NRSCC

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ESA–MOST China Dragon 4 Cooperation

→ 2019 ADVANCED INTERNATIONAL TRAINING COURSE IN LAND REMOTE SENSING

18–23 November 2019 | Chongqing University | Chongqing, P.R. China

Urban mapping

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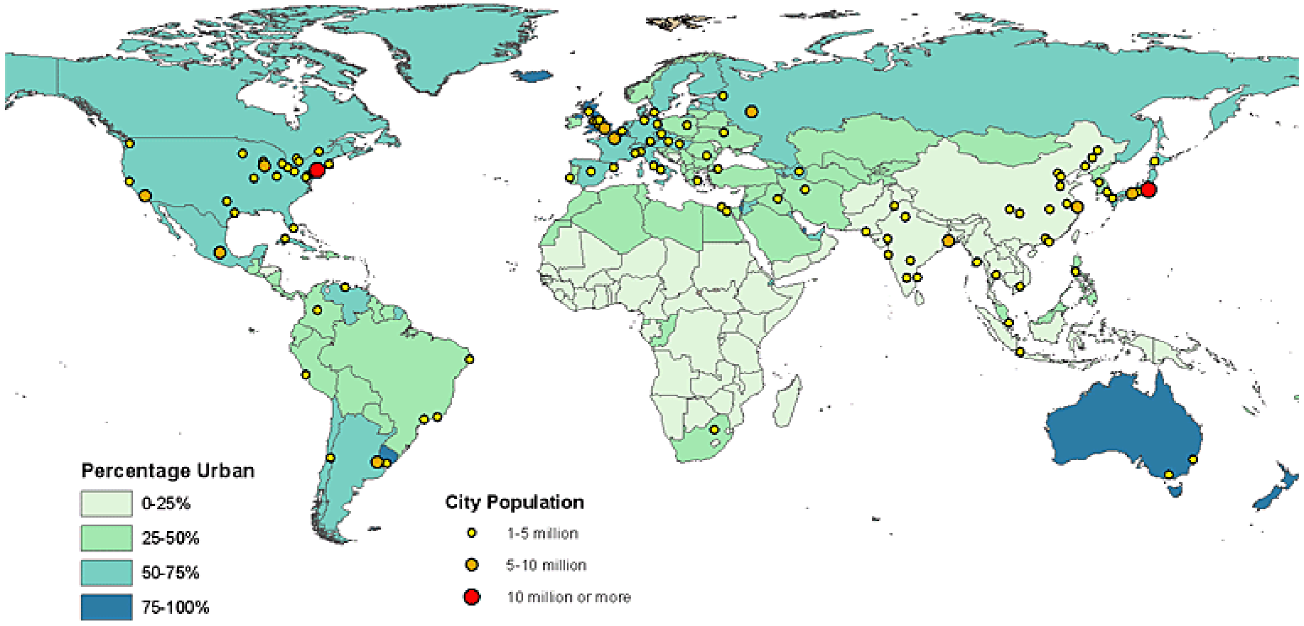
Content

1 Urban remote sensing

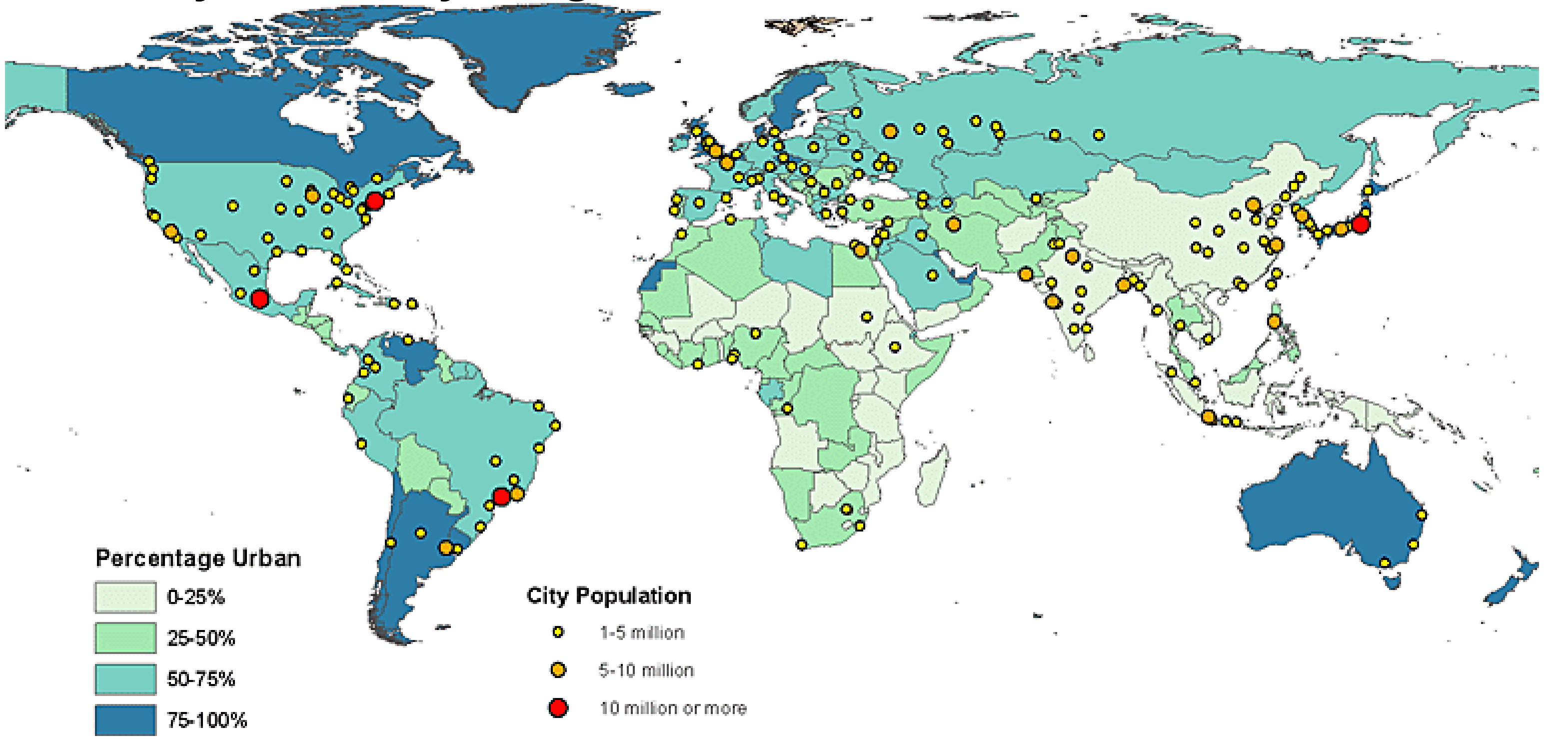
Urbanization is the physical growth of urban areas as a result of rural migration and even suburban concentration into cities, particularly the very largest ones.



Percentage of urban population and agglomerations by size class, 1960

World Urbanization Prospects, the 2011 Revision http://esa.un.org/unpd/wup/index.html

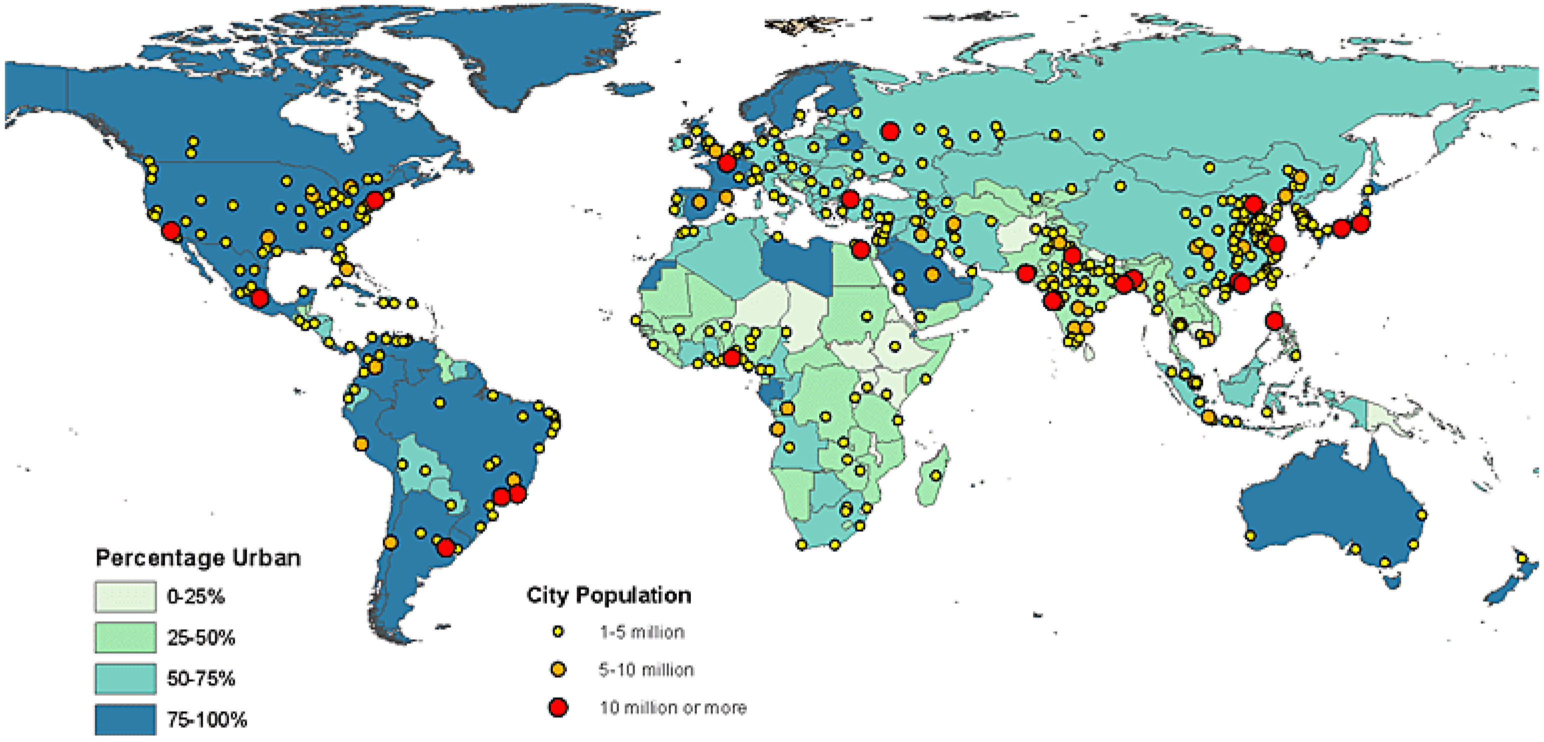
Urbanization is the **physical growth of urban areas** as a result of rural migration and even suburban concentration into cities, particularly the very largest ones.



Percentage of urban population and agglomerations by size class, 1980

World Urbanization Prospects, the 2011 Revision http://esa.un.org/unpd/wup/index.html

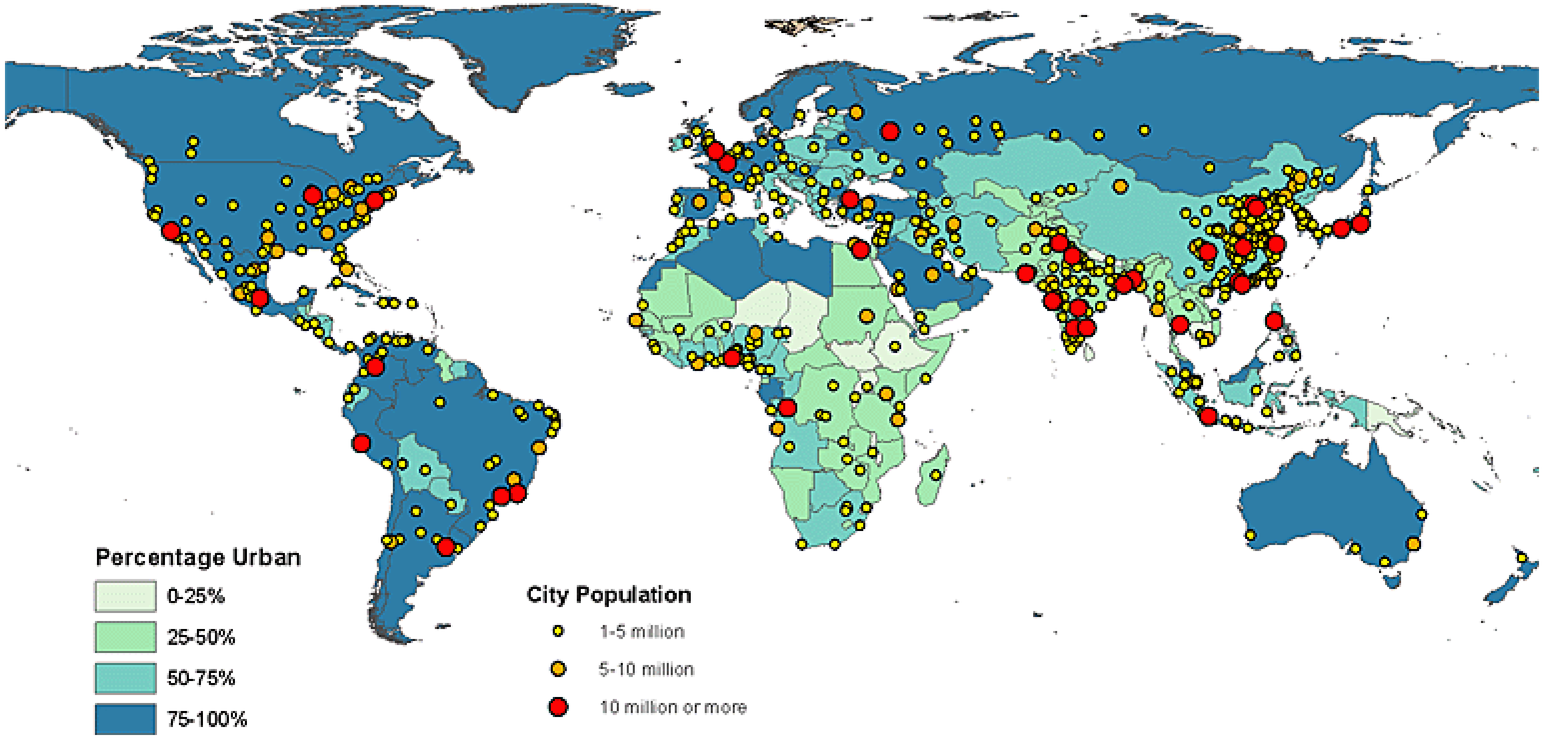
Urbanization is the physical growth of urban areas as a result of rural migration and even suburban concentration into cities, particularly the very largest ones.



Percentage of urban population and agglomerations by size class, 2011

World Urbanization Prospects, the 2011 Revision http://esa.un.org/unpd/wup/index.html

Urbanization is the physical growth of urban areas as a result of rural migration and even suburban concentration into cities, particularly the very largest ones.



Percentage of urban population and agglomerations by size class, 2025

World Urbanization Prospects, the 2011 Revision http://esa.un.org/unpd/wup/index.html

Urban Remote Sensing: (Esch et al. 2010)

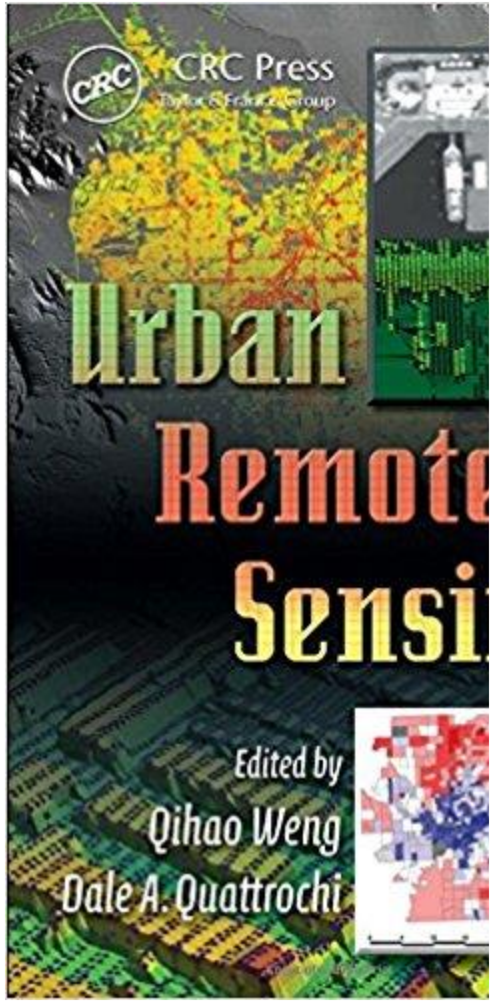
The constantly increasing availability and accessibility of modern remote sensing technologies has provided new opportunities for a wide range of urban applications such as:

- mapping and monitoring of the urban environment (land cover, land use, morphology, urban structural types),
- socio-economic estimations (population density),
- characterization of urban climate (microclimate, human health conditions),
- analysis of regional and global impacts – (ground water and climate modelling, urban heat islands)
- urban security and emergency preparedness (sustainability, vulnerability).

Esch et al., Urban Remote Sensing, 46th ISOCARP Congress 2010

Urban remote sensing

How can earth observation support the sustainable development of urban environments?



2006

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18–23 Novembe

2016

18–23 Novembe

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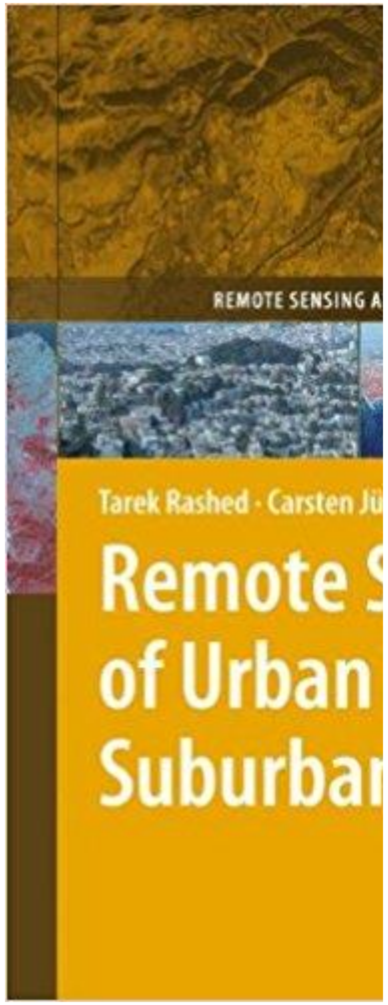
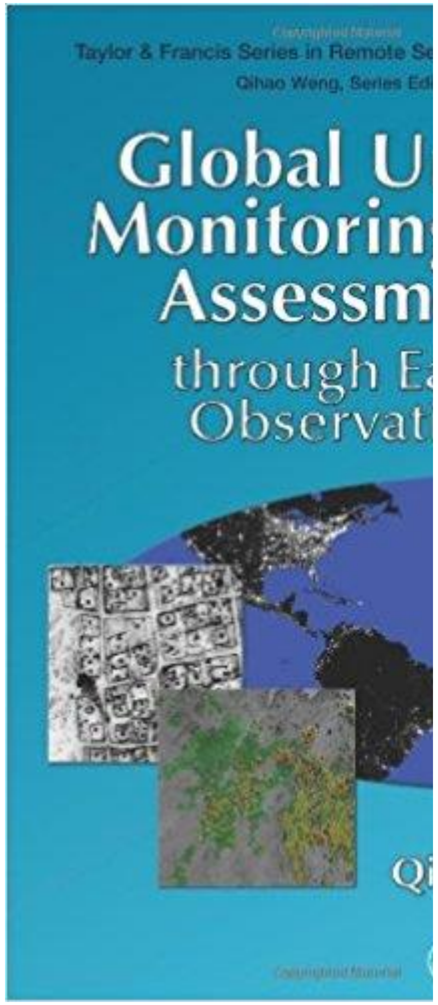


2010

Contents



2014

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SECTION IV Innovative Concepts and Techniques in Urban Remote Sensing

Urban remote sensing

Diverse objectives

- Urban extent extracting
- Urban mapping, map updating
- Target identification (road, tree)
- Land cover / land use
- Urban growth and simulation (CA+MAS)
- 3D modeling
- Change detection
- Environmental monitoring
- Disaster(earthquake, subsidence, landslide)
- Modeling, simulation and prediction

Urban remote sensing

Using various data sources:

- optical (multi/hyperspectral, high resolution)
- SAR, high resolution SAR (TerreSAR)
- LiDAR (airborne, Vehicle-Based)
- Photogrammetry
- Nighttime images
- UAV data: Unmanned Vehicle
- Demography and census
- GPS
- GIS data
- VGI / Crowdsourcing data

Urban remote sensing

Integration (Fusion) of multi-source data

- Optical + SAR
- PAN (Satellite or airborne) + MS
- LiDAR / DSM + Hyperspectral
- Thermal RS + MSS/SAR
- RS data + census
- RS data + GIS data
- Optical / SAR + Nightlight images
- RS + VGI / Crowdsourcing data

Urban remote sensing

Multi-scale study

◆ Scale of data

----multi-resolution remote sensing

◆ Scale of urban objects

----Global, continental, national, regional, sub-area of city

◆ Temporal scale

----Hour, Day, Month, Year, Selected periods

Urban remote sensing

Novel algorithms for information extraction

- Novel fusion algorithms
- Multiple classifier system
- Multiple agent system
- Semi-supervised classification
- Object-oriented paradigm
- Kernel methods
- SVM, ANN, morphology
- ant colony optimization (ACO)

Urban remote sensing

Linking natural and social science

- Social equality
- Urban structure and function
- The correlation of urban morphology with socioeconomic parameters
- Physical Characterisation of Deprivation in Cities
- Socio-Economic Conditions and Accessibility

Content

Case 1: Urban Dynamics: Temporal Urban Mapping (USGS)

Temporal urban mapping develops a historical perspective of urban development by combining a variety of data sources into an integrated, multi-scale, and multi-resolution database.

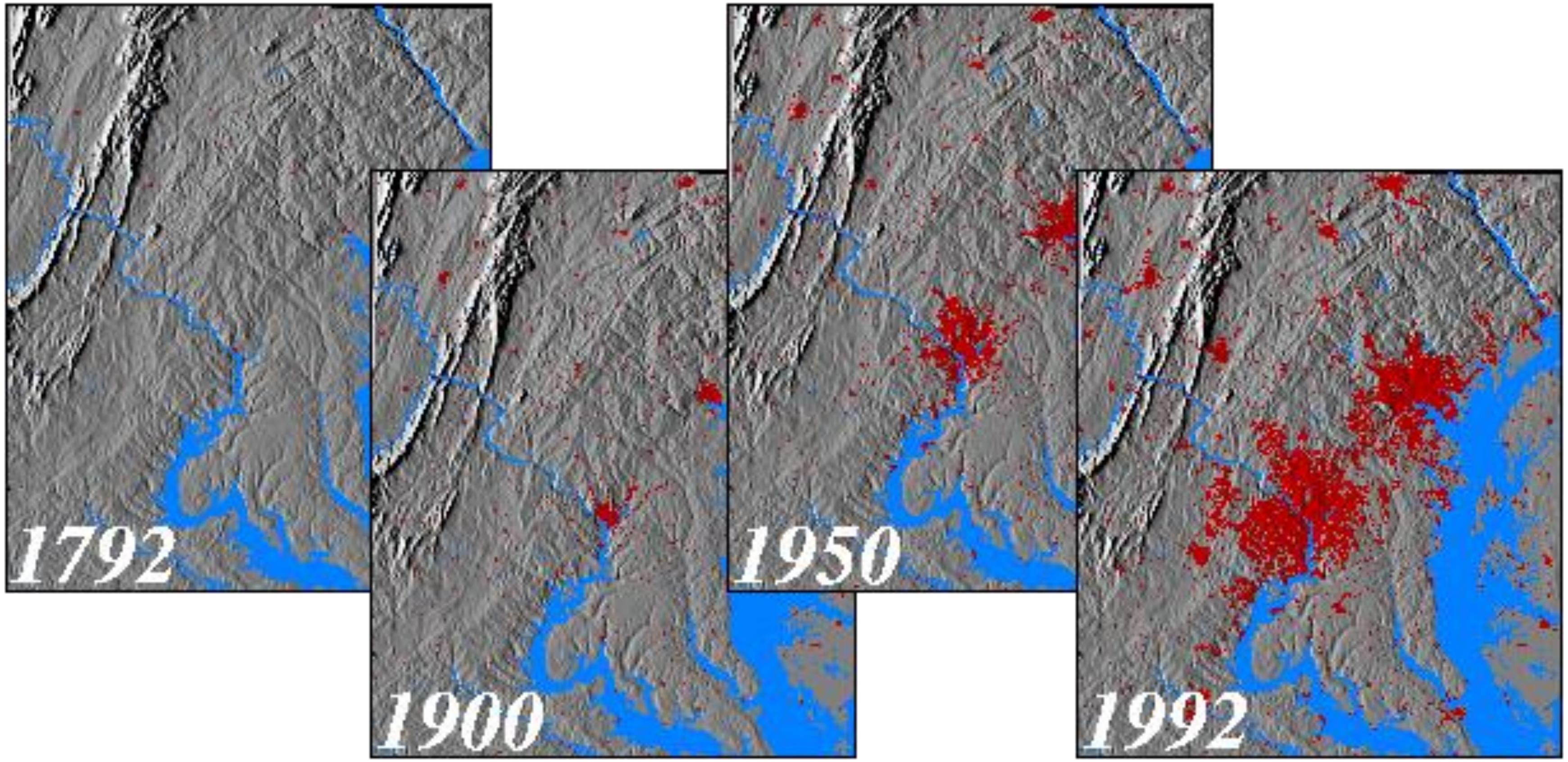
The database provides the baseline information to model and predict regional patterns of urbanization.

