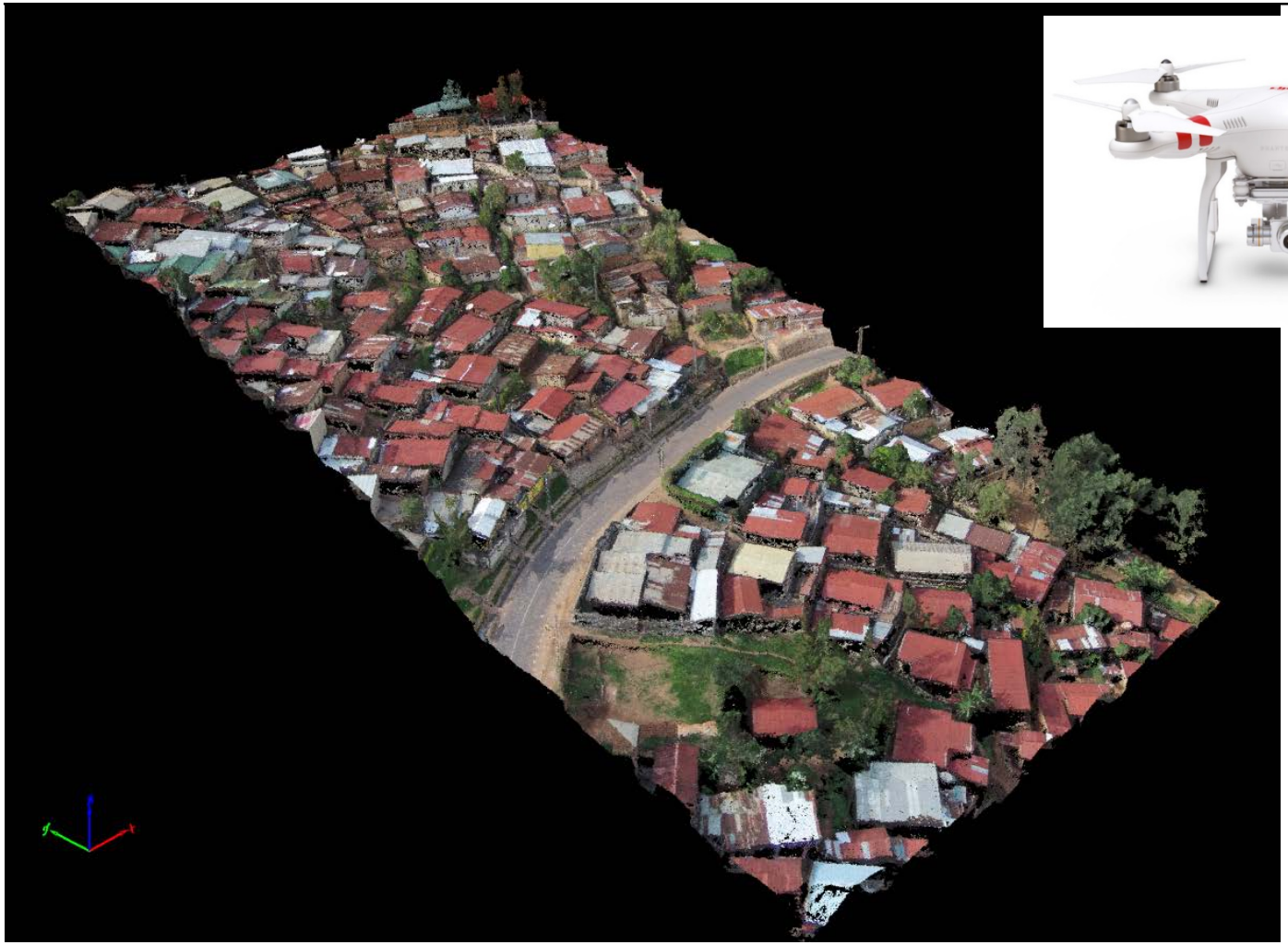
6. N. Mboga, C. Persello, J.R. Bergado, A. Stein, “Detection of Informal Settlements from VHR Satellite Images using Convolutional Neural Networks, *IGARSS 2017*.