Temporal urban mapping relies on modern mapping techniques, such as remote sensing and geographic information systems (GIS), to capture information from both historical and modern records.

The database highlights the profound changes to the landscape that have incrementally developed over time.

http://landcover.usgs.gov/urban/umap/

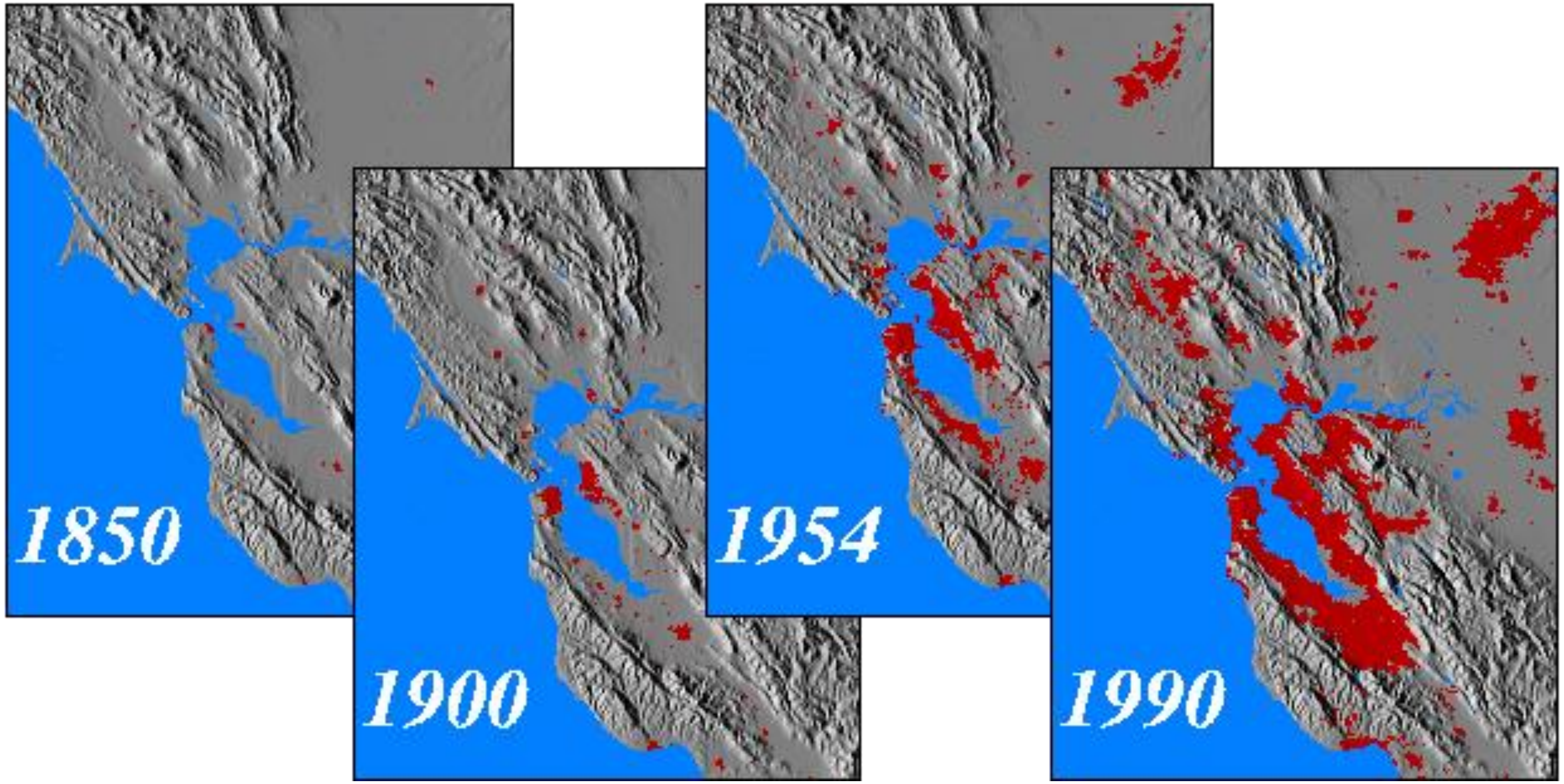
Urban Dynamics: Temporal Urban Mapping



Baltimore-Washington area

http://landcover.usgs.gov/urban/umap/

Urban Dynamics: Temporal Urban Mapping



San Francisco-Sacramento temporal database http://landcover.usgs.gov/urban/umap/

Case 2: Global Rural-Urban Mapping Project (GRUMP)

Global Rural-Urban Mapping Project (GRUMP) renders the spatial distribution of human populations in a common geo-referenced framework.

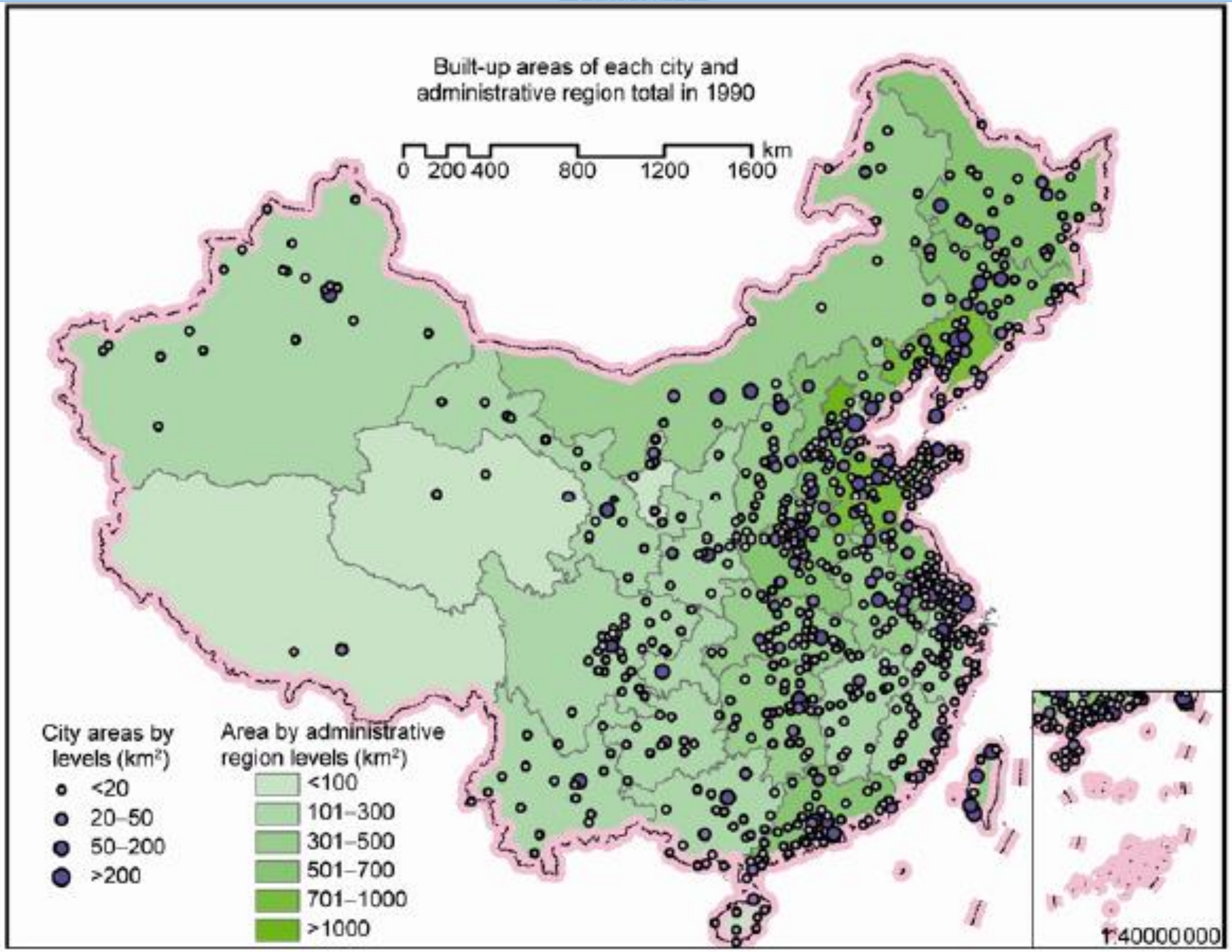
GRUMP incorporates urban and rural information derived from satellite data and other sources, encouraging new insights into urban population distribution and the global extents of human settlements.

http://www.ifpri.org/dataset/global-rural-urban-mapping-project-grump

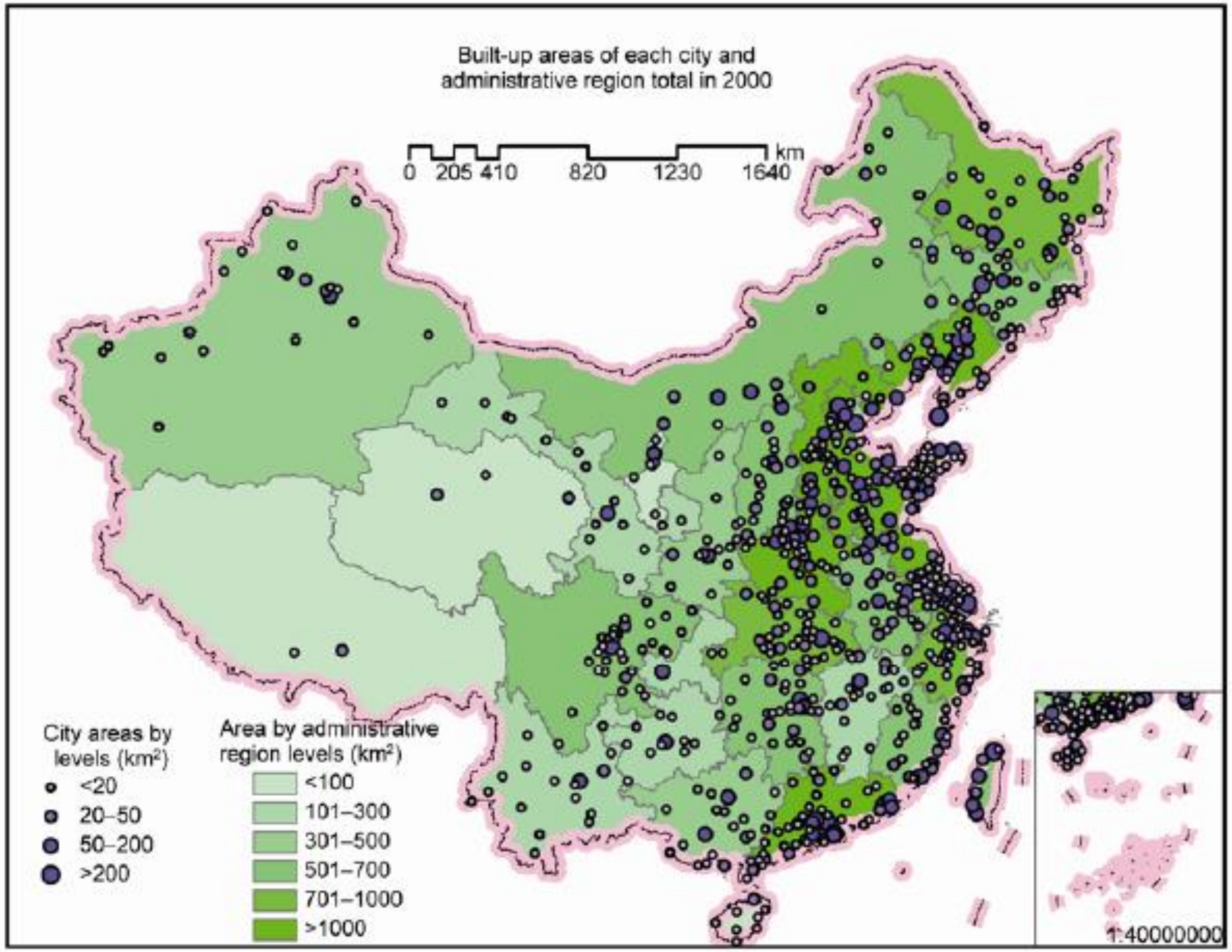
http://sedac.ciesin.columbia.edu/gpw

Case 3: China's urban expansion from 1990 to 2010

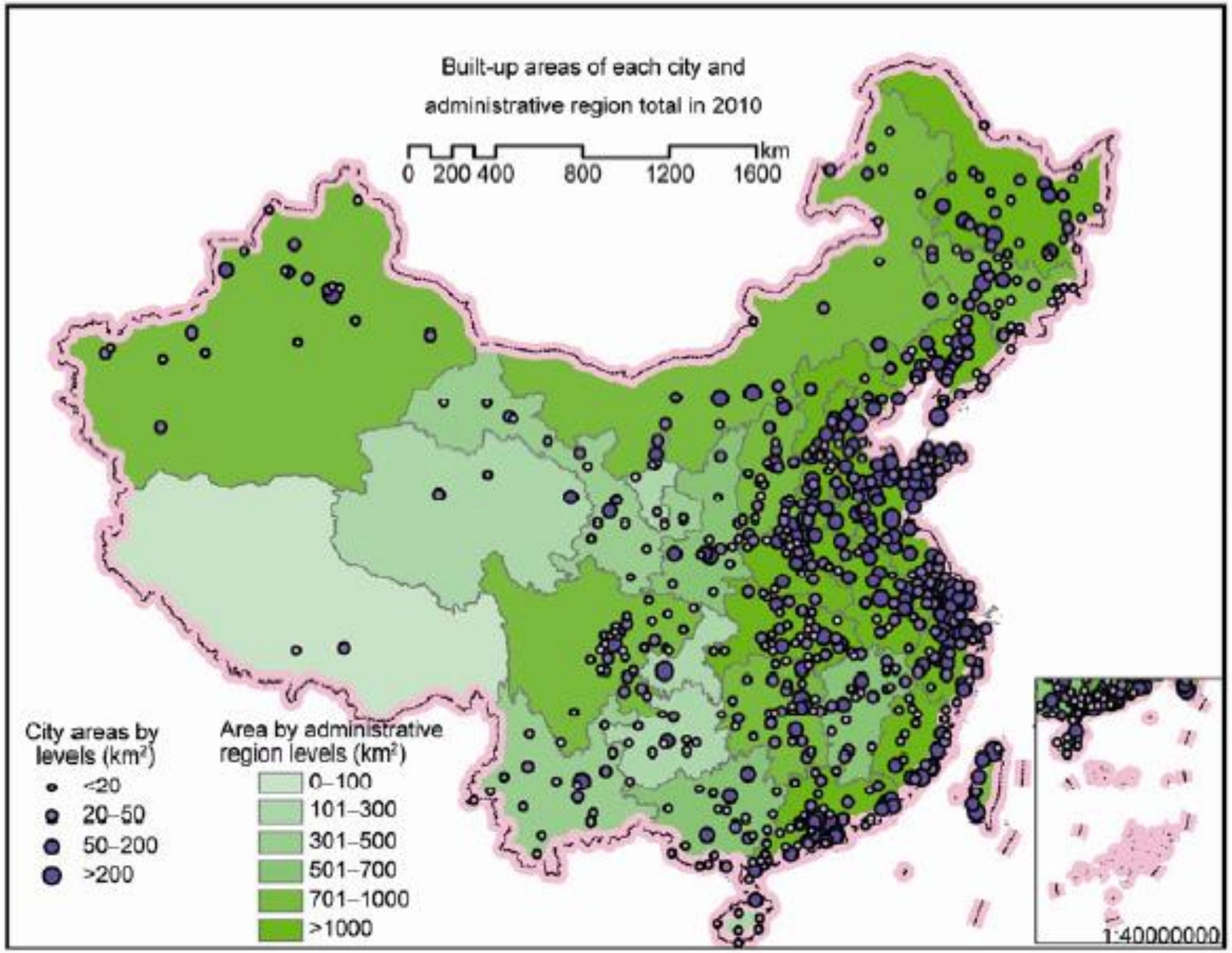
WANG Lei, LI CongCong, YING Qing, et al. **China's urban expansion from 1990 to 2010 determined with satellite remote sensing.** Chinese Science Bulletin 2012 Vol. 57 (22): 2802-2812



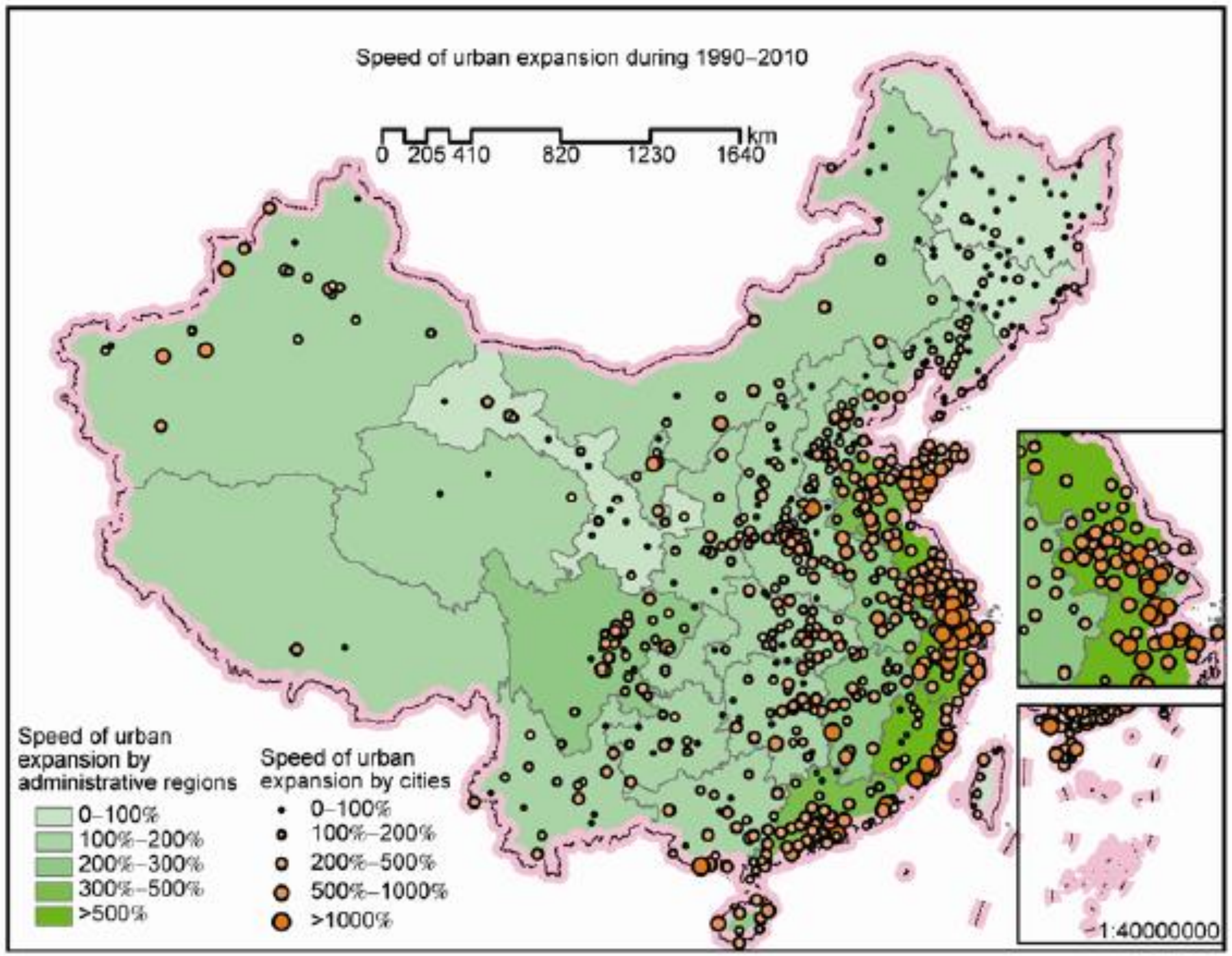
Built-up areas of each city in different size classes and administrative region total of different classes in the background for 1990 period.



Built-up areas of each city in different size classes and administrative region total of different classes in the background for 2000 period.



Built-up areas of each city in different size classes and administrative region total of different classes in the background for the 2010 period.



Speed of urban expansion during the 20 years.

Urban monitoring and mapping by remote sensing plays an important role in different fields at different geographic scales.

- Monitoring (Information extraction).
- Mapping.
- Modeling.
- Management.

In order to map urban extent and monitor changes and growth of urban areas **it is necessary to distinguish between urban and non-urban land cover**.

Urban area or Built-up Land: the core in urban mapping

Urban or built-up land is defined as areas characterized by buildings, asphalt, concrete, suburban gardens, and a systematic street pattern.

Classes of urban development include residential, commercial, industrial, transportation, communications, utilities, and mixed urban.

Undeveloped land completely surrounded by developed areas, such as cemeteries, golf courses, and urban parks is recognized within urban areas.

http://landcover.usgs.gov/urban/umap/

Urban or Built-up Land: how to define or classify?

The classification scheme adopted for temporal urban mapping is a subset of the land use and land cover (LULC) classification system described in the USGS Professional Paper 964.

- A flexible **hierarchical system** for use at multiple levels, depending on the level of detail and scale required by the application.
- Most urban areas within the database were categorized as Level I, Urban or Built-up Land and Level II category 16, mixed urban or built-up land.
- When enough information was available from the source material classification was carried to Level II and III.

http://landcover.usgs.gov/urban/umap/

Urban or Built-up Land

LEVEL I	LEVEL II	LEVEL III
1 Urban Development	11 Residential	111 High Density Residential 112 Low Density Residential
	12 Commercial and Services	
	13 Industrial	
	14 Transportation, Communications, and Services	
	15 Industrial and Commercial Complexes	
	16 Mixed Urban or Build-up Land	
	17 Other Urban or Built-up Land	

http://landcover.usgs.gov/urban/umap/

Urban Area or Built-up Land Collection Criteria

Urban areas were compiled using criteria **based on either housing density, road density, spectral reflectance, or degree of land disturbance** depending on the source materials.

A residential density of three houses per 2.5 acres was established as the minimum level of development interpreted as urban.

The extent of urban areas was determined by the existence of a dense systematic street patterns and the relative concentration of buildings.

The Transportation, Communications, and Utilities subcategory encompasses only the areas of intensive use.

http://landcover.usgs.gov/urban/umap/

Urban or Built-up Land Collection Criteria

For example, areas delineated as airport facilities include only the runways, terminals, and parking lots, but not the surrounding open land.

Major freeways and highways were not delineated unless they were surrounded by urban development.

Major roads were instead captured as a separate principle transportation data layer.

http://landcover.usgs.gov/urban/umap/

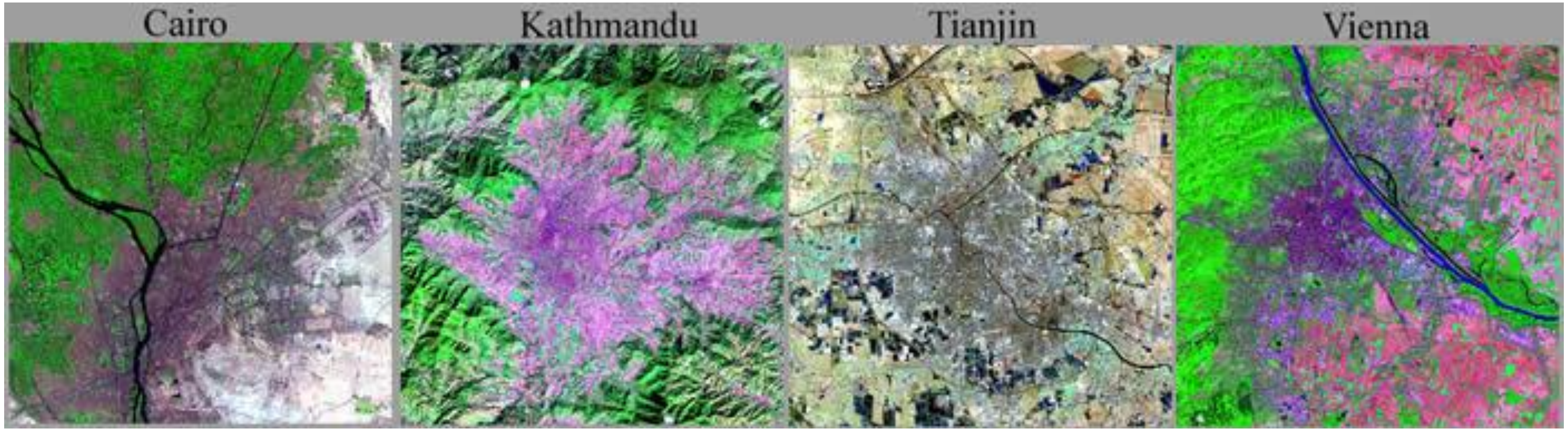
Urban or Built-up Land Collection Criteria

All areas identified as built-up, where individual uses could not be separated using the available source material, were assigned to the Mixed Urban or Built-up category.

Land with less intensive use, such as urban parks, golf courses, cemeteries, and undeveloped surrounded by built-up land was delineated as Other Urban or Built-up Land, category.

http://landcover.usgs.gov/urban/umap/

Data for urban mapping: medium multispectral images



Landsat 7 ETM+

http://www.ldeo.columbia.edu/~small/Urban/

Data for urban mapping: medium multispectral images

Landsat 8 OLI + TIRS

	Channel	Band number	Wavelength (µm)	Resolution (m)
OLI	Coastal aerosol	1	0.433–0.453	30
	Blue	2	0.450–0.515	30
	Green	3	0.525–0.600	30
	Red	4	0.630–0.680	30
	NIR	5	0.845–0.885	30
	SWIR1	6	1.560–1.660	30
	SWIR2	7	2.100–2.300	30
	Panchromatic	8	0.500–0.680	15
	Cirrus	9	1.360–1.390	30
TIRS	TIRS1	10	10.6–11.2	100
	TIRS2	11	11.5–12.5	100

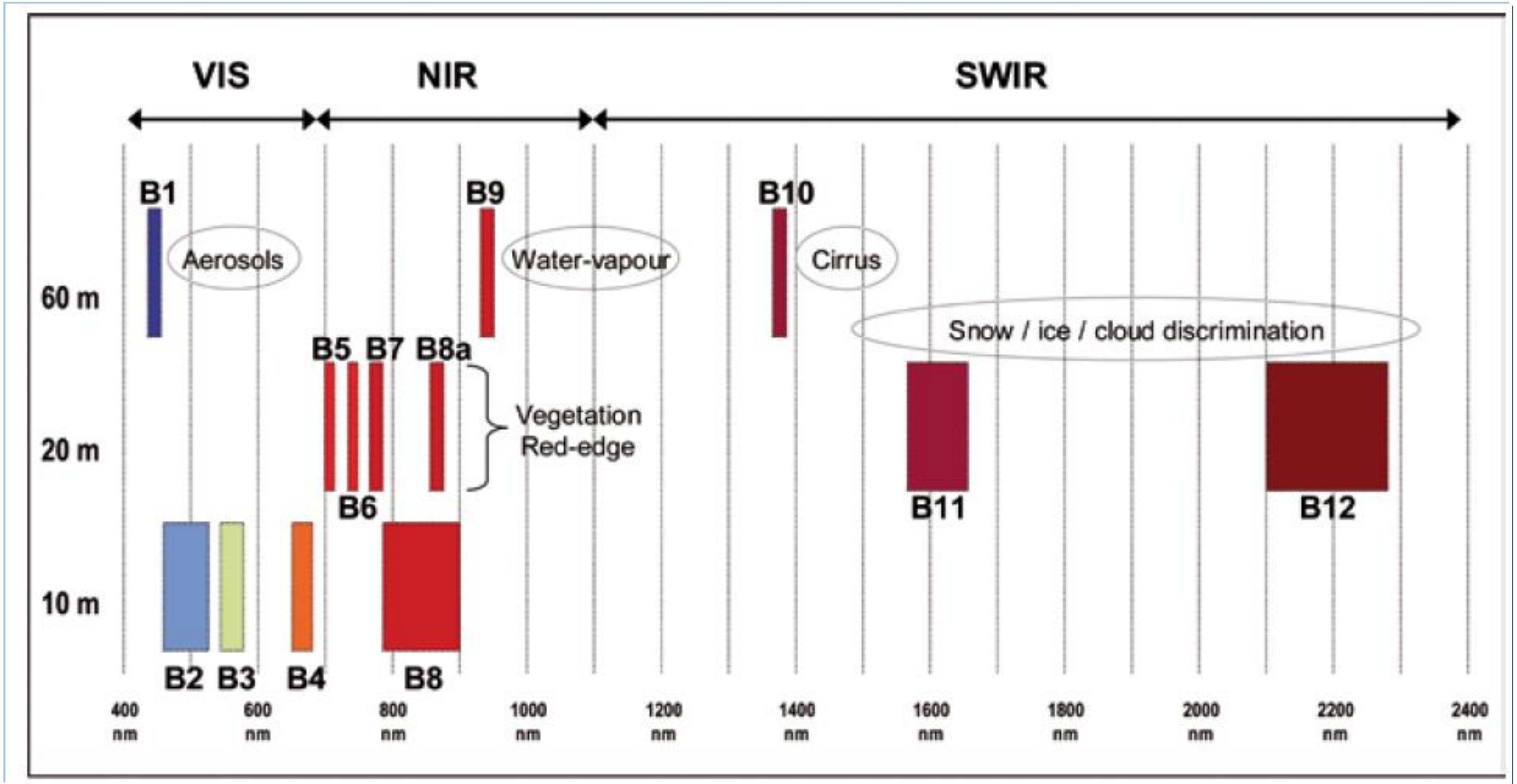
Data for urban mapping: medium multispectral images

Sentinel 2 MS images

Table 6.1. Spectral bands and signal-to-noise ratio requirements for the Sentinel-2 mission.

Band number	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)	L_{ref} ($W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$)	SNR @ L_{ref}
1	443	20	60	129	129
2	490	65	10	128	154
3	560	35	10	128	168
4	665	30	10	108	142
5	705	15	20	74.5	117
6	740	15	20	68	89
7	783	20	20	67	105
8	842	115	10	103	174
8b	865	20	20	52.5	72
9	945	20	60	9	114
10	1380	30	60	6	50
11	1610	90	20	4	100
12	2190	180	20	1.5	100

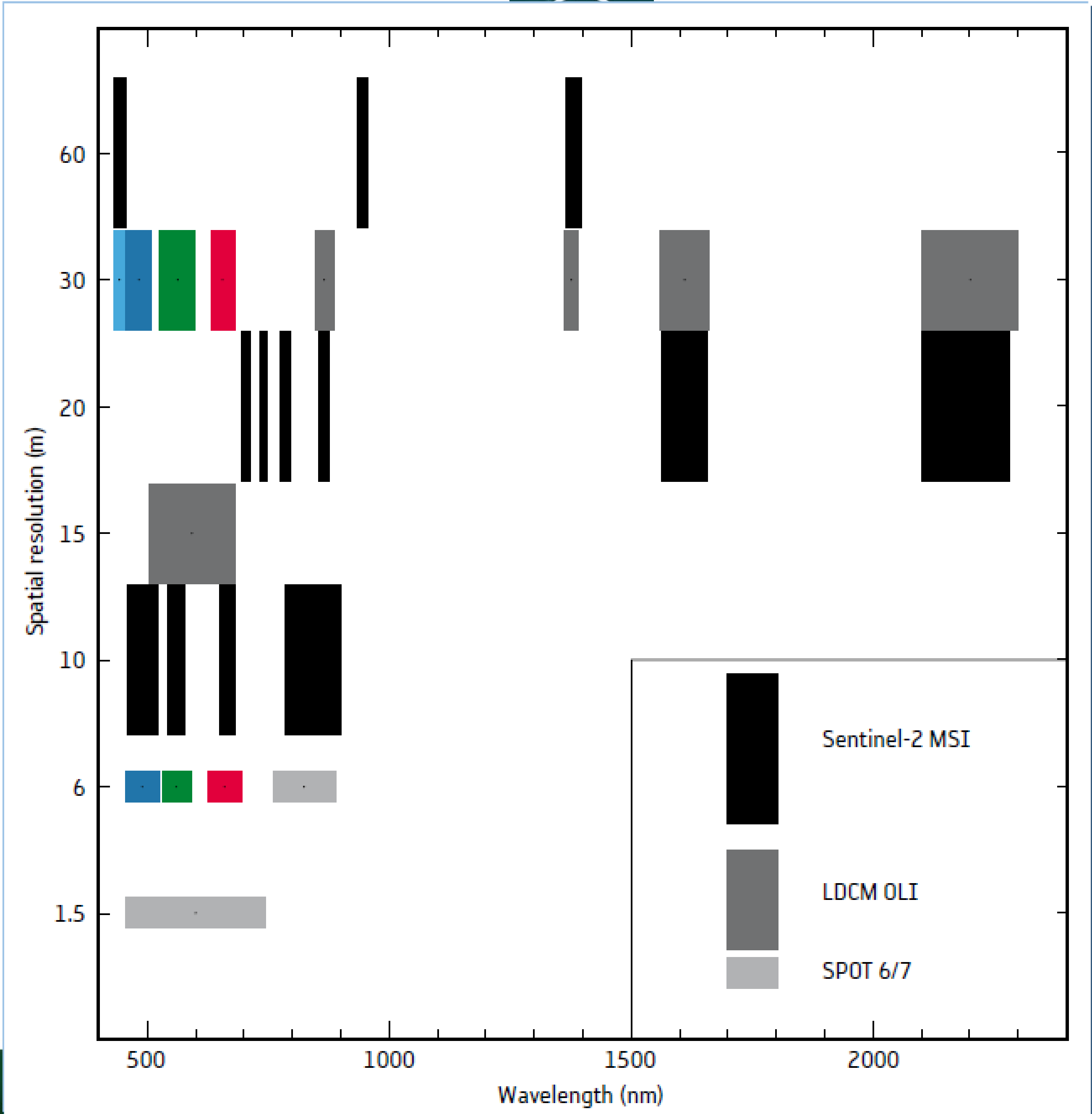
Sentinel 2 MS images



	Landsat	SPOT	Sentinel-2	
Number in series	7+1*	5**	starting with 2	
Launch	1972 to 1999*	1986 to 2002	S2-A launch end 2013	
Measurement principle	scanner	pushbroom	pushbroom	
Earth coverage	16	26	5	days
Swath	185	2 × 60	290	km
Multispectral bands	7(8*)	4+1 (panchromatic)	13	
Spatial sampling distance	30, 60	10, 20, (2.5)	10, 20, 60	m

* LCDM mission targeted early 2013

** SPOT-6 targeted end 2012



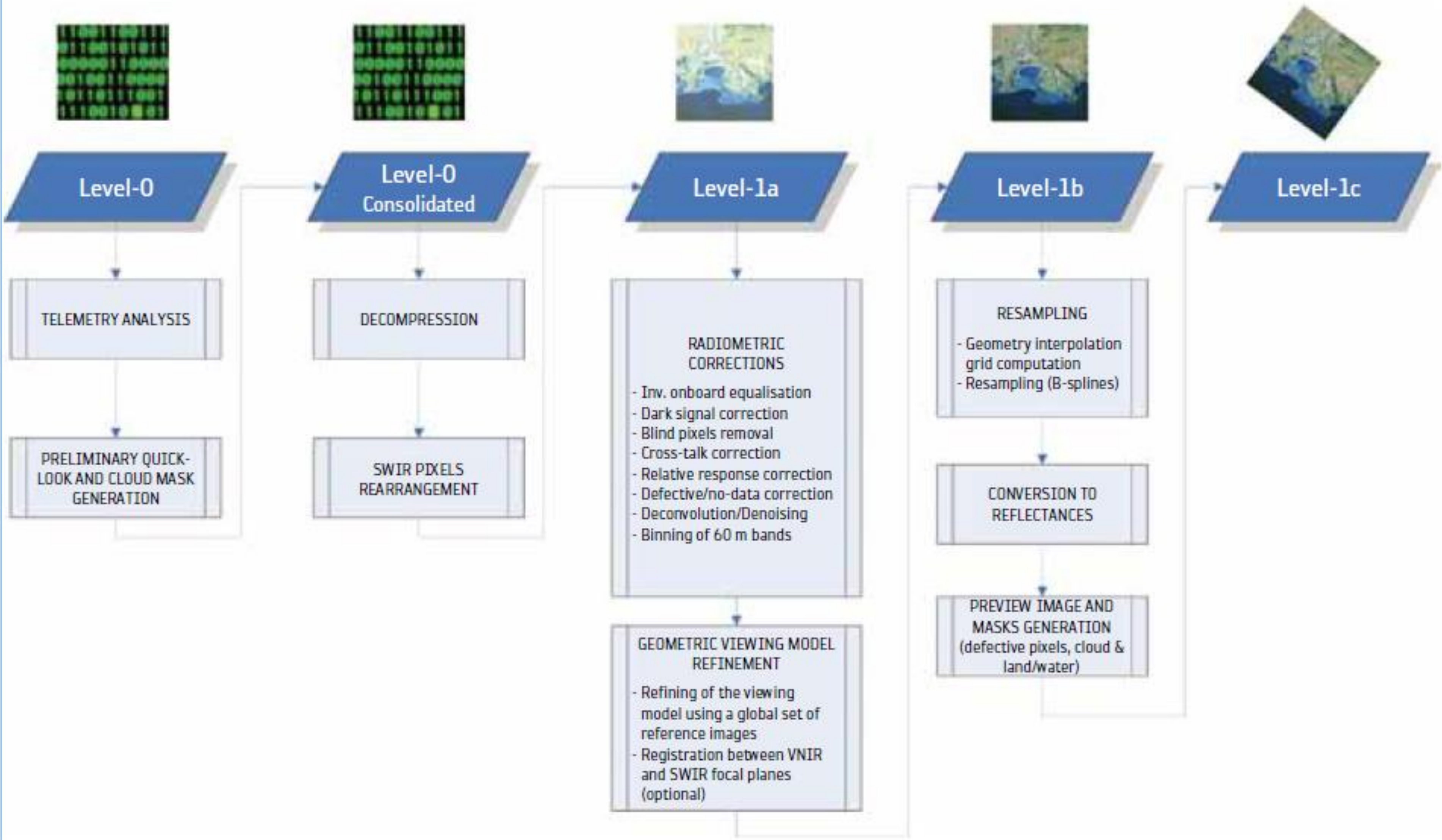
60
30
20
15
10
6
1.5
Spatial resolution (m)
500
1000
1500
2000
Wavelength (nm)
Sentinel-2 MSI
LDCM OLI
SPOT 6/7

Sentinel 2 MS images

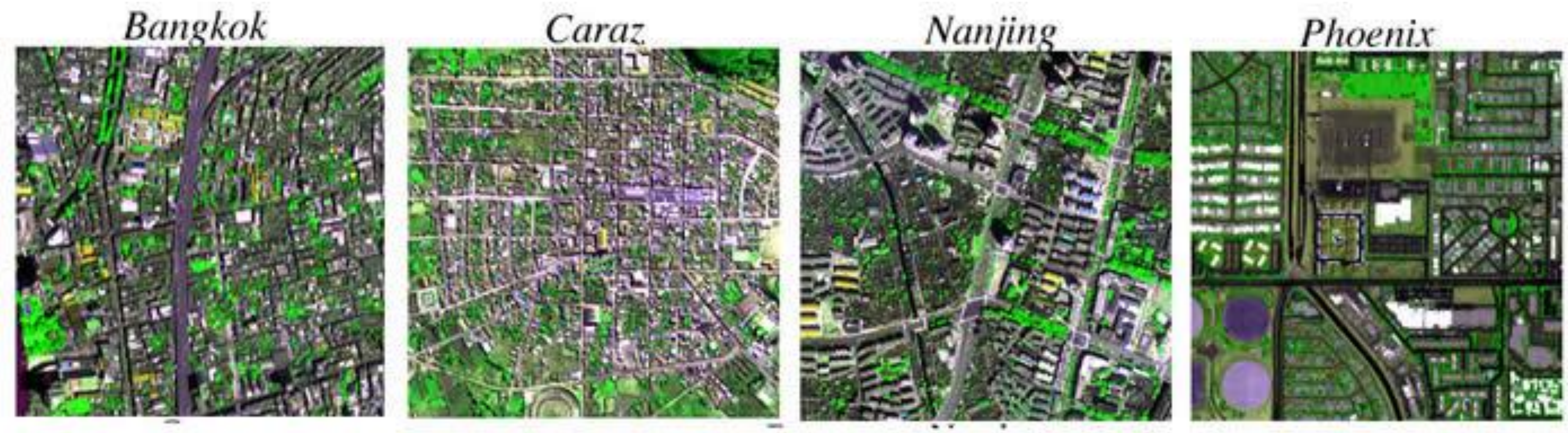
Table 4.2. Sentinel-2 data product dissemination strategies.

Sentinel-2 product type	Online product retention	Offline product retention	Product storage strategy
Housekeeping telemetry data	1 week	Mission lifetime	Data available online at the station for 1 week, then stored in the long-term archive
Level-0 data products	3 months	Mission lifetime	Data available online at the station for 1 week, and stored in the medium-term archive for 3 months (swift data reprocessing, e.g. during commissioning), in parallel storage in the long-term archive
Level-1a data products	1 month	No	Products available online from the medium-term archive for 1 month
Level-1b data products	1 month	Mission lifetime	Products maintained online for 1 month, then accessible from the long-term archive
Level-1c data products	1 month global 1 year global cloud free 1 year over Europe	Mission lifetime	All products with cloudiness below a threshold (e.g. 80%) archived offline for 1 year. Over Europe, all products are archived regardless of cloud cover. All data are kept online for at least 1 month, after which all products can be retrieved from the long-term archive offline

Figure 7.1. Level-1 data processing chart.



Data for urban mapping: high-resolution images



Ikonos and Quickbird.

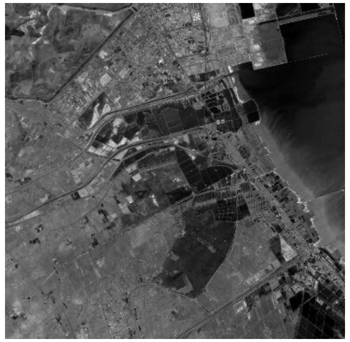
http://www.ldeo.columbia.edu/~small/Urban/

Data for urban mapping: high-resolution images

GF -1(China)

	Band number	Wavelength (μm)	Resolution (m)
Panchromatic & multispectral camera	1	0.45–0.90	2
	2	0.45–0.52	8
	3	0.52–0.59	
	4	0.63–0.69	
	5	0.77–0.89	
Multispectral camera	6	0.45–0.90	16
	7	0.45–0.52	
	8	0.52–0.59	
	9	0.63–0.69	

Panchromatic image



Multispectral Image (8 m)

Multispectral Image (16 m)

Data for urban mapping: high-resolution images

GF -2(China)

	Band number	**Wavelength (μm)**	**Resolution (m)**
Panchromatic & multispectral camera	1	0.45–0.90	1
	2	0.45–0.52	4
	3	0.52–0.59	
	4	0.63–0.69	
	5	0.77–0.89	

Panchromatic image

Multispectral image

Data for urban mapping: high-resolution images

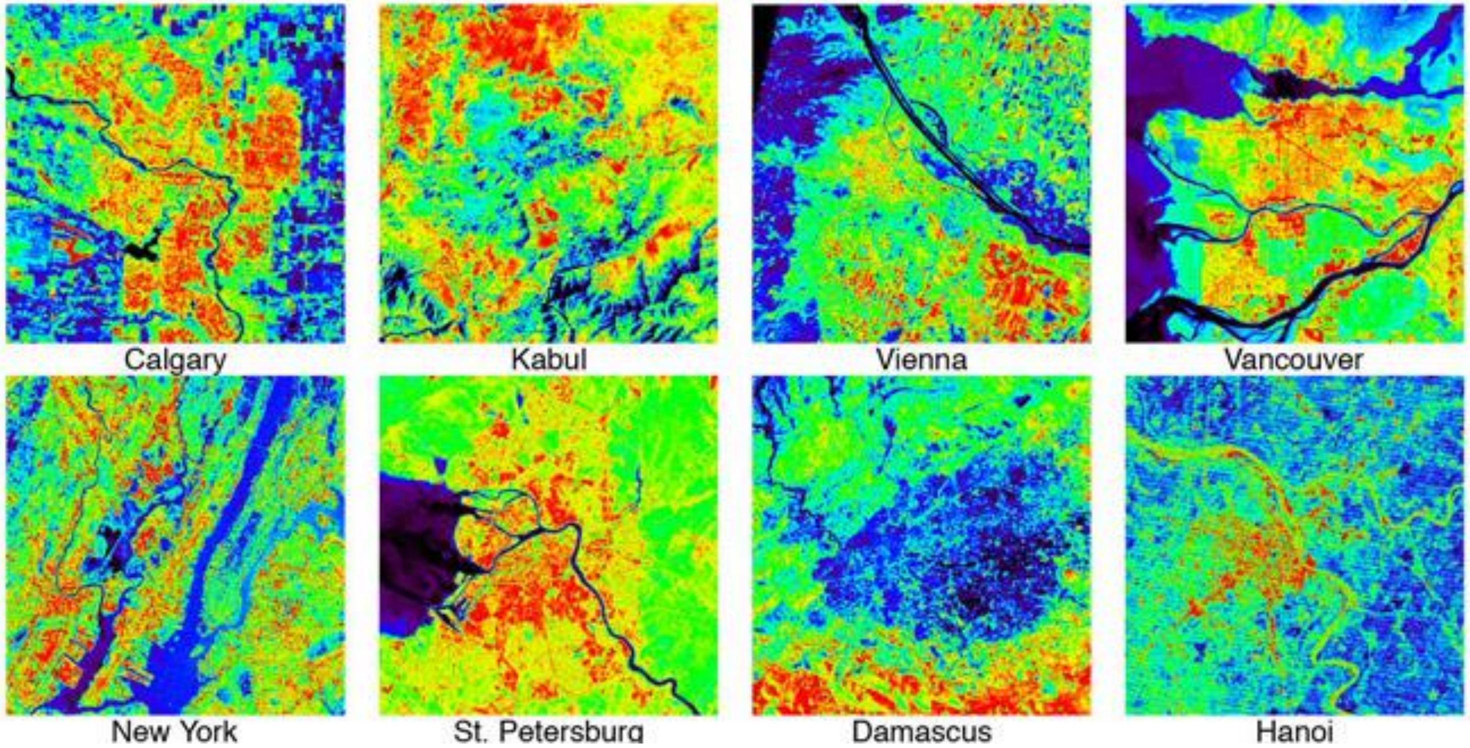
ZY-3(China)

	Band number	Wavelength (μm)	Resolution (m)
Forward looking camera	–	0.50–0.80	3.5
Backward looking camera	–	0.50–0.80	3.5
Orthophoric looking camera	–	0.50–0.80	2.1
Multispectral camera	1	0.45–0.52	6
	2	0.52–0.59	
	3	0.63–0.69	
	4	0.77–0.89	

Fused image

(Beijing National Day military parade, 2015)