RESULTS - CLASSIFIED MAPS

	Raw image	Reference	SVM	SVM+GLCM	CNN-5
Tile 1					
Tile 2					
Tile 3					
	OA OVER COMBINED TILES		68.84%	86.65%	91.71%
	Informal		Other		

6. N. Mboga, C. Persello, J.R. Bergado, A. Stein, "Detection of Informal Settlements from VHR Satellite Images using Convolutional Neural Networks, *IGARSS 2017*.

DENSE POINT CLOUD FROM UAV IMAGES, KIGALI, RWANDA (IMAGE BY C. GEVAERT)



MULTIPLE KERNEL LEARNING

Overall Accuracy:

Single-kernel SVM: 85.4%

Random forest: 86.5%

MKL: 90.6%

6. Gevaert, C.M.; Persello, C.; Sliuzas, R.; Vosselman, G. Informal settlement classification using point-cloud and image-based features from UAV data. *ISPRS J. Photogramm. Remote Sens.* **2017**, *125*, 225–236.

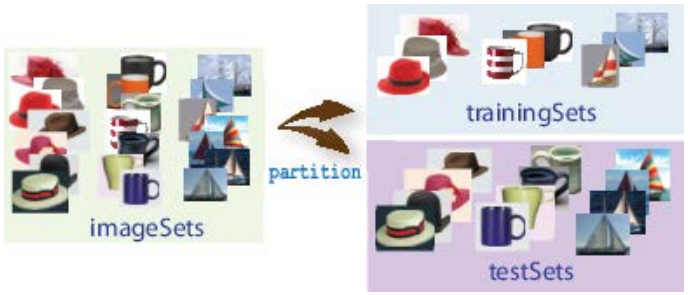
CLASSIFICATION RESULTS EXTENDED STUDY AREA

- Extended study area (Kigali, Rwanda)

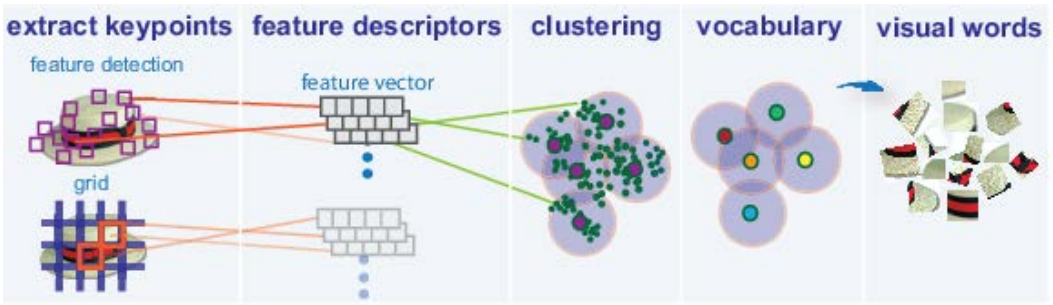
Source: Gevaert

DETECTING SLUMS WITH BOVW FRAMEWORK (DYNASLUM)