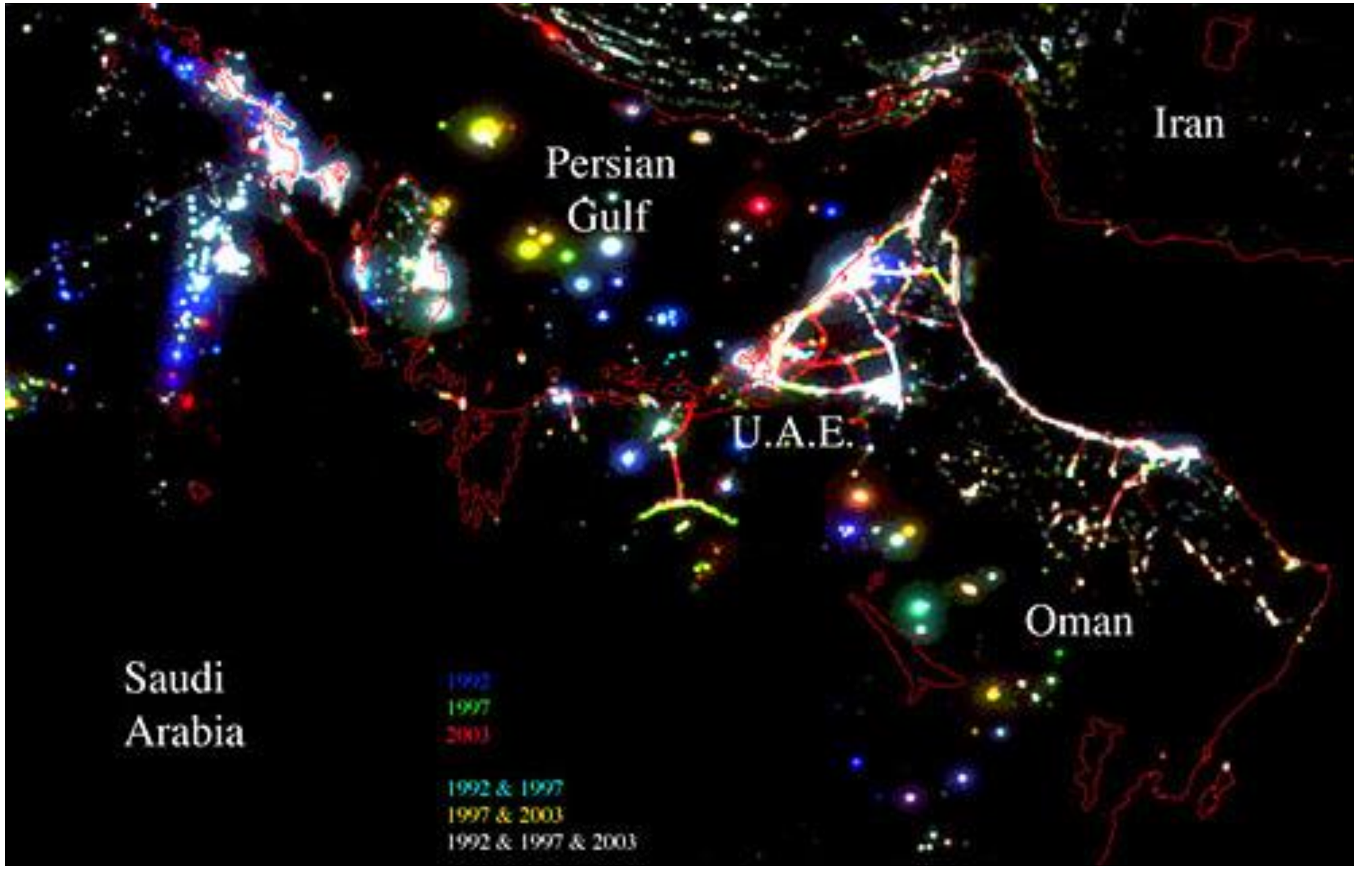
Data for urban mapping: thermal images



Thermal - *Comparative analysis of thermal properties of mixed urban land covers using Landsat 7*

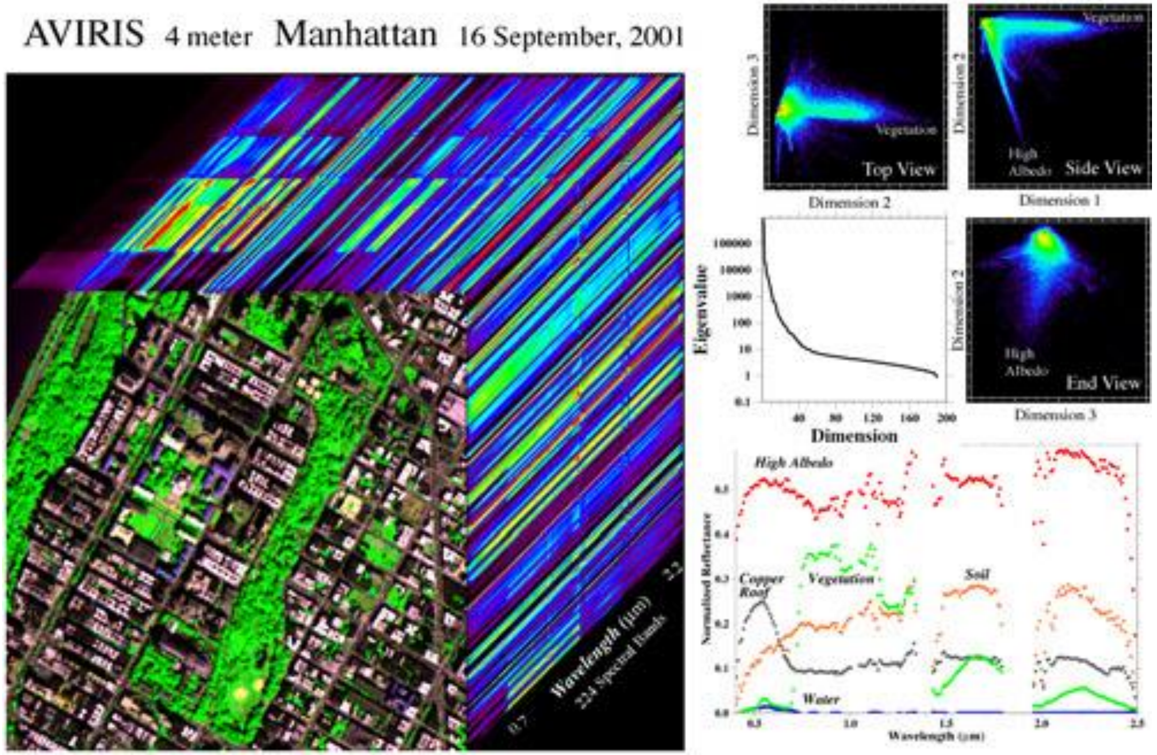
http://www.ldeo.columbia.edu/~small/Urban/

Data for urban mapping: Nighttime data



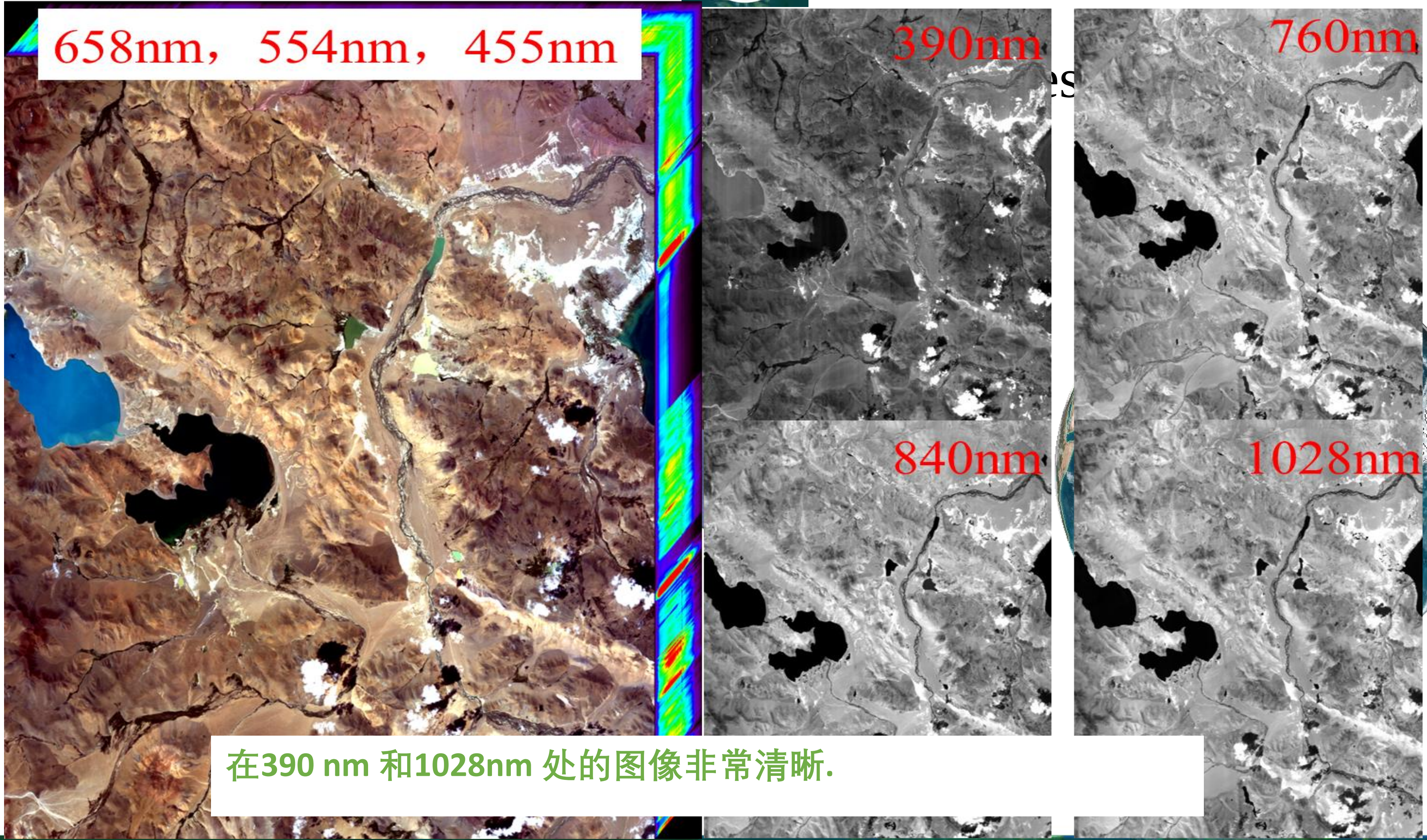
Night Lights - *Global spatial analysis and comparison of DMSP night lights with Landsat 7*

Data for urban mapping: Hyperspectral images

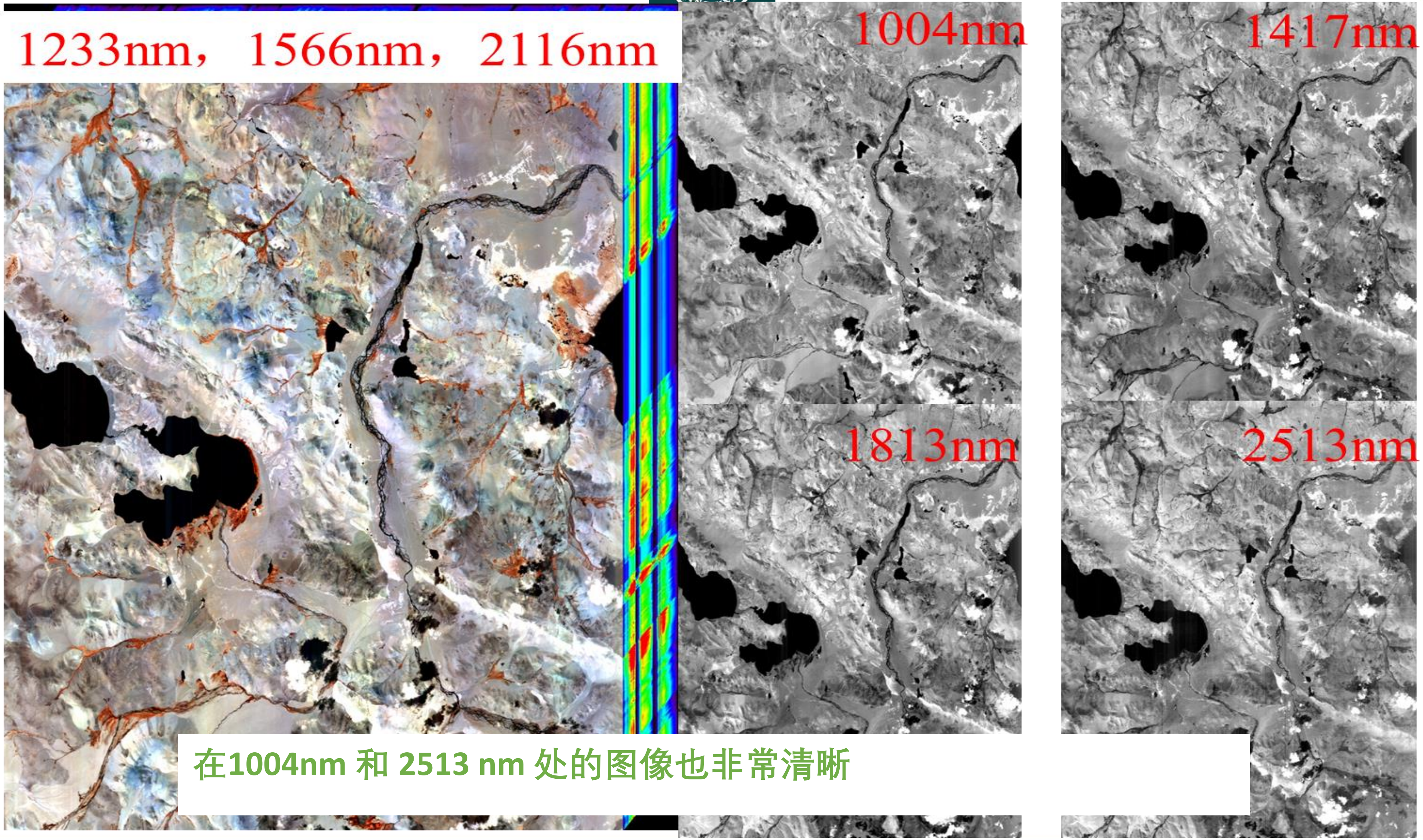


[Hyperspectral](http://www.ldeo.columbia.edu/~small/Urban/) - *Comparison of pervious and impervious surface reflectance properties*

http://www.ldeo.columbia.edu/~small/Urban/

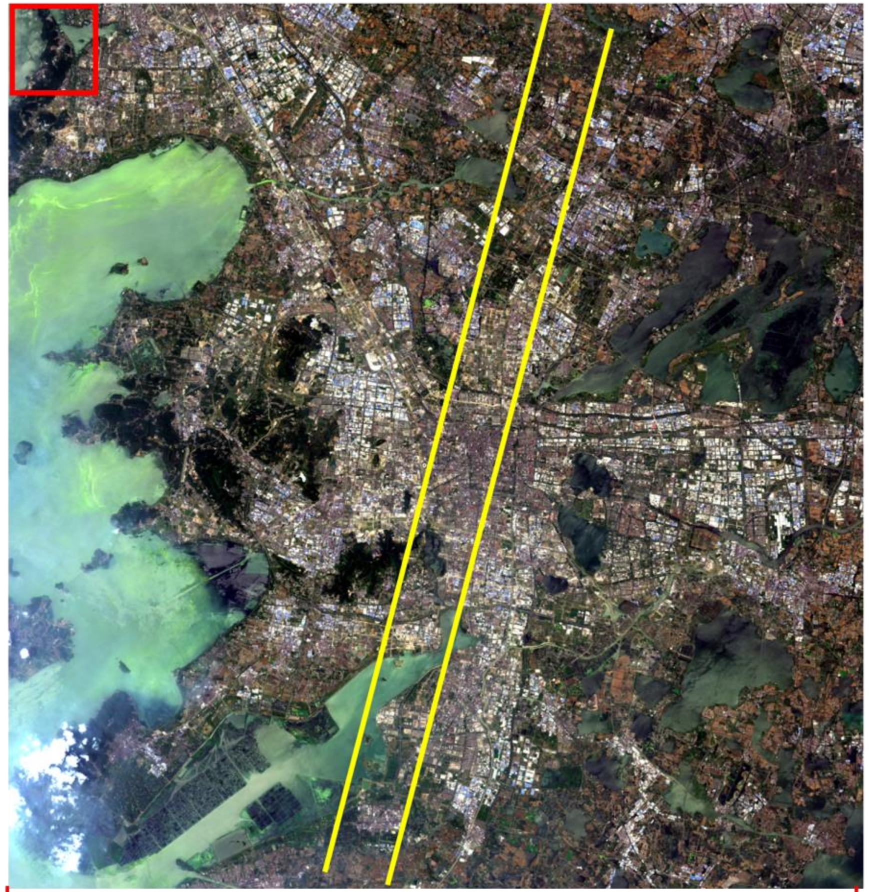


在390 nm 和1028nm 处的图像非常清晰.

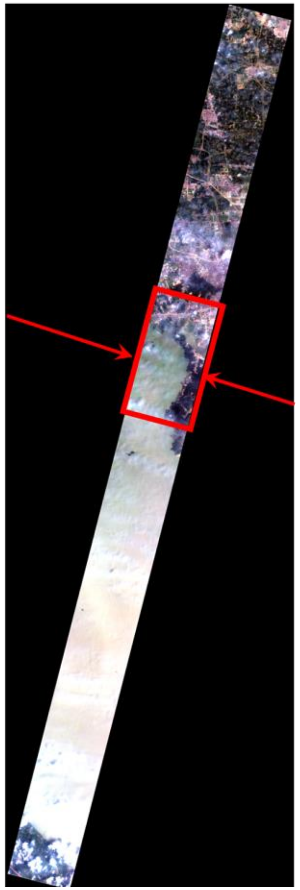


在1004nm 和 2513 nm 处的图像也非常清晰

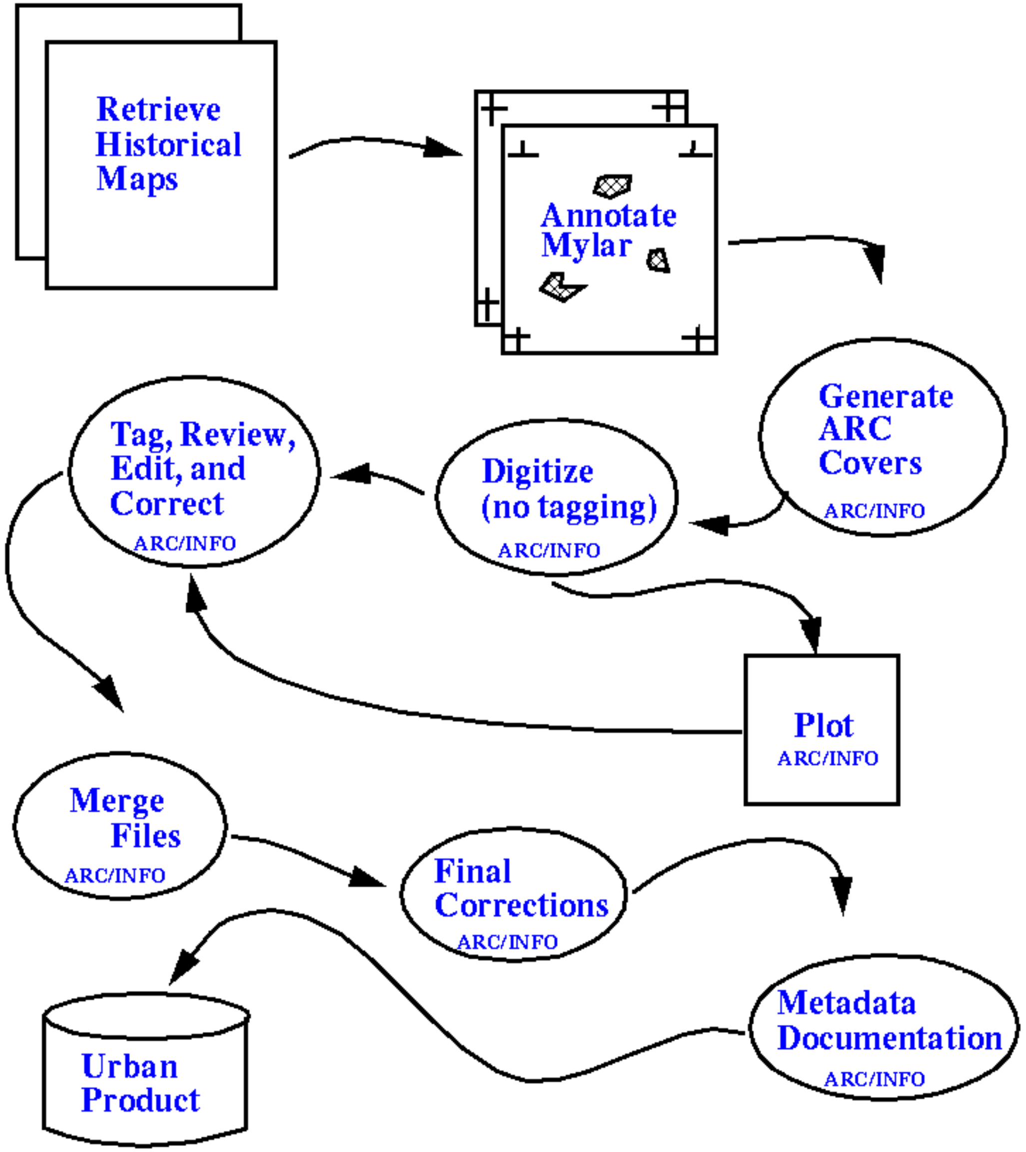
GF-5 AHSI苏州太湖　Hyperion苏州太湖



60 Km



7.5 Km



Flow chart depicting the steps involved in delineating urban extent from topographic maps.

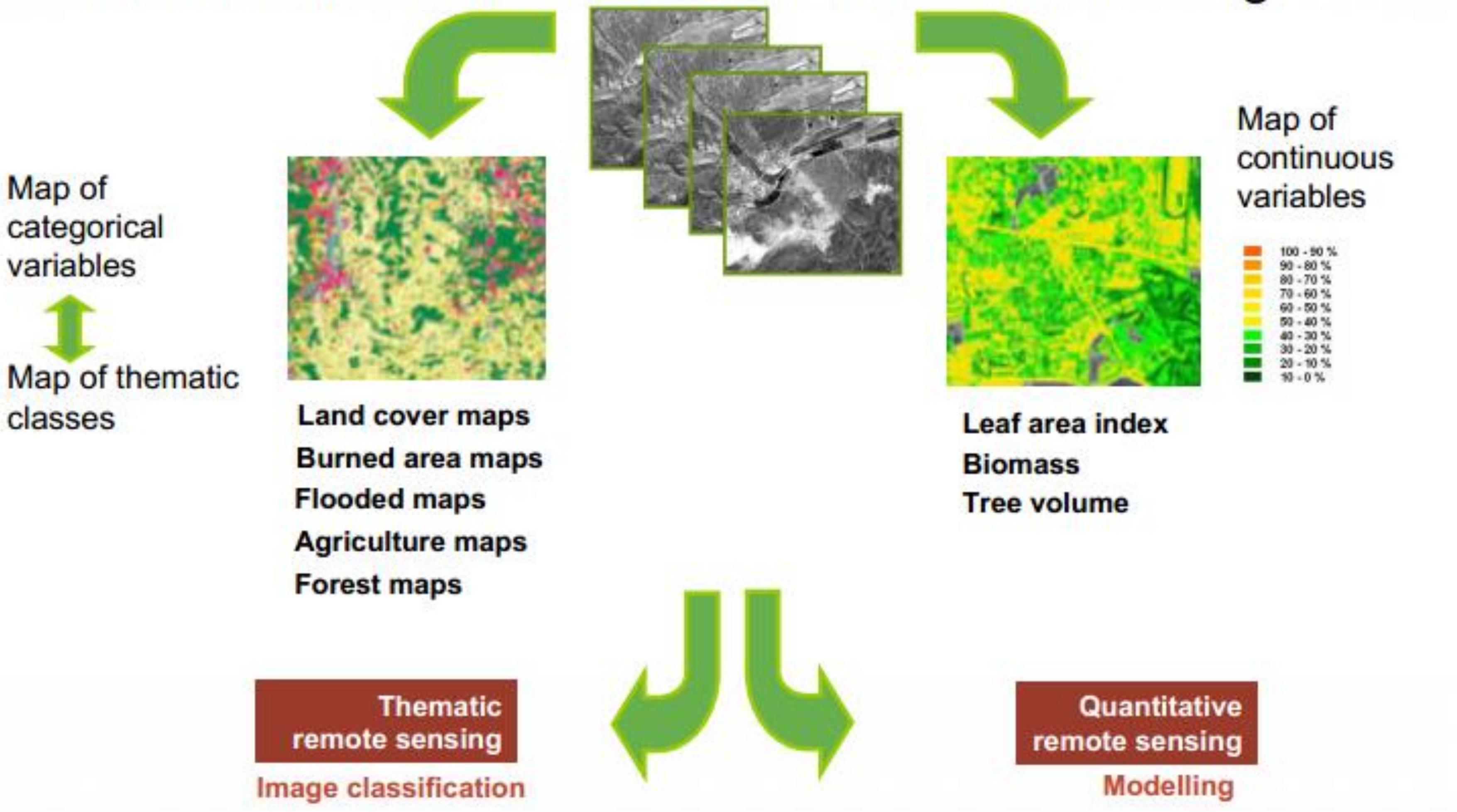
http://landcover.usgs.gov/urban/umap/

This talk focuses on urban mapping using remote sensing images, specifically, optical images obtained by Chinese and ESA sensors (CBERS 2/2B/2C, HJ-1, Beijing-1, Sentinel-2)

Conversion: from remote sensing data to thematic maps

Remote sensing image processing + mapmaking

Land information extraction from satellite images



Urban mapping:
Remote sensing image processing + mapmaking

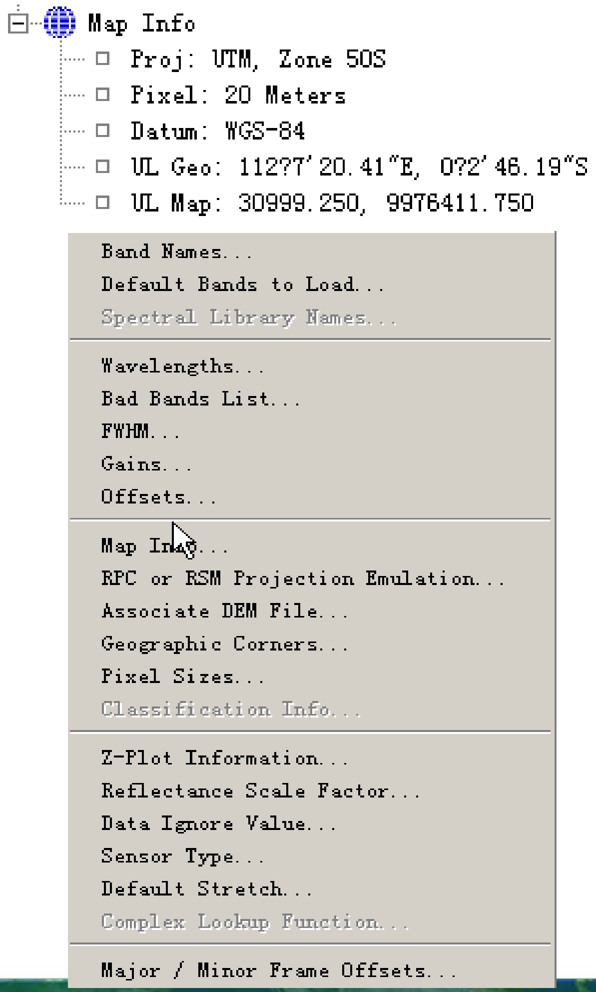
Step 1: Mapping standards and Geo-reference system

Step 2: Data selection and image preprocessing

Step 3: Classification / thematic information extraction

Step 4: Post-processing and map layout

Step 1: Mapping standards and Geo-reference system



- Mapping standards
  - Positional accuracy (relative/absoluate),
  - Resolution
  - Format of output files
  - Category

- Geo-reference system
  - U.S. National Grid (USNG)
  - Latitude Longitude
  - Global Area Reference System (GARS)
  - Georeferencing Matrix

- ENVI provides full support for georeferenced images in numerous predefined map projections including UTM and State Plane.

Step 2: Data selection and image preprocessing

- Data Selection
  - modes of image formation (optical, SAR, LiDAR etc)
  - spatial/spectral/temporal resolution
  - matching with applications
  - affordable
- Image Pre-processing: eliminate data registration errors
  - geometric correction
    - earth rotation
    - earth curvature
    - instability of the platform (altitude, velocity, pitch, roll and yaw)
    - topographic effects
  - radiometric correction
  - noise removal
  - georeferencing

Step 3: Classification / thematic information extraction

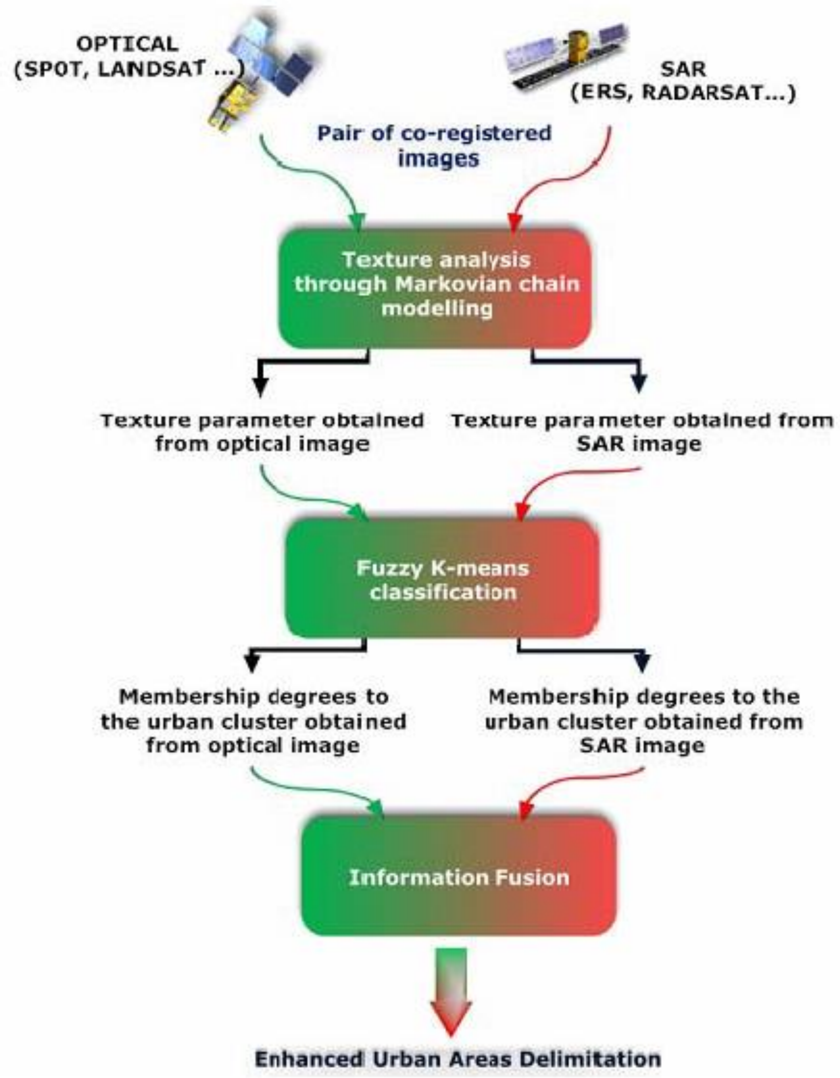
- Classification
  - Level selection (object-oriented, pixel, sub-pixel)
  - Classes determination (land cover/use types, hierarchical class system)
  - Feature selection/extraction and combination
  - Single classifier *vs* multiple classifiers
  - Post-processing (clump classes, sieve classes)
  - Accuracy assessment
- Thematic information extraction
  - Types (vegetation, impervious surface area, land surface temperature etc)
  - Vegetation/Impervious surface/water derived from classification map
  - NDVI (vegetation), NDBI (built-up area), NDWI (water), NDBaI (bare soil)
  - Vegetation-Impervious surface-Soil (VIS) model etc
  - Mono/split window etc (LST)

……

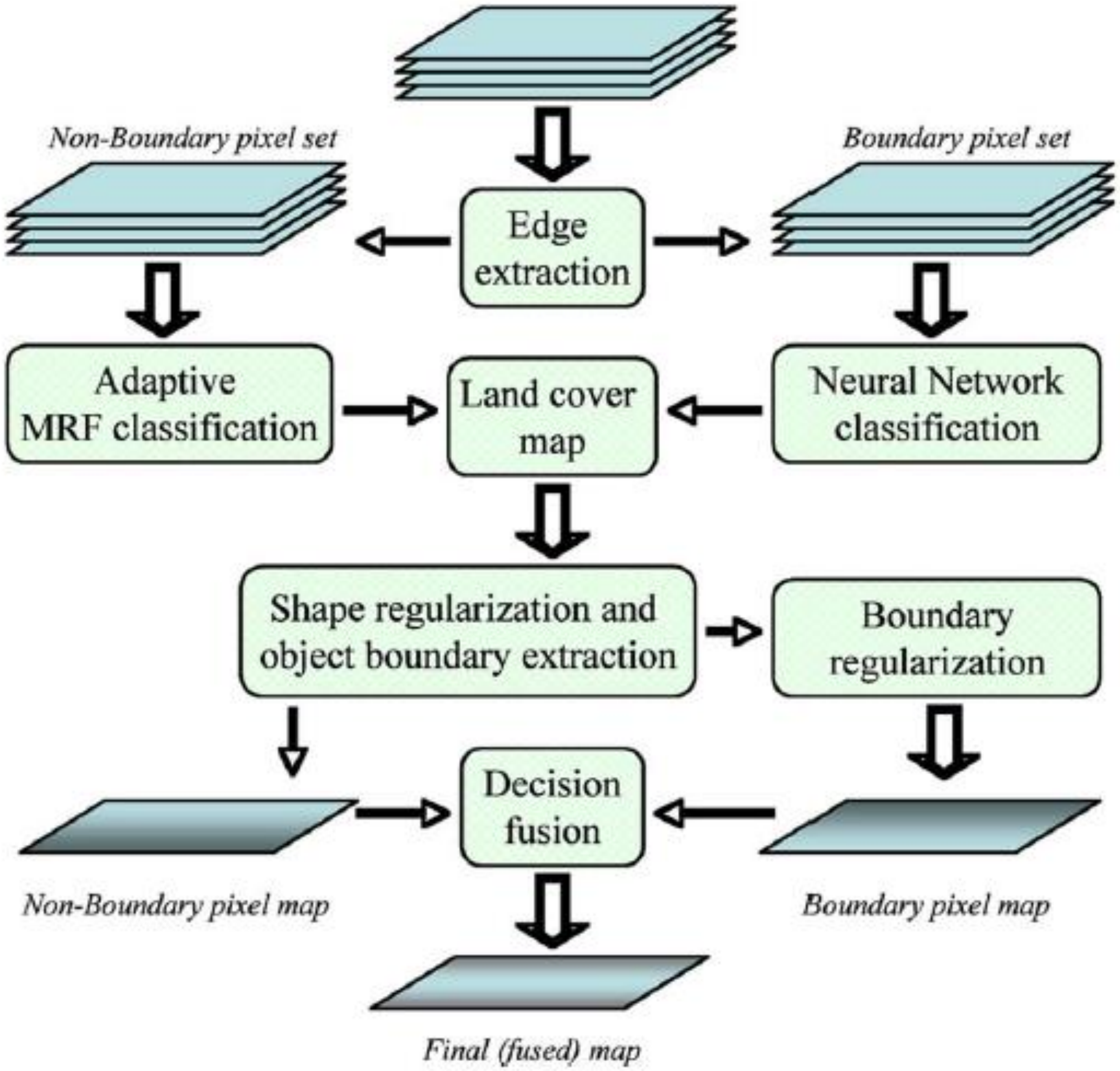
Step 4: Post-processing and map layout

- Post-processing
  - Clumping and sieving class
  - Combining Classes
  - Overlaying Classes
- Map layout consists of
  - Map pieces (title, legend, scale, explanatory text, directional indicator etc)
  - Focus: where do the readers typically focus on?
  - Balance: How can map elements be balanced to enhance understanding of the map?
  - Grid: How can a layout be proportioned into horizontal and vertical spaces to enhance understanding of the map?

Figure 1. Flow chart of the three-step procedure for rapid urban mapping based on the synergy between SAR and optical sensors.



Christina Corbane , Jean-François Faure, Nicolas Baghdadi , Nicolas Villeneuve and Michel Petit.
Rapid Urban Mapping Using SAR/Optical Imagery Synergy.
Sensors ***2008, 8, 7125-7143; DOI: 10.3390/s8117125***



Paolo Gamba, *Fabio Dell'Acqua,* Gianni Lisini, and Giovanna Trianni. Improved VHR Urban Area Mapping Exploiting Object Boundaries. IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 45, NO. 8, AUGUST 2007

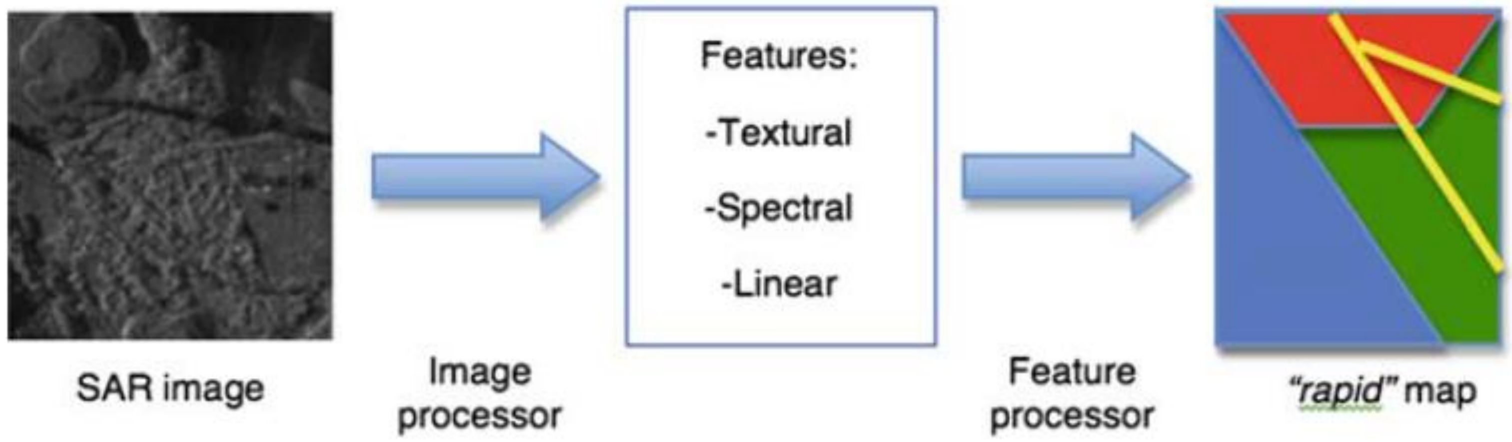


Fig. 2.4 The urban area extraction procedure

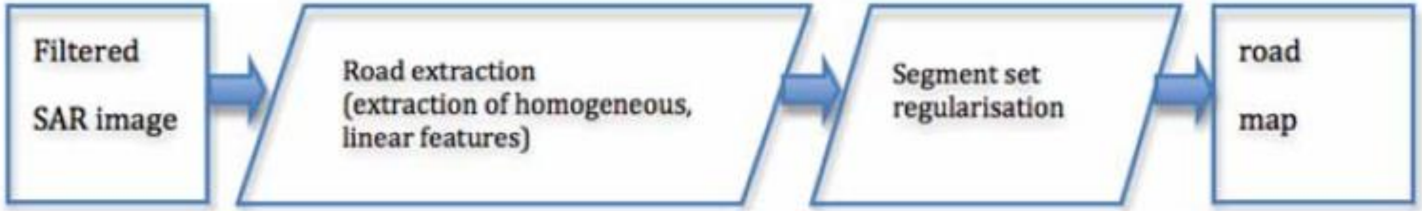


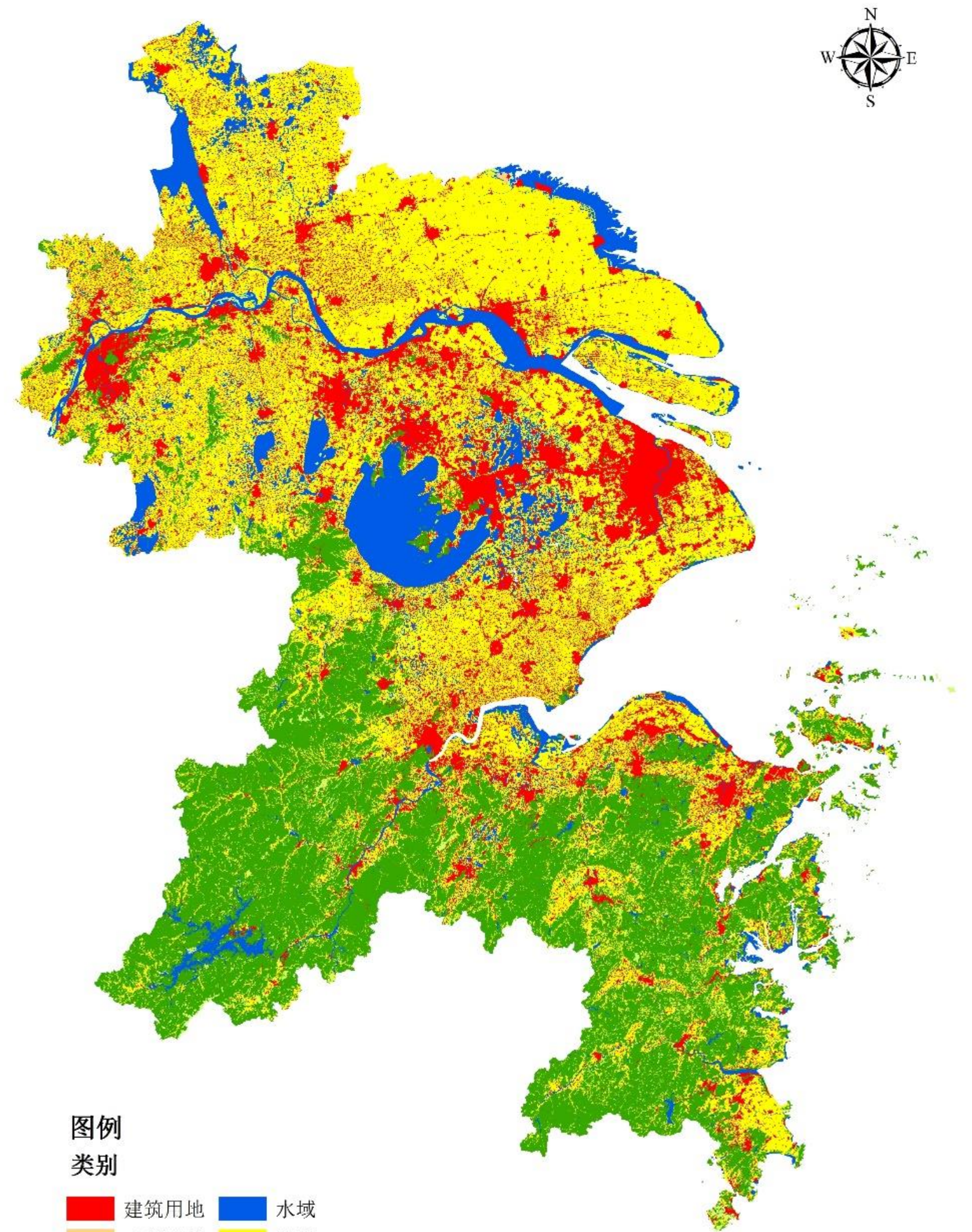
Fig. 2.6 The road extraction procedure

Fabio Dell'Acqua and Paolo Gamba. Rapid Mapping Using Airborne and Satellite SAR Images. In: Global mapping of human settlement: Experiments, datasets and prospects (Edited by Paolo Gamba and Martin Herold)

Content

- Urban administrative boundary (urban planning)
- Urban physical boundary (remote sensing, field investigation)

It is **incorrect** to view built-up land (impervious surface area) as urban land because some of the components of the urban mosaic (e.g. vegetation, water, buildings) are also found in non-urban areas.



Distinguish between urban and non-urban land cover

This distinction depends on both the aggregate and component physical properties of the urban mosiac as well as those of the surrounding non-urban land cover types.

The task is complicated by the fact that some of the components of the urban mosaic (e.g. vegetation, water) are also found in non-urban areas.

The task is further complicated by the fact that the spatial scales of the individual components in the urban mosaic (e.g. buildings, streets) is generally comparable to the spatial scale of the Ground Instantaneous Field Of View (GIFOV) of the sensors used to map urban extent (e.g. Landsat, SPOT).

The task is still further complicated by the inter-urban and intra-urban diversity of land covers and their physical properties.

http://www.ldeo.columbia.edu/~small/Urban/

Distinguish between urban and non-urban land cover

These three complications largely preclude the use of traditional thematic classification algorithms for urban mapping because these algorithms are generally based on assumptions of spectral homogeneity that are very rarely met in urban environments.

For this reason, it is important to focuses on robust physical characterization of urban reflectance properties and on comparative analyses of diverse urban environments.

Spectral Mixture Analysis is investigated as a means to accommodate the variable spatial scale and spectral heterogeneity of the urban mosaic.

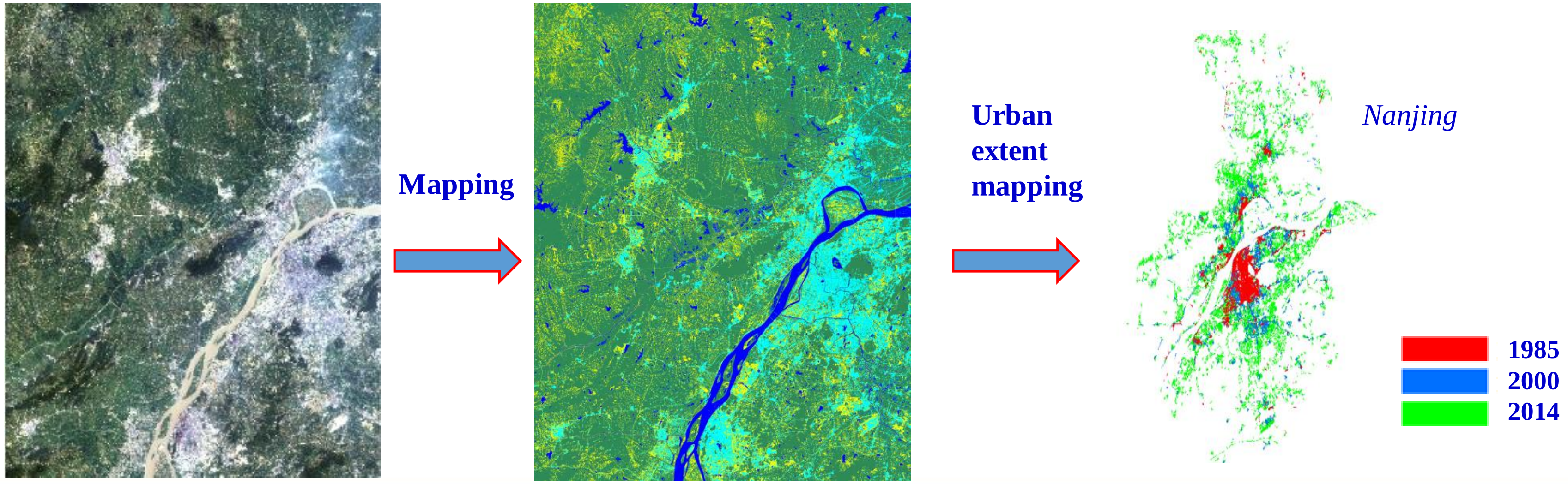
http://www.ldeo.columbia.edu/~small/Urban/

Solution 1: **Knowledge-based solution**

- Urban centre (seed point) (and boundary, if necessary)
- Image preprocessing
- Built-up land extraction (NDBI, or classification, or ISA)
- Urban areas recognition: using criteria based on either housing density, road density, spectral reflectance, or others (for example, A residential density of three houses per 2.5 acres was established as the minimum level of development interpreted as urban; The extent of urban areas was determined by the existence of a dense systematic street patterns and the relative concentration of buildings).
- Mapping

Solution 2: **remote sensing based solution**

- Image preprocessing
- Built-up land extraction (NDBI, or IBI, or classification, or ISA)
- Identification of urban area
- Mapping



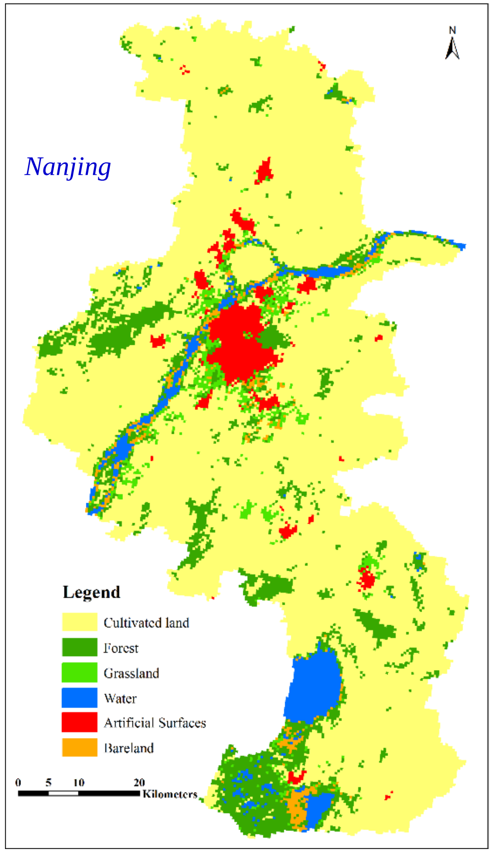
Solution 3: **multi-scale images based solution**