1. Set Up Image Category Sets

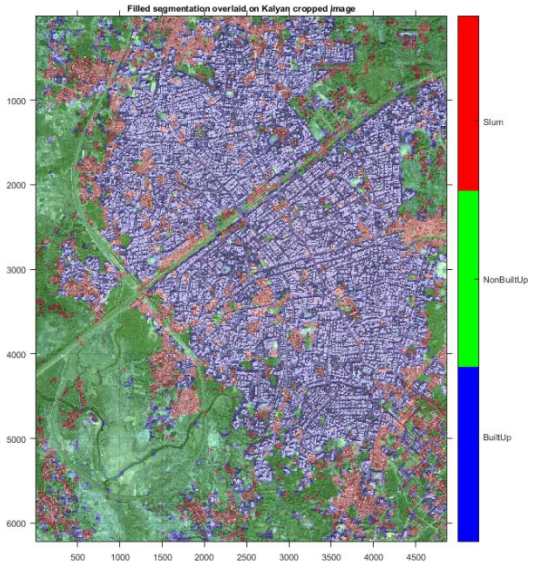


2. Create Bag of Features



3. Train an Image Classifier with BoVW

4. Classify an Image or Image Set



Slum Accuracy: **88.124**

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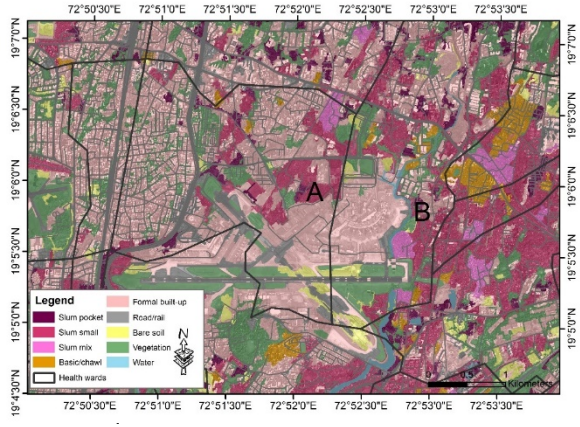
1. Ranguelova et al.. Image based classification of slums, built-up and non-built-up areas in Kalyan, India. In *EARSeL Symposium*, Prague, 2017.

CHALLENGE 1: UNDERSTANDING SLUMS/POVERTY NOT AS BINARY PROBLEM

- Mapping the diversity of deprived areas (multi-class approach): *Kuffer, Pfeffer, Sliuzas, Baud, van Maarseveen (2017)*

TYPE 1	TYPE 2	TYPE 3	TYPE 4	TYPE 5
Slum pocket *	Slum area, small buildings (slum small *)	Slum area, mix small/larger buildings (slum mix *)	Basic formal and chawl (basic/chawl *)	Formal areas (formal *)
Geometry: Small roofs Density: High Pattern: Organic Environment: Pockets along roads or within formal areas	Geometry: Small roofs Density: High Pattern: Organic Environment: Large areas with diverse uses	Geometry: Small–medium roofs Density: Mix Pattern: Diverse Environment: Some areas in more elevated terrain	Geometry: Mediu Density: High-me Pattern: Some str Environment: Lit vegetation within	



- Relationship between image features and urban poverty:

Engstrom, R.; Newhouse, D.; Haldavanekar, V.; Copenhaver, A.; Hersh, J. In Evaluating the relationship between spatial and spectral features derived from high spatial resolution satellite data and urban poverty in Colombo, Sri Lanka, JURSE, 6-8 March 2017.

CHALLENGE 2:
CAN WE COMPUTE A GLOBAL SLUM MAP?

- What are the most robust image features?

- How can we incorporate different slum development stages, dynamics and typologies?

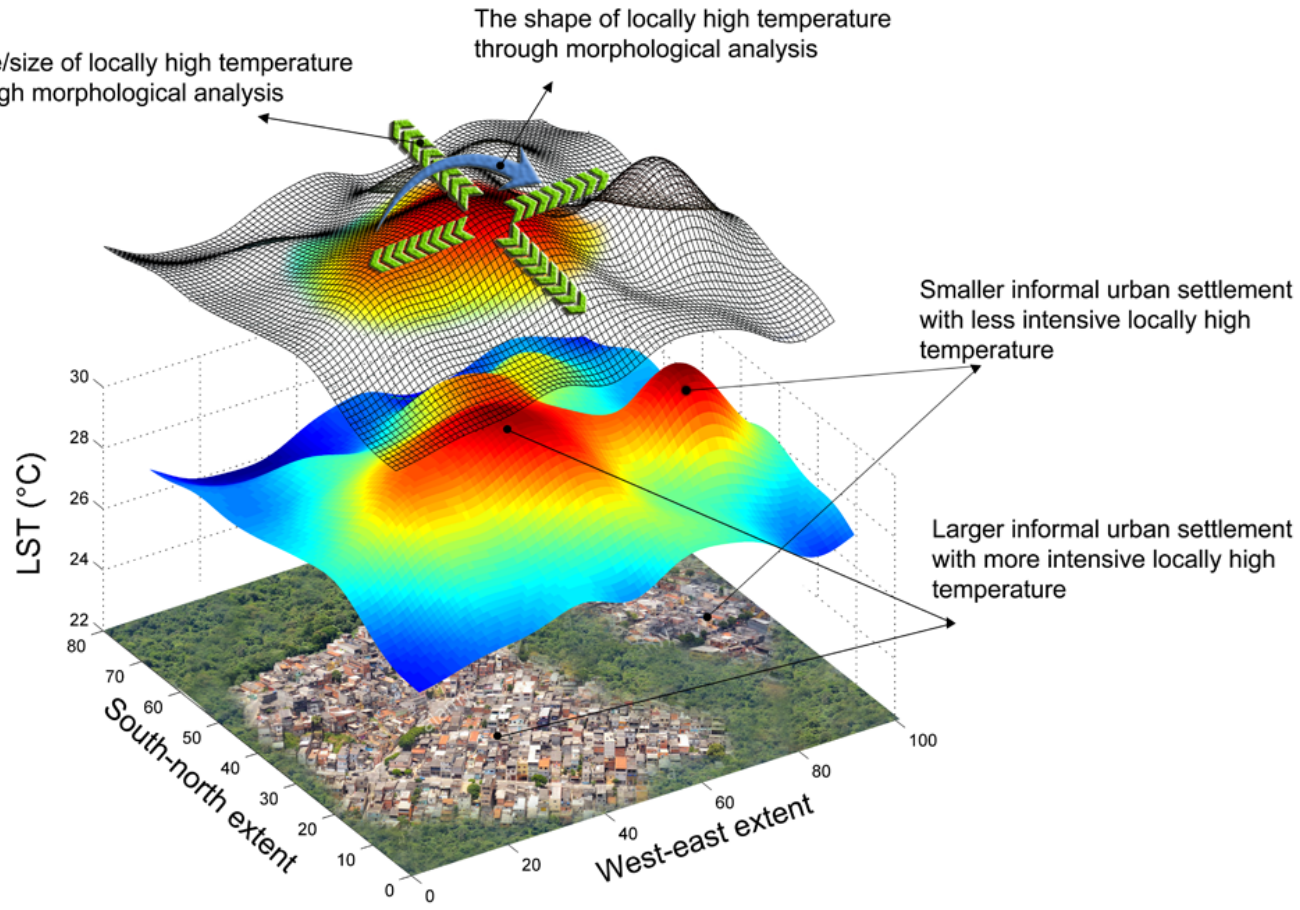
- Feature selection – training – assessment – which algorithms and reference data?

- Towards global slum mapping - reference cases, e.g.
  - *Kemper, T. et al. Towards an automated monitoring of human settlements in South Africa using high resolution SPOT satellite imagery, 2015.*
  - *Duque, J.C. et al.. Exploring the Potential of Machine Learning for Automatic Slum Identification from VHR Imagery. Remote Sensing 2017, 9, 895.*
  - *Graesser, J. et al. Image based characterization of formal and informal neighborhoods in an urban landscape. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2012, 5, 1164–1176.*