Assumption: rural areas, villages or other built-up land can’t be identified in low resolution images (e.g., MODIS)

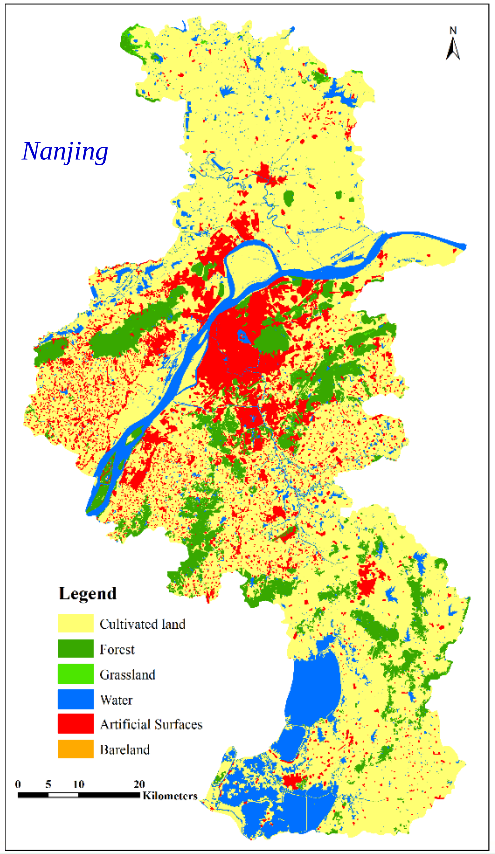
- Image preprocessing
- Low resolution image extraction to reduce target area
- Masking of medium-resolution or high resolution image
- Built-up land extraction (NDBI, or classification, or ISA)
- Mapping

Solution 3: **multi-scale images based solution**

- Nanjing, MODIS, Landsat TM



MODIS (2010)



Landsat TM (2010)

Solution 4: **Object-based image classification**

Key point: segmentation scale, features for classification

- Image preprocessing
- Image segmentation (scale selection, or multi-scale)
- Feature selection (spectral, spatial)
- Classification
- Mapping

Extraction of Built-up area by **NDBI** (Normalized Difference Build-up Index):

$$NDBI = \frac{(MIR - NIR)}{(MIR + NIR)}$$

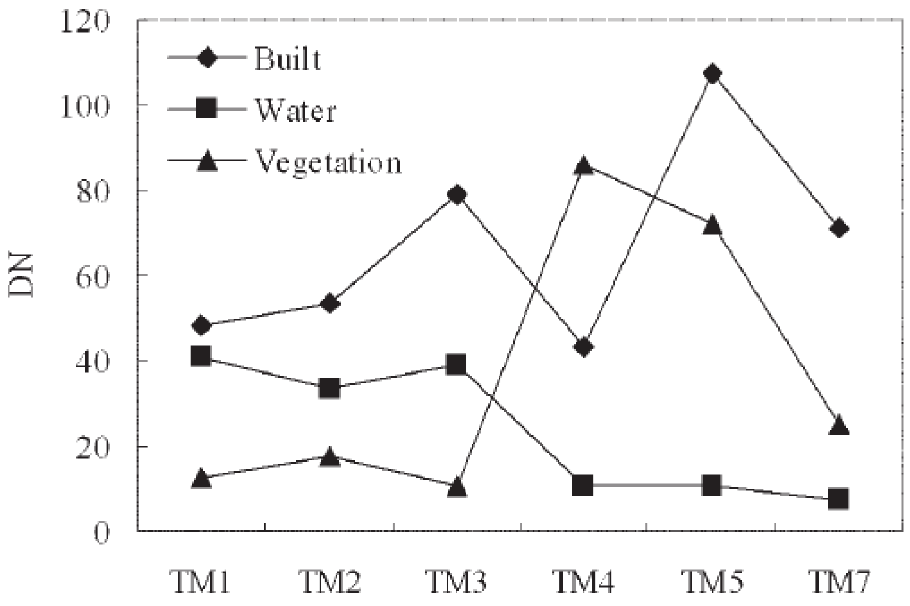
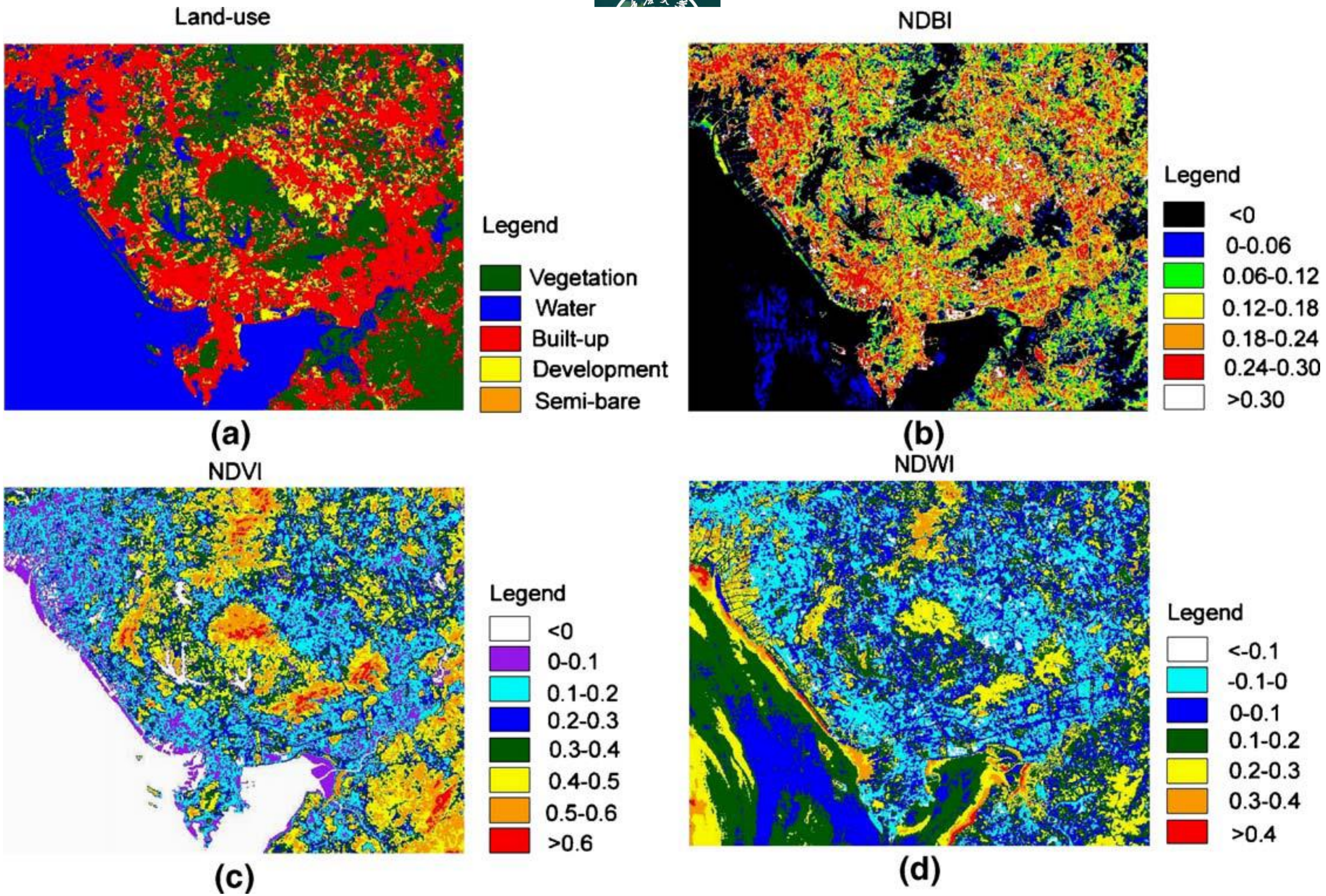


Figure 3. Spectral signatures represented by the mean of three urban land-use classes taking the Quanzhou image as an example.

For Landsat TM/ETM+ images

$$NDBI = (d(band5) - d(band4))/(d(band5) + d(band5))$$


Land-use
Legend
Vegetation
Water
Built-up
Development
Semi-bare
(a)
NDBI
Legend
<0
0-0.06
0.06-0.12
0.12-0.18
0.18-0.24
0.24-0.30
>0.30
(b)
NDVI
Legend
<0
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
>0.6
(c)
NDWI
Legend
<-0.1
-0.1-0
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
>0.4
(d)

Extraction of Built-up area by **IBI** (Index-Based Built-up index, Xu Hanqiu, IJRS, 2008):

$$\mathrm{IBI} = \frac{[\mathrm{NDBI} - (\mathrm{SAVI} + \mathrm{MNDWI})/2]}{[\mathrm{NDBI} + (\mathrm{SAVI} + \mathrm{MNDWI})/2]}.$$

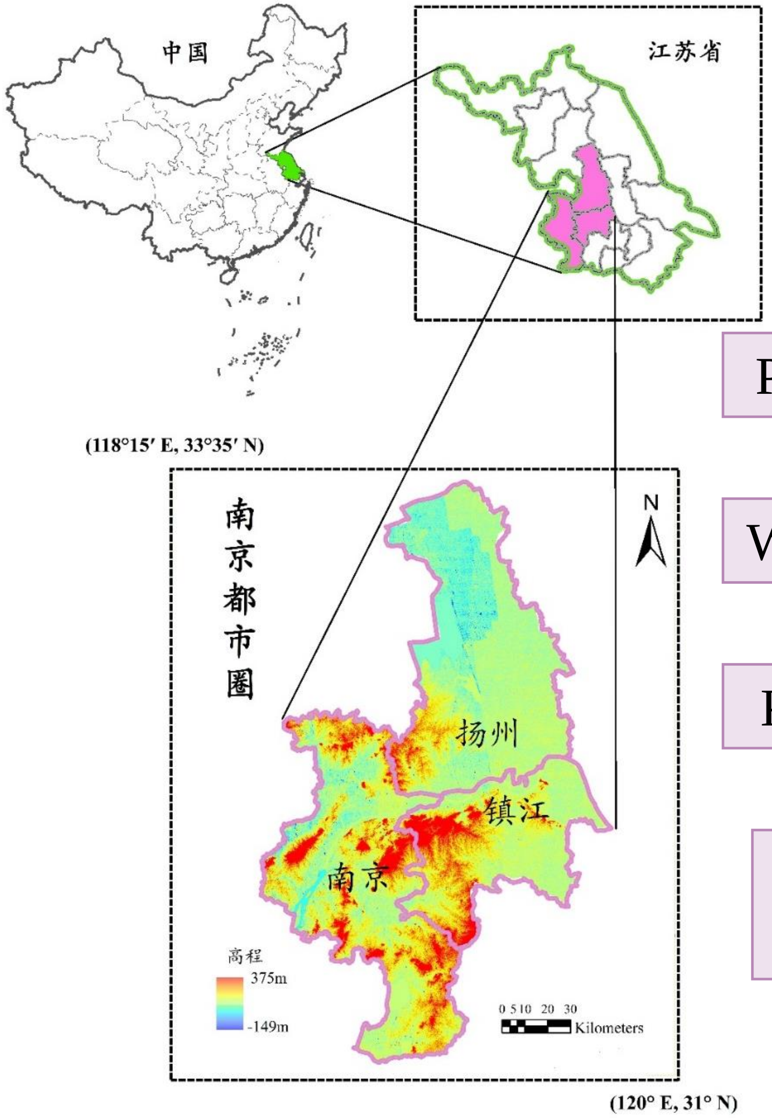
$$\mathrm{NDBI} = \frac{(\mathrm{MIR} - \mathrm{NIR})}{(\mathrm{MIR} + \mathrm{NIR})},$$

$$\mathrm{SAVI} = \frac{(\mathrm{NIR} - \mathrm{Red})(1 + l)}{(\mathrm{NIR} + \mathrm{Red} + l)}$$

$$\mathrm{MNDWI} = \frac{(\mathrm{Green} - \mathrm{MIR})}{(\mathrm{Green} + \mathrm{MIR})},$$

$$\mathrm{IBI} = \frac{2\mathrm{MIR}/(\mathrm{MIR} + \mathrm{NIR}) - [\mathrm{NIR}/(\mathrm{NIR} + \mathrm{Red}) + \mathrm{Green}/(\mathrm{Green} + \mathrm{MIR})]}{2\mathrm{MIR}/(\mathrm{MIR} + \mathrm{NIR}) + [\mathrm{NIR}/(\mathrm{NIR} + \mathrm{Red}) + \mathrm{Green}/(\mathrm{Green} + \mathrm{MIR})]}$$

- BCI (Biophysical Composition Index, Deng *et al.*2012)



Preprocessing → Water masking → KT transform → BCI calculation

Water masking → MNDWI, segmentation, water masking

KT transform → TC_i components

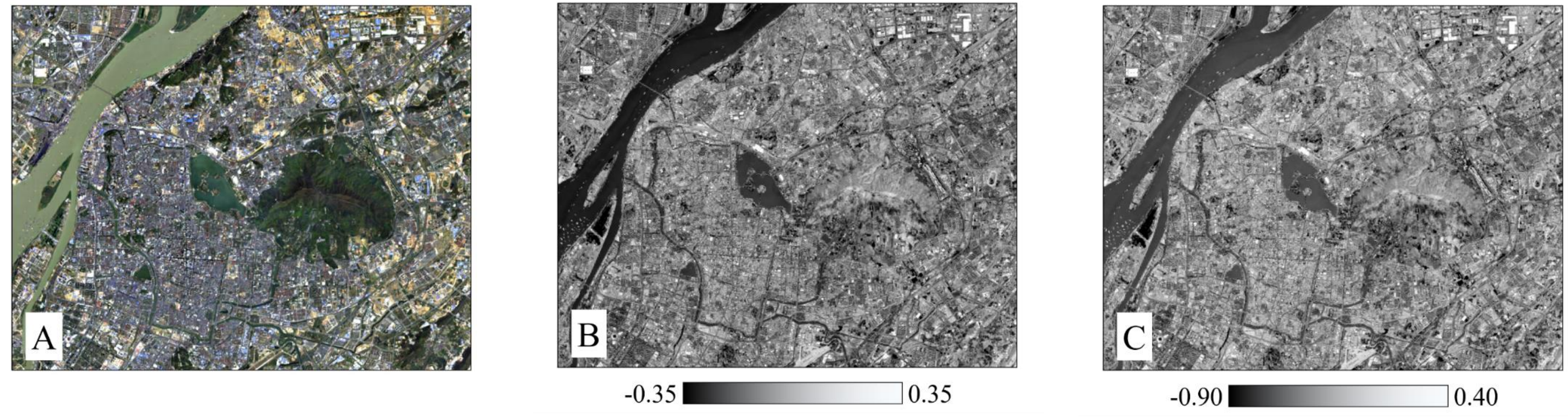
$$H = \frac{TC1 - TC1_{min}}{TC1_{max} - TC1_{min}}$$

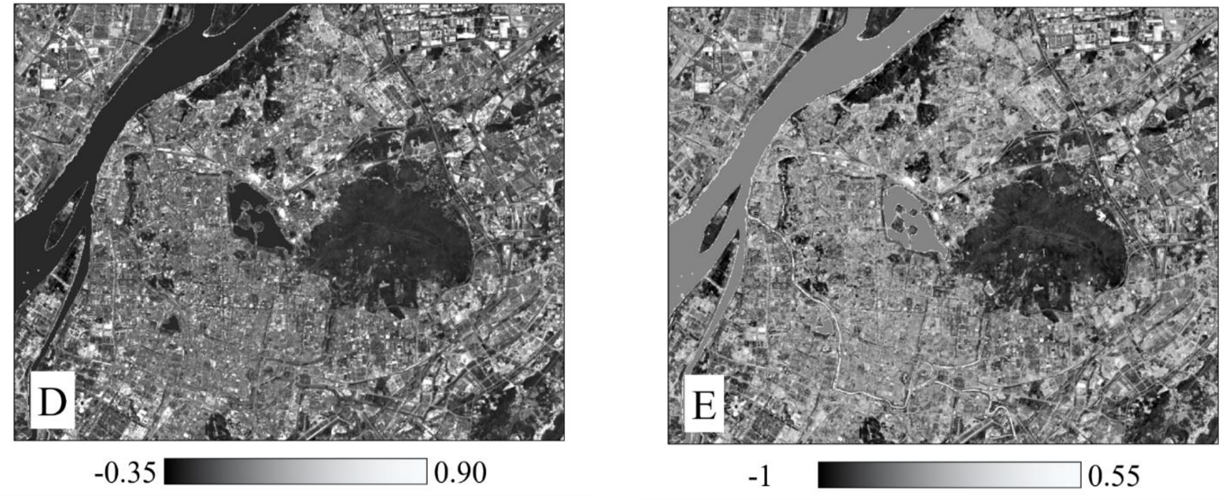
$$V = \frac{TC2 - TC2_{min}}{TC2_{max} - TC2_{min}}$$

$$L = \frac{TC3 - TC3_{min}}{TC3_{max} - TC3_{min}}$$

BCI calculation →

$$BCI = \frac{\frac{H+L}{2} - V}{\frac{H+L}{2} + V}$$





A. True color image

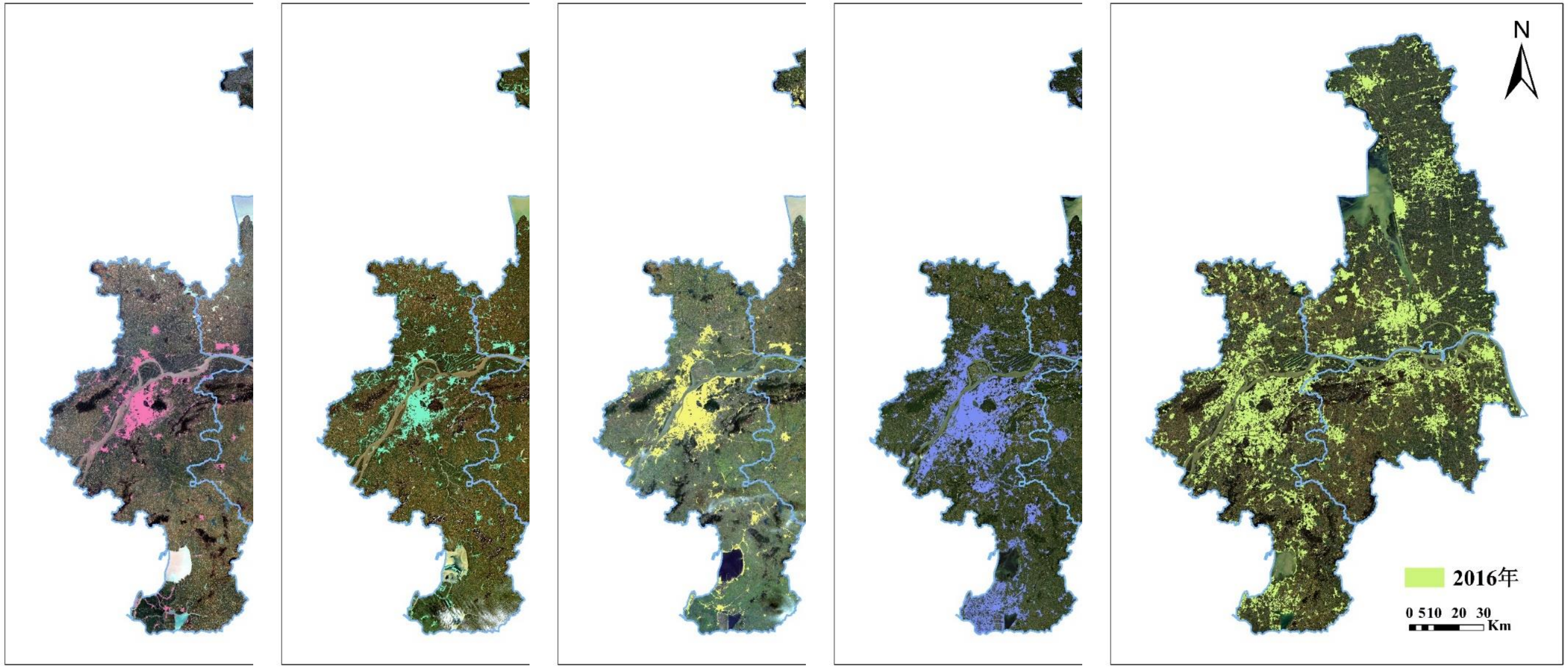
B. NDBI

C. IBI

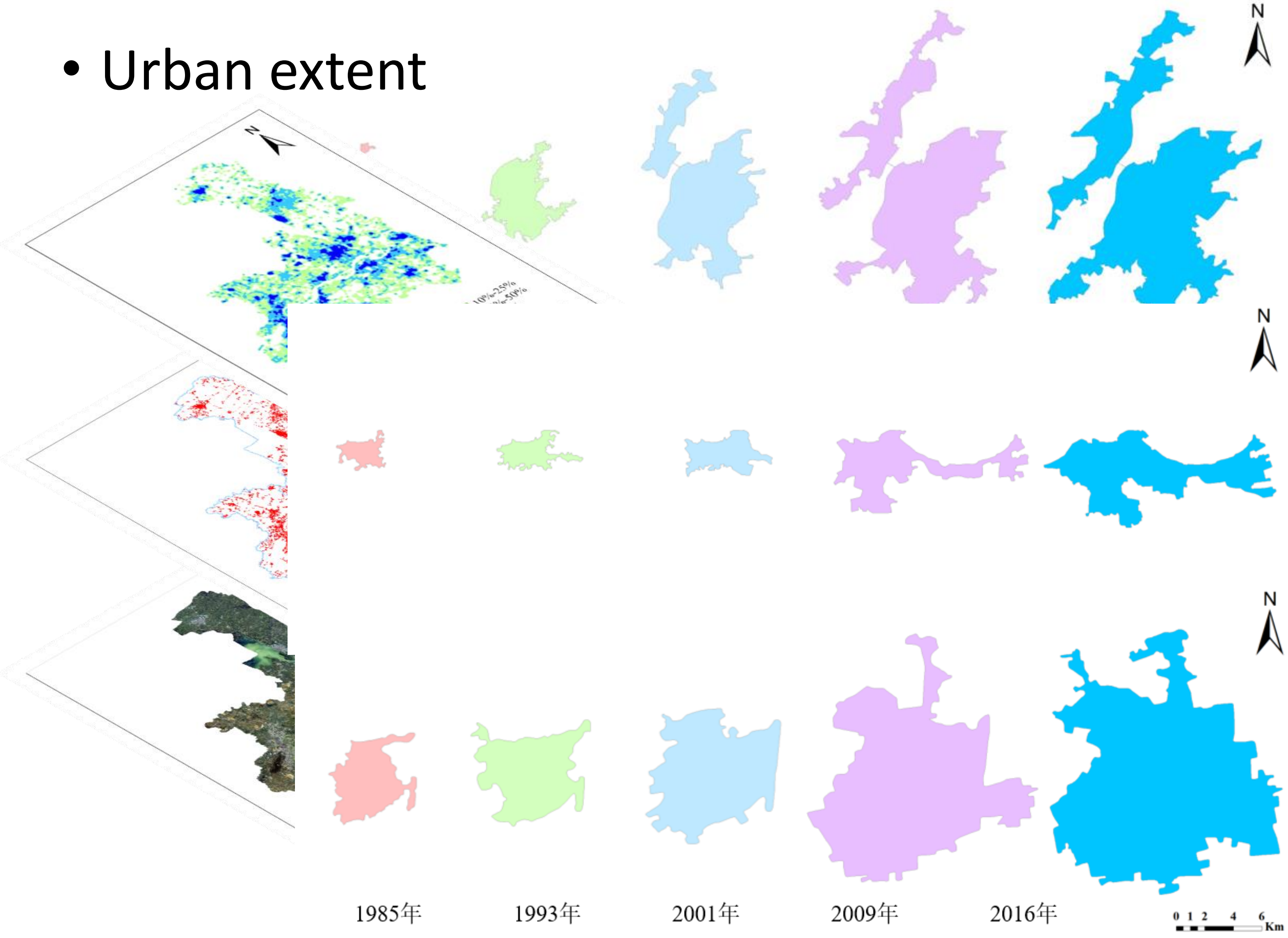
D. BCI

E. CBI

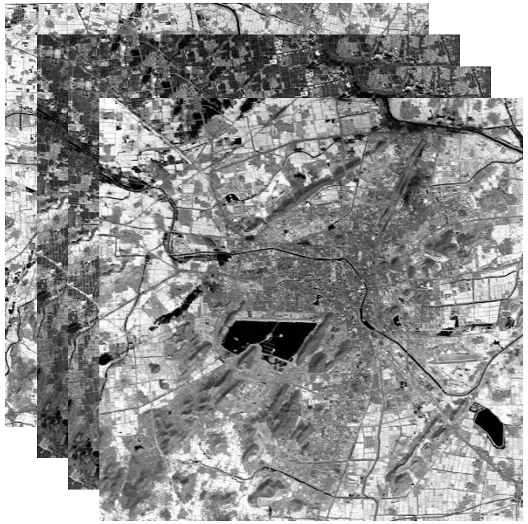
BCI → threshold → MM filtering → vectorization