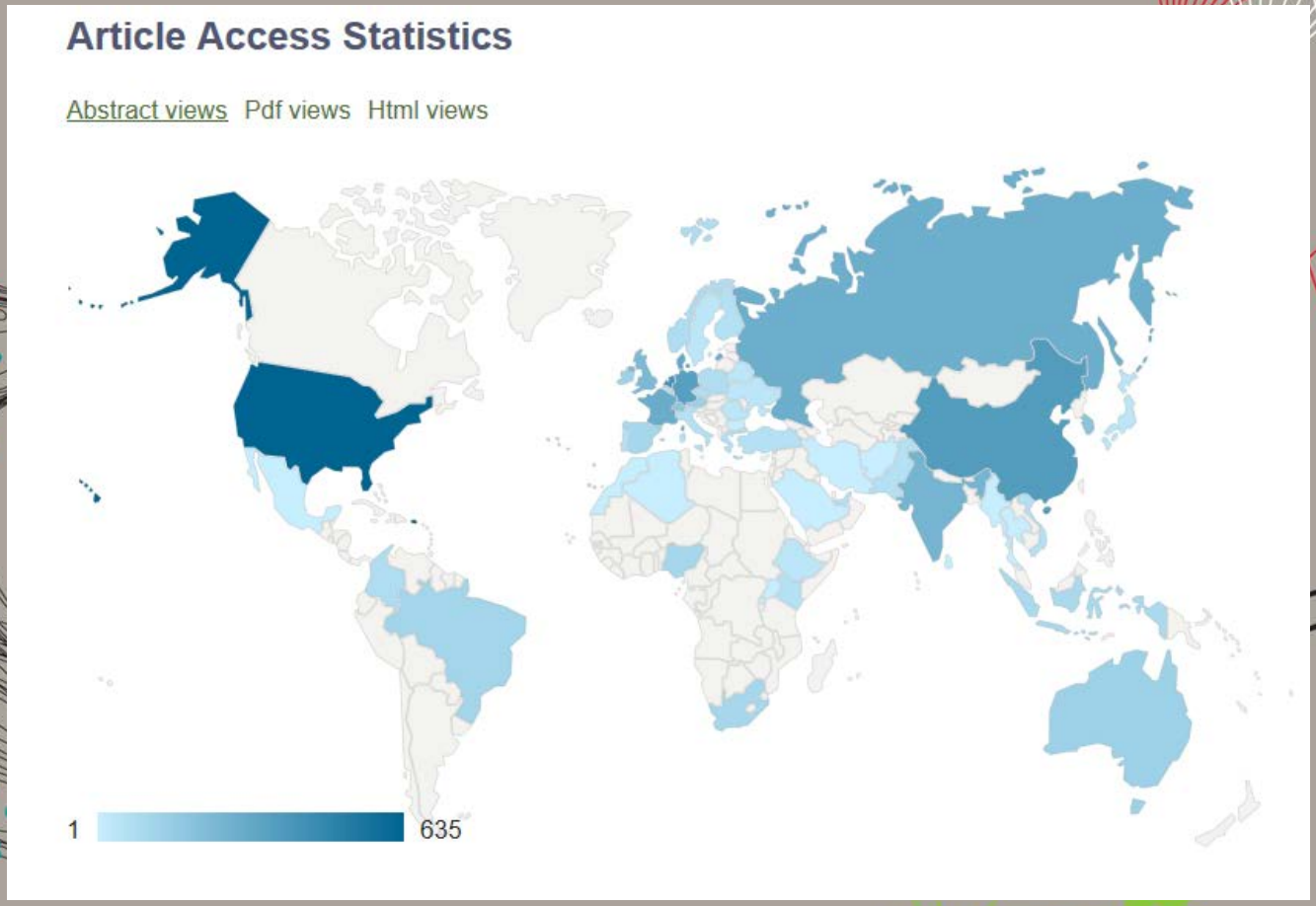
CHALLENGE 3:
INFORMATION NEEDS AND ETHIC CONSIDERATIONS

(image by C. Gevaert)

CHALLENGE 4:
UNDERSTAND BETTER ENVIRONMENTAL CONDITIONS OF SLUMS



WANG, J. et al. Characterizing the thermal patterns of informal urban settlements. Forthcoming.



THANKS FOR YOUR ATTENTION