- Urban extent



Content



Allocation of a class to each pixel

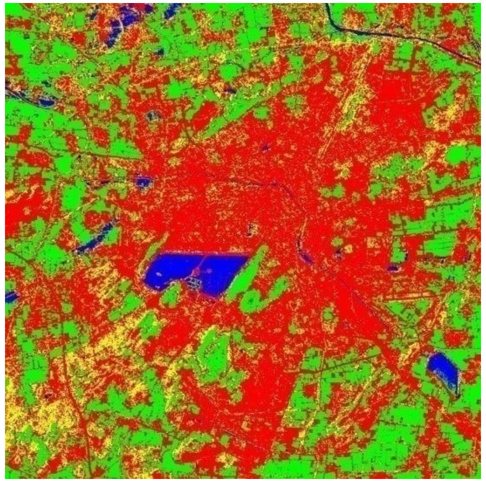


Image spatial space

Classification map

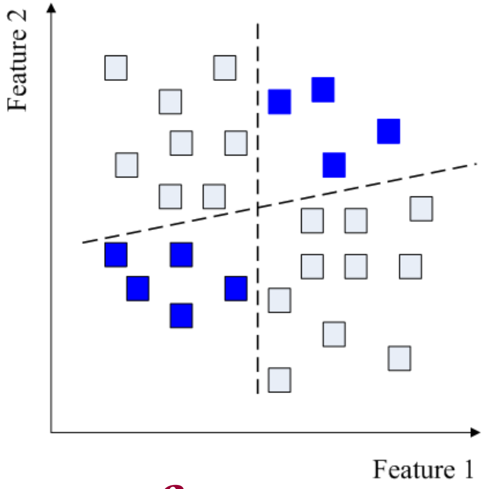


Image feature space

- Each pixel is represented by a vector, consisting of a set of measurements (e.g. spectral values, spatial information etc)
- Definition of decision boundaries to separate classes

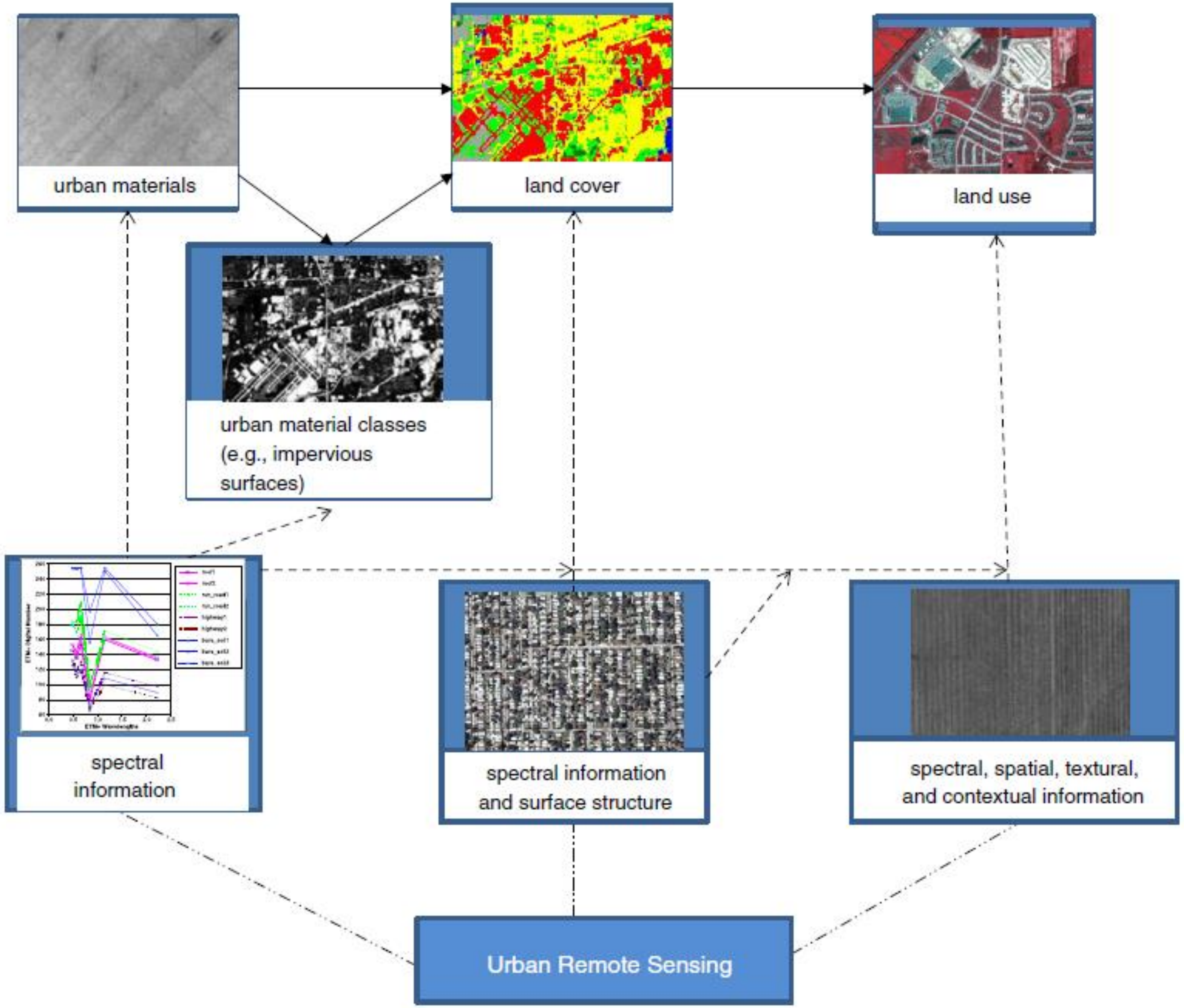
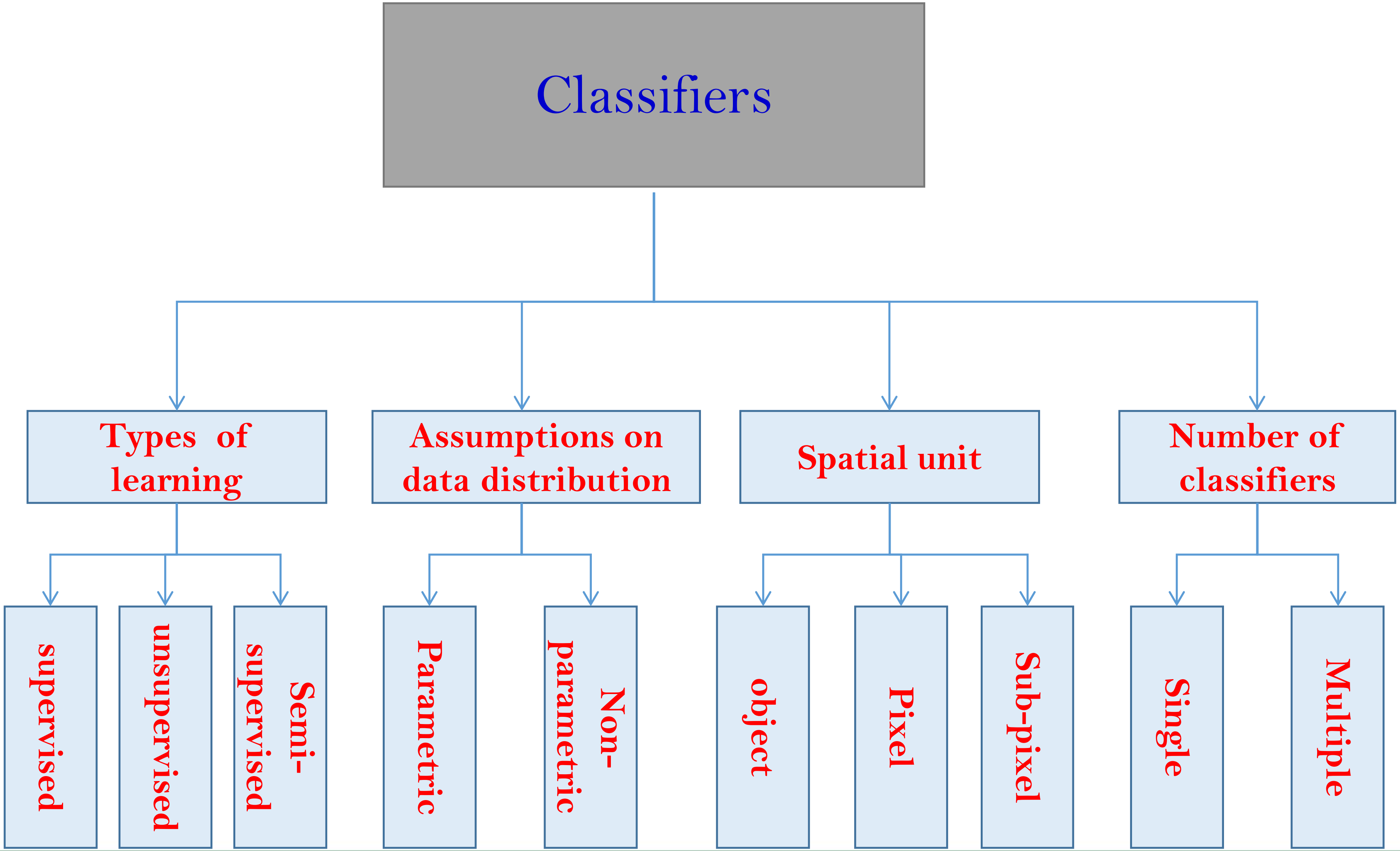
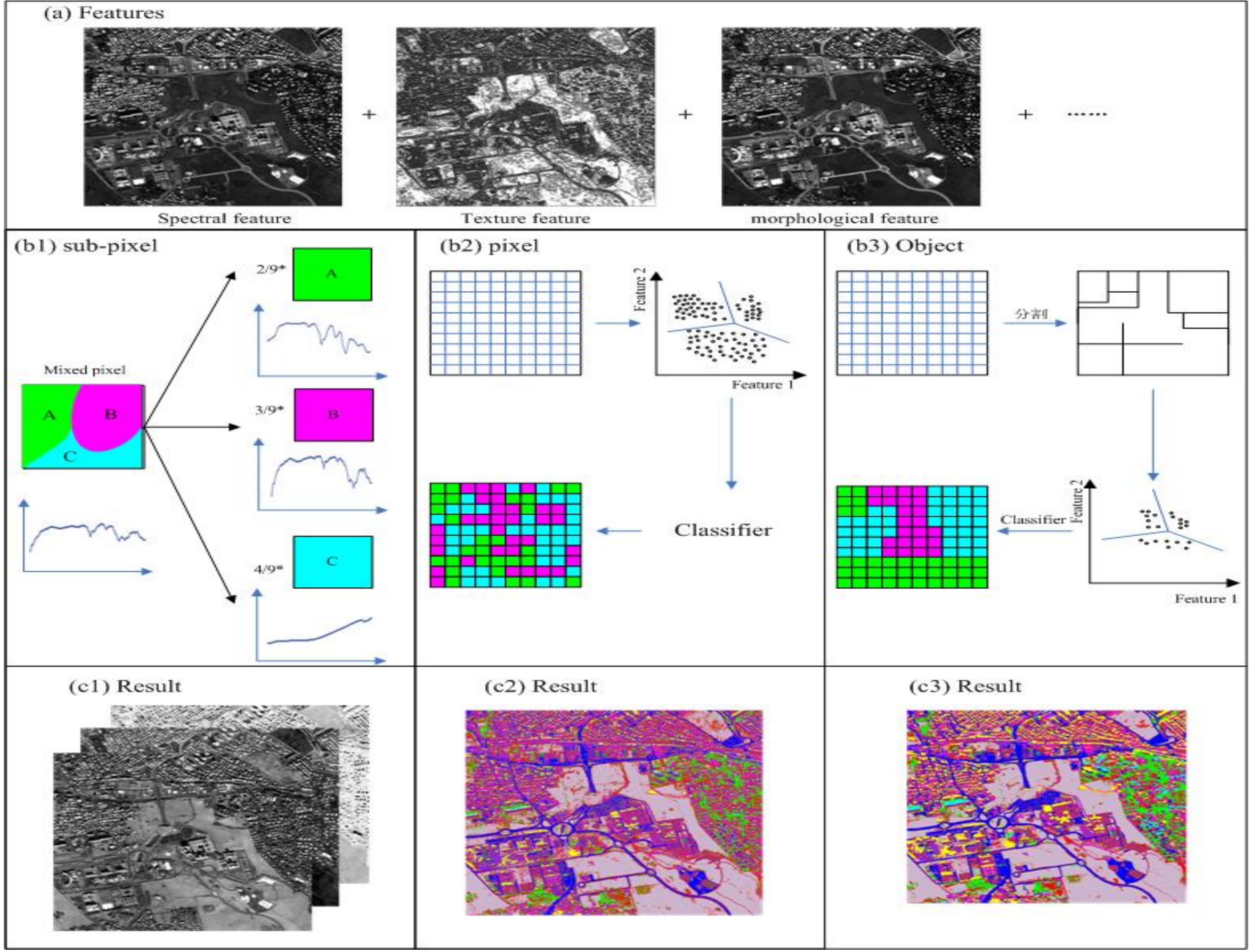


Illustration of the relationship among remote sensing of urban materials, land cover, and land use (after Weng & Lu, 2009).

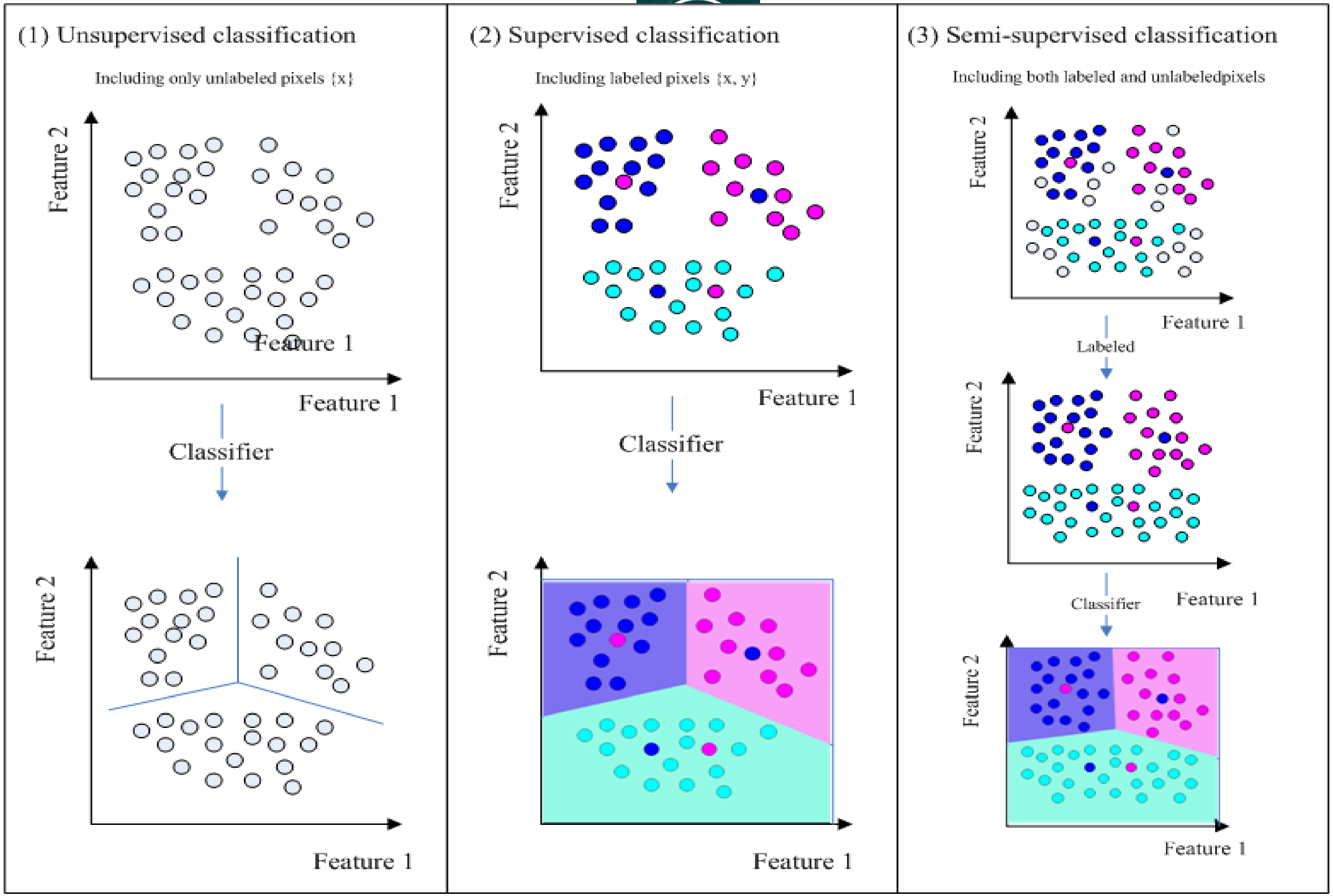
Major steps of image classification

- determination of a suitable classification system
- selection of training samples
- Image preprocessing
- feature extraction
- selection of suitable classification approaches
- post-classification processing
- accuracy assessment

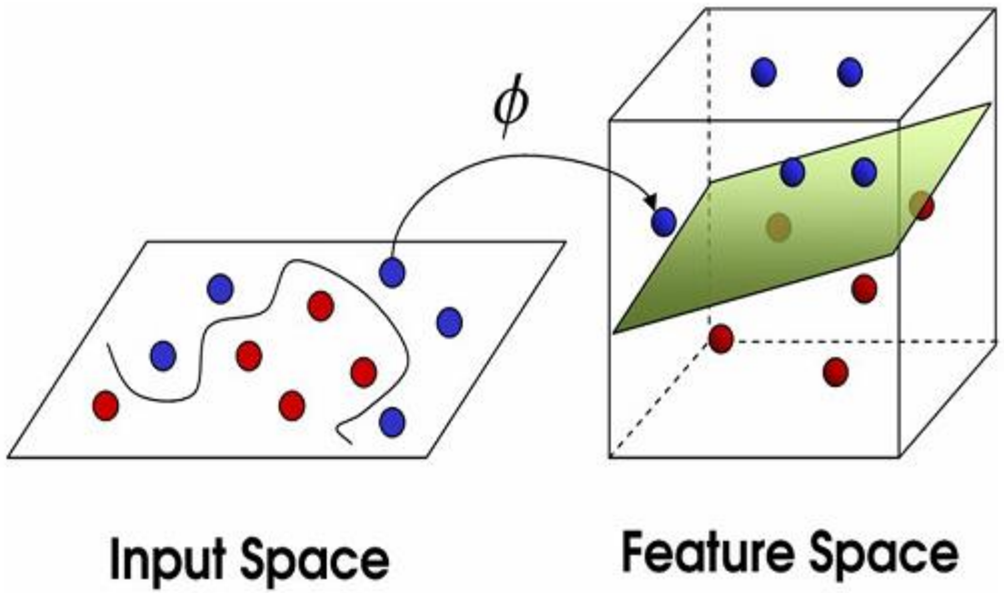

Classifiers
Types of learning
Assumptions on data distribution
Spatial unit
Number of classifiers
supervised
unsupervised
Semi-supervised
Parametric
Non-parametric
object
Pixel
Sub-pixel
Single
Multiple

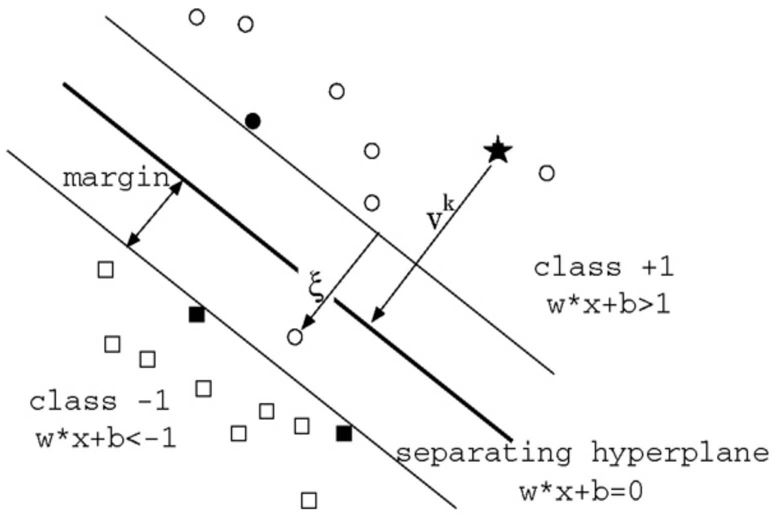


(a) Features
Spectral feature
Texture feature
morphological feature
(b1) sub-pixel
Mixed pixel
2/9*
3/9*
4/9*
(b2) pixel
Feature 2
Feature 1
Classifier
(b3) Object
分割
Classifier
Feature 2
Feature 1
(c1) Result
(c2) Result
(c3) Result


(1) Unsupervised classification
Including only unlabeled pixels {x}
Feature 2
Feature 1
Classifier
Feature 2
Feature 1
(2) Supervised classification
Including labeled pixels {x, y}
Feature 2
Feature 1
Classifier
Feature 2
Feature 1
(3) Semi-supervised classification
Including both labeled and unlabeledpixels
Feature 2
Feature 1
Labeled
Feature 2
Feature 1
Classifier
Feature 2
Feature 1

Support Vector Machines (SVM)



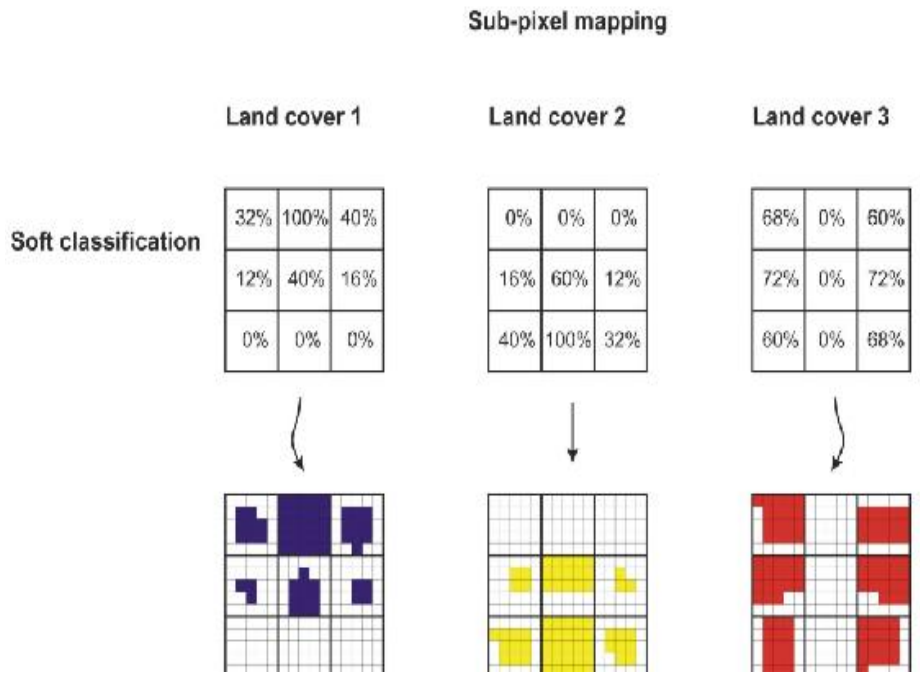


- ➢ SVMs can efficiently perform non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces

- ➢ SVM training algorithm aims to find a hyperplane that separates the dataset into a discrete predefined number of classes in a fashion consistent with the training examples.

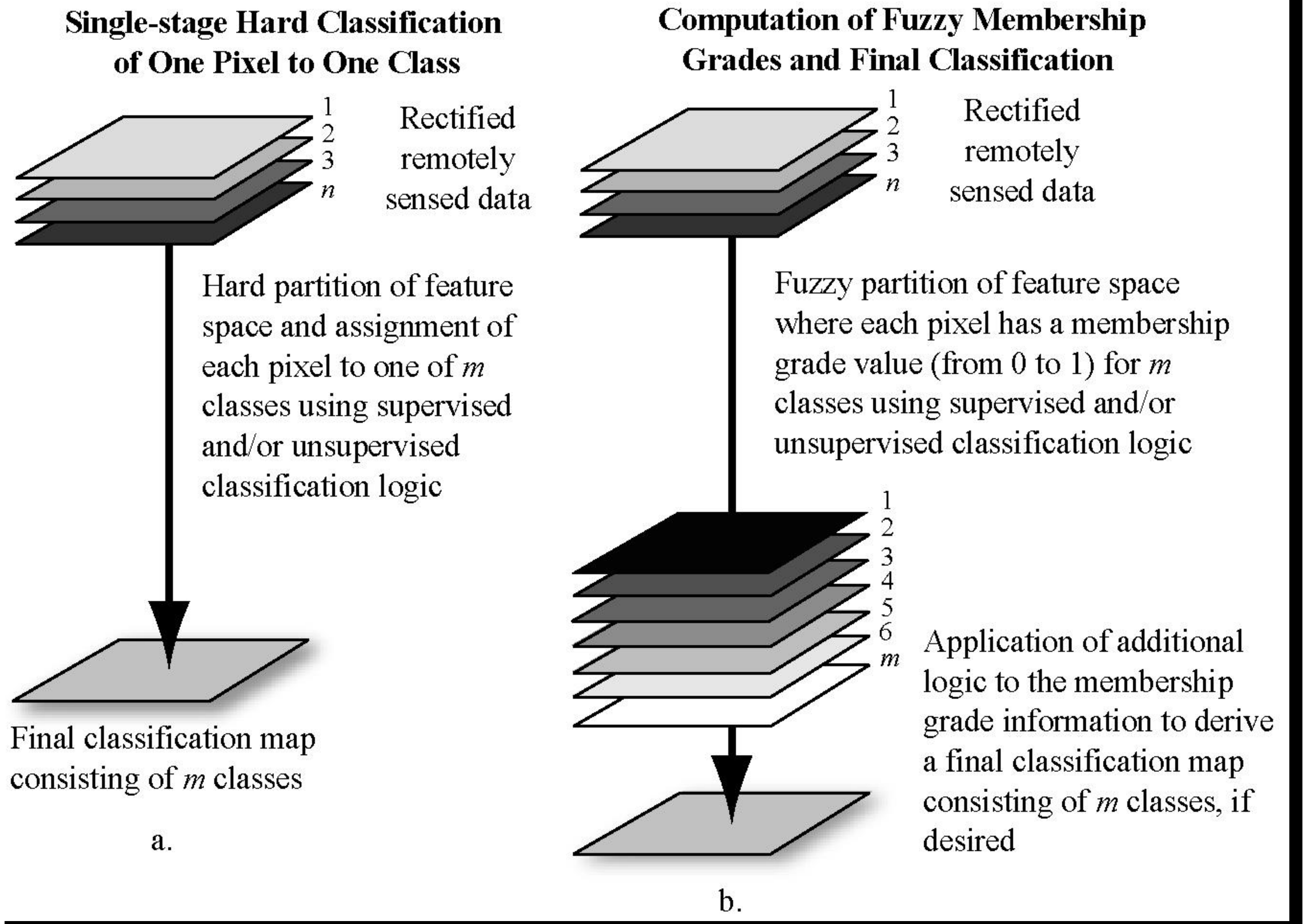
Sub-pixel classification or soft classification

Sub-pixel classification has been proposed as an alternative to pixel classification because of its ability to deal with mixed pixels.



- Mixed pixels in an image varies mainly with
  - Landscape fragmentation
  - Sensor's spatial resolution
- Mixed pixel exists
  - Presence of small, sub-pixel targets
  - Presence of boundaries of discrete land cover classes
  - Gradual transition between land cover classes
  - Contribution of areas outside the area represented by a pixel

Classification of Remotely Sensed Data Based on Hard versus Fuzzy Logic

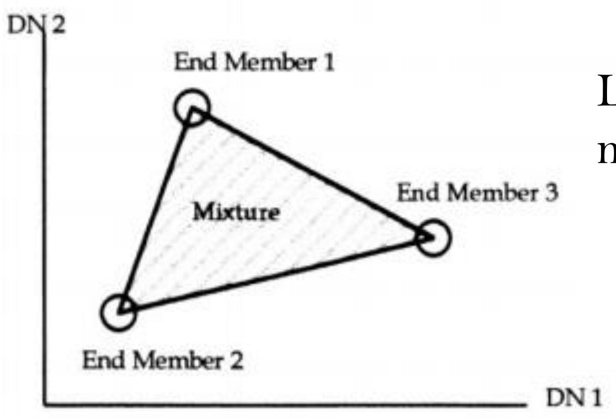


Pixel classification	Training stage	**Sub-pixel classification**
Dominant classes	Training	Individual class proportions
Pixel is allocated to a single class	Allocation	Membership grade to all Classes
Dominant class	Testing	Individual class proportions

Common sub-pixel classifiers: fuzzy c-means, possibility c-means, fuzzy rule based classifications, fuzzy set theory, ANN

Spectral unmixing:

➢ Spectral unmixing, Spectral mixture modeling, Spectral mixture analysis
➢ an alternative to soft classification for sub-pixel analysis
➢ based on the assumption that spectral signature of satellite images results essentially from a mixture of a small number of pure components (endmembers) with characteristic spectra.



Linear spectral mixture model (LSMM) is the most common models used in satellite image analysis:

$$L_{i\lambda} = \sum_{k=1}^{n} f_{ki} R_{k\lambda} + \epsilon_{i\lambda} \quad \sum_{k=1}^{n} f_{ki} = 1 \text{ and } f_{ki} \geq 0$$

Applications: urban impervious surface extraction etc.

Other classification approaches:

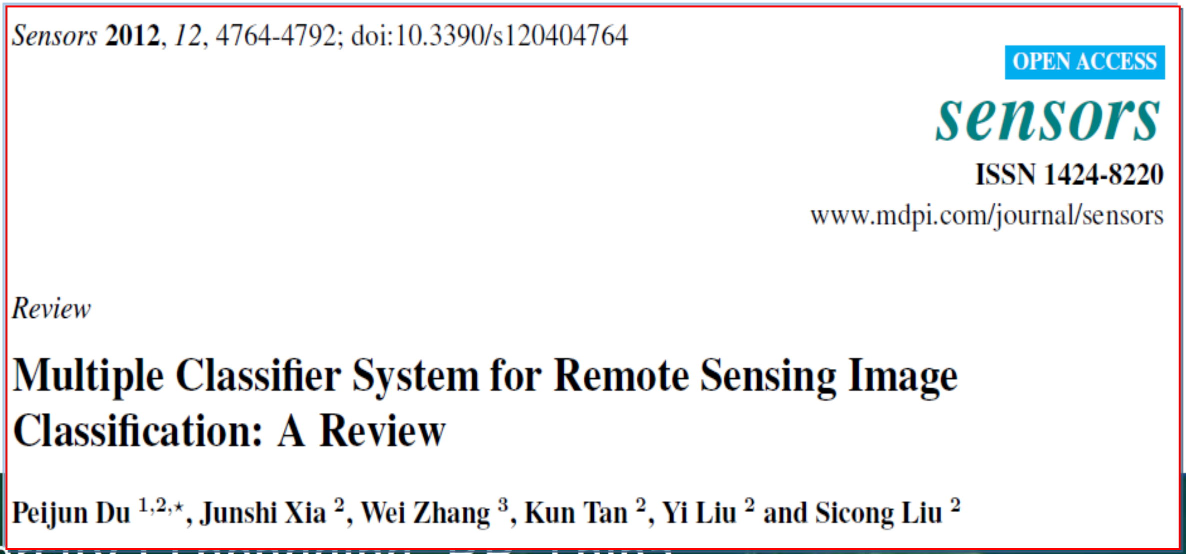
- Object-oriented classification: eCognition, ENVI FX
- Spectral-spatial classification
- Super-resolution mapping

Multiple classifier system (MCS) or classifier ensemble:

- Different classifiers originate different classes for the same spatial unit

- There is not a single classifier that performs best for all classes. In fact it appears that many of the methods are complementary

- Combination of decision rules can bring advantages over the single use of a classifier



Sensors **2012**, *12*, 4764-4792; doi:10.3390/s120404764

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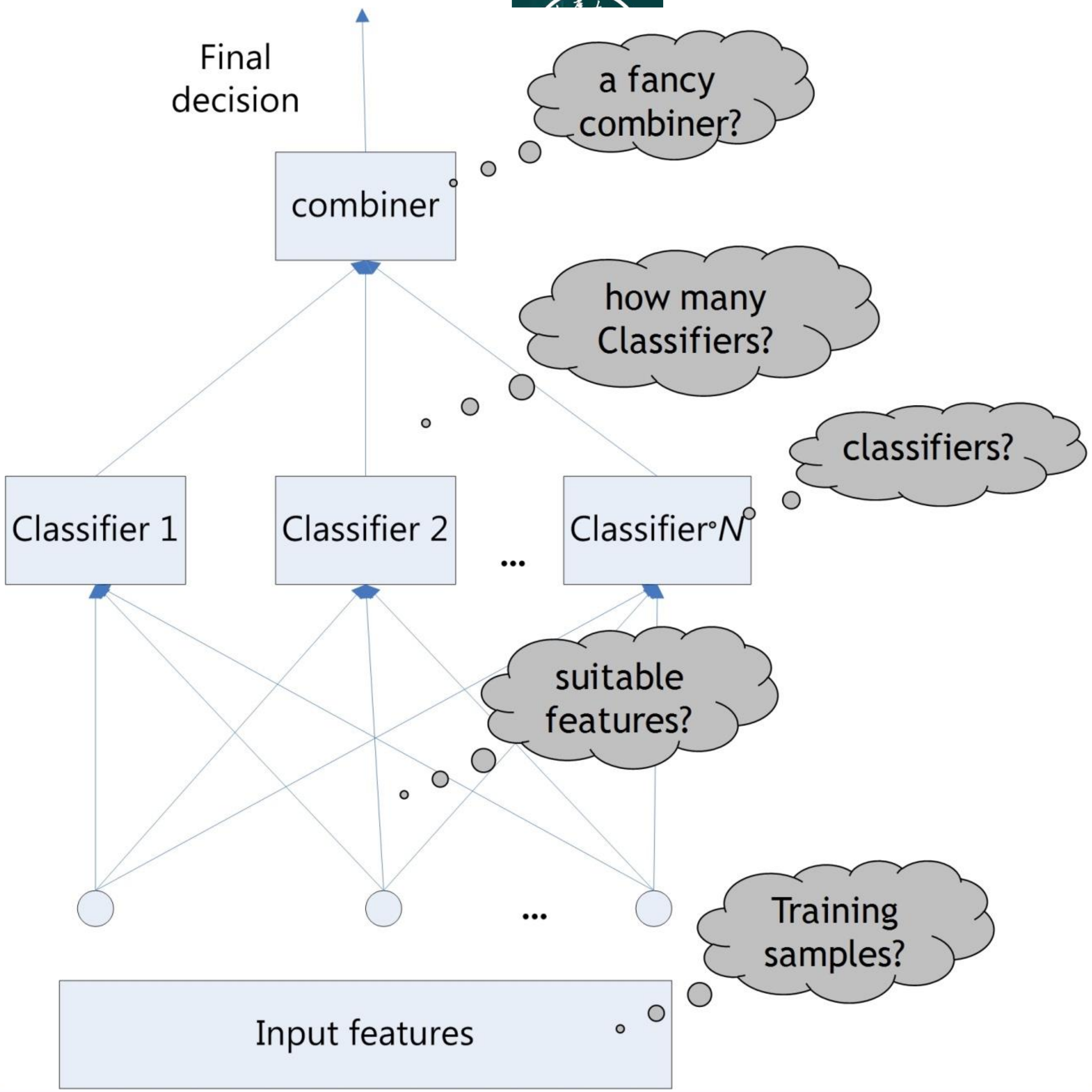
Review

Multiple Classifier System for Remote Sensing Image Classification: A Review

Peijun Du [1,2,*], Junshi Xia [2], Wei Zhang [3], Kun Tan [2], Yi Liu [2] and Sicong Liu [2]

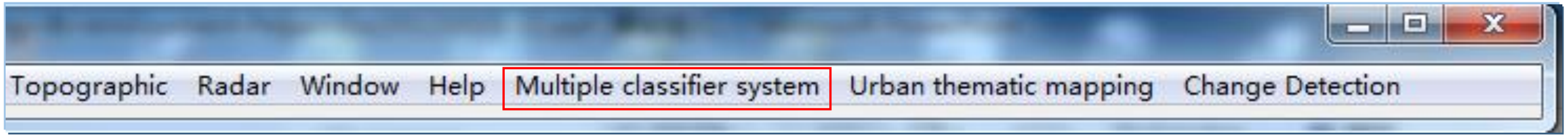

Final
decision
combiner
a fancy
combiner?
how many
Classifiers?
classifiers?
Classifier 1
Classifier 2
...
Classifier N
suitable
features?
...
Training
samples?
Input features

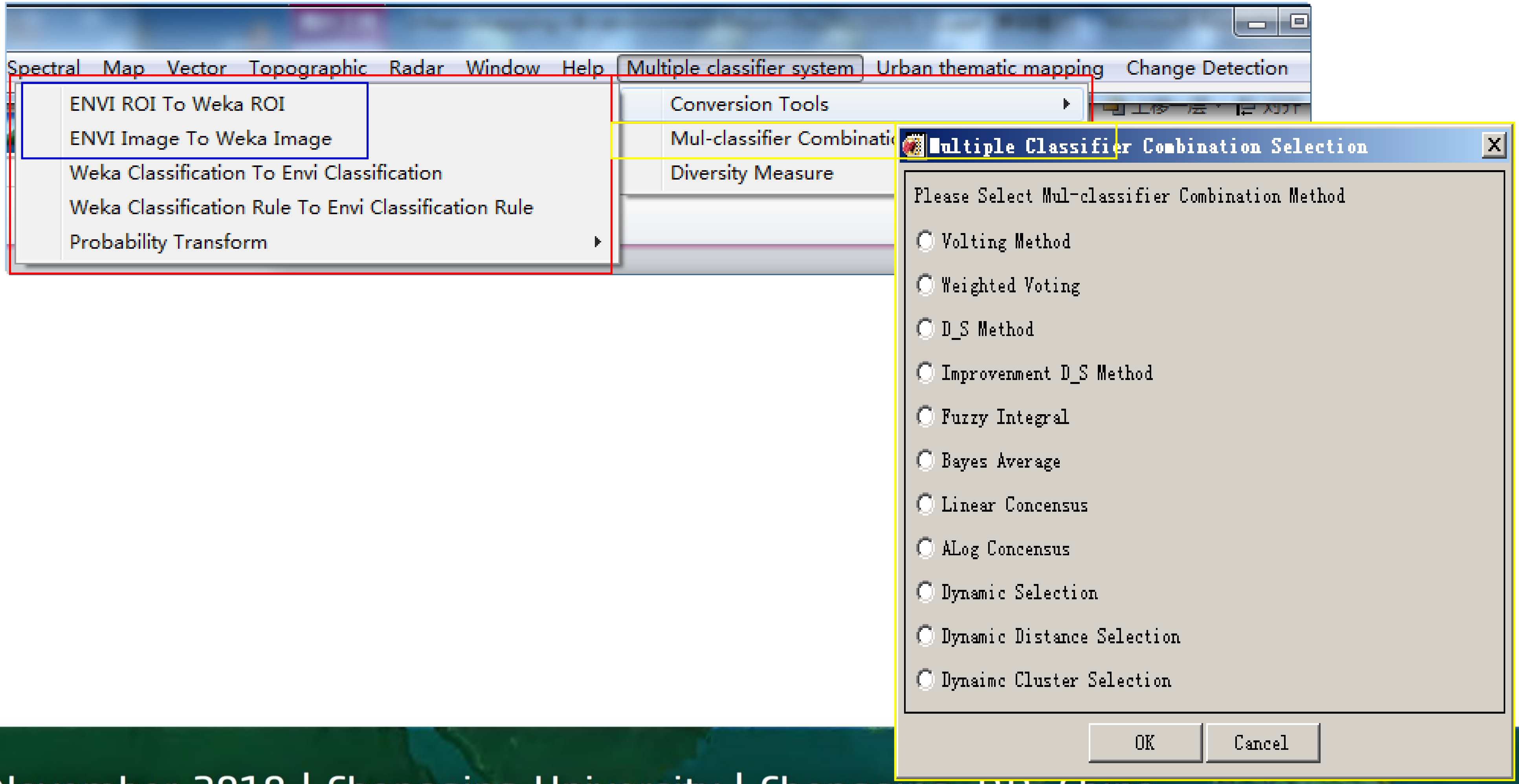
Ensemble in different processing sites

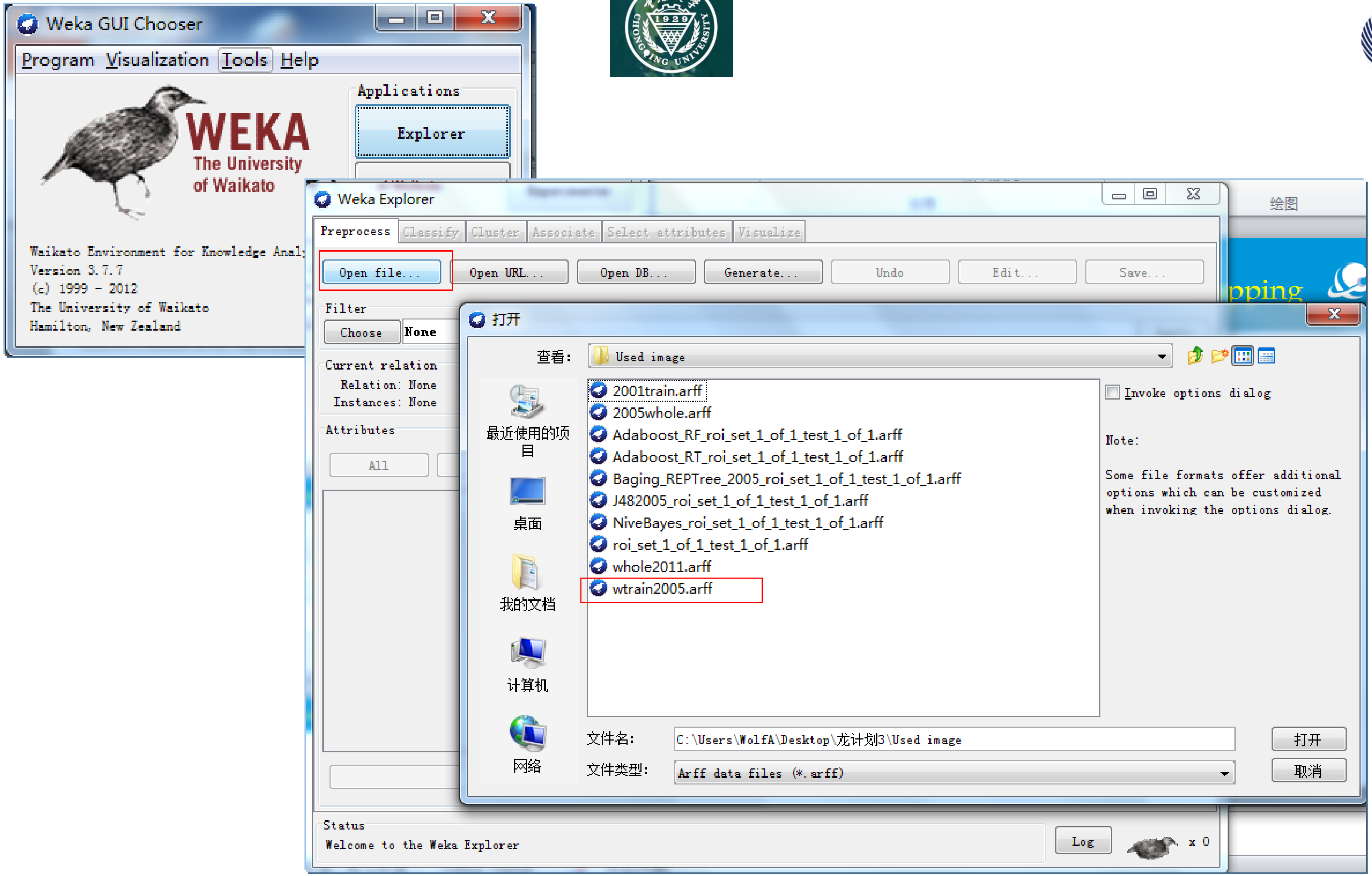
- Data sources
- Training: Bagging , AdaBoost, MultiBoost
- Feature sets: Random Subspace, Random Forest, Dynamic subspace, Rotation Forest
- Results: majority vote etc

Name	hard labels	soft labels	test sample
Majority vote	Y	N	N
Weighted vote	Y	N	Y
Bayes compution	N	Y	N
Dempster-shafer evidence theory	N	Y	N
Fuzzy integral	Y	N	Y
Consensus theory	Y	Y	Y
Dynamic classifier selection	Y	N	Y

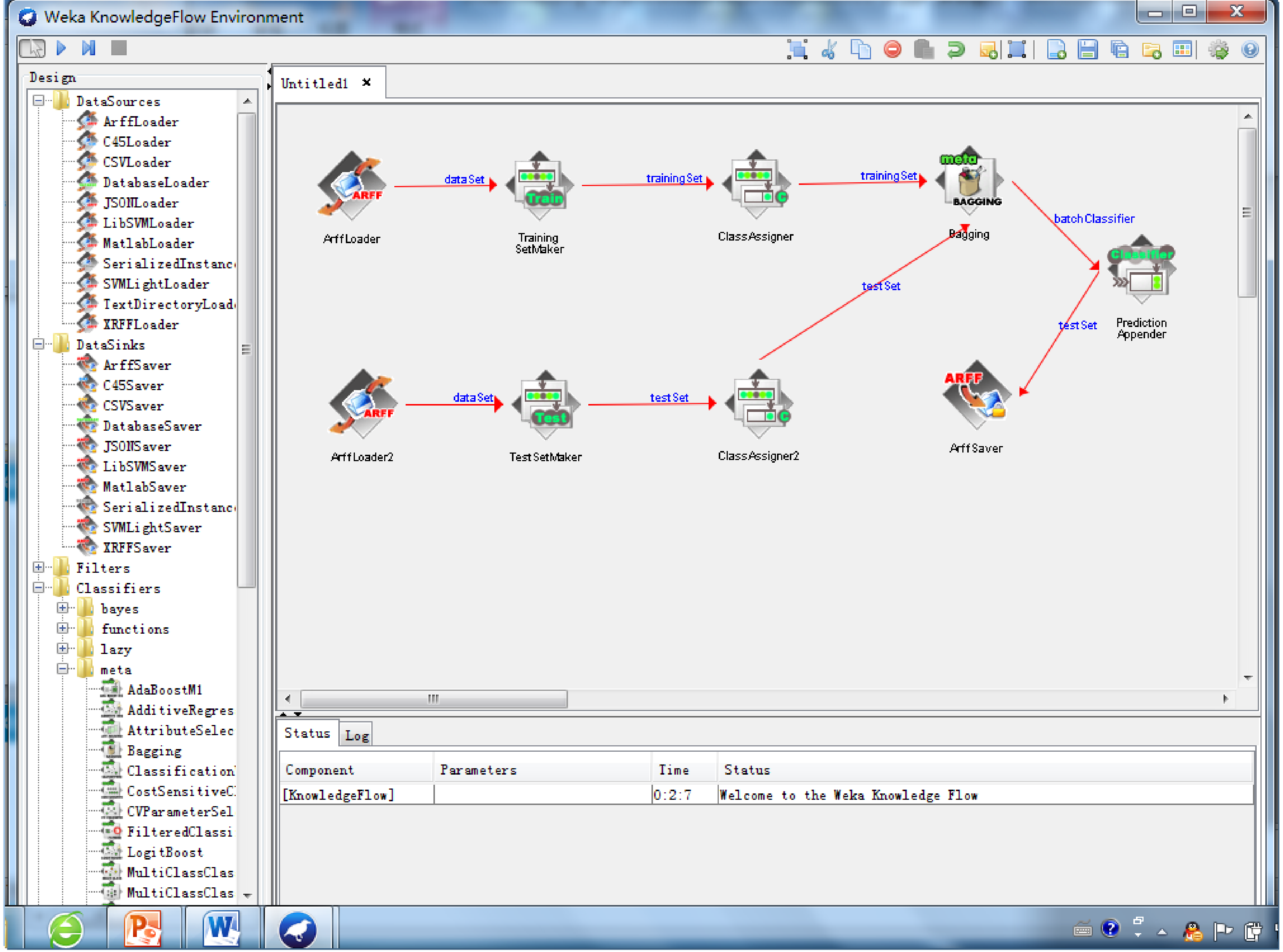
* Note: 'Y' and 'N' mean need the hard labels, soft labels or test sample whether or not. Dynamic classifier selection method needs the original image to calculate the distance.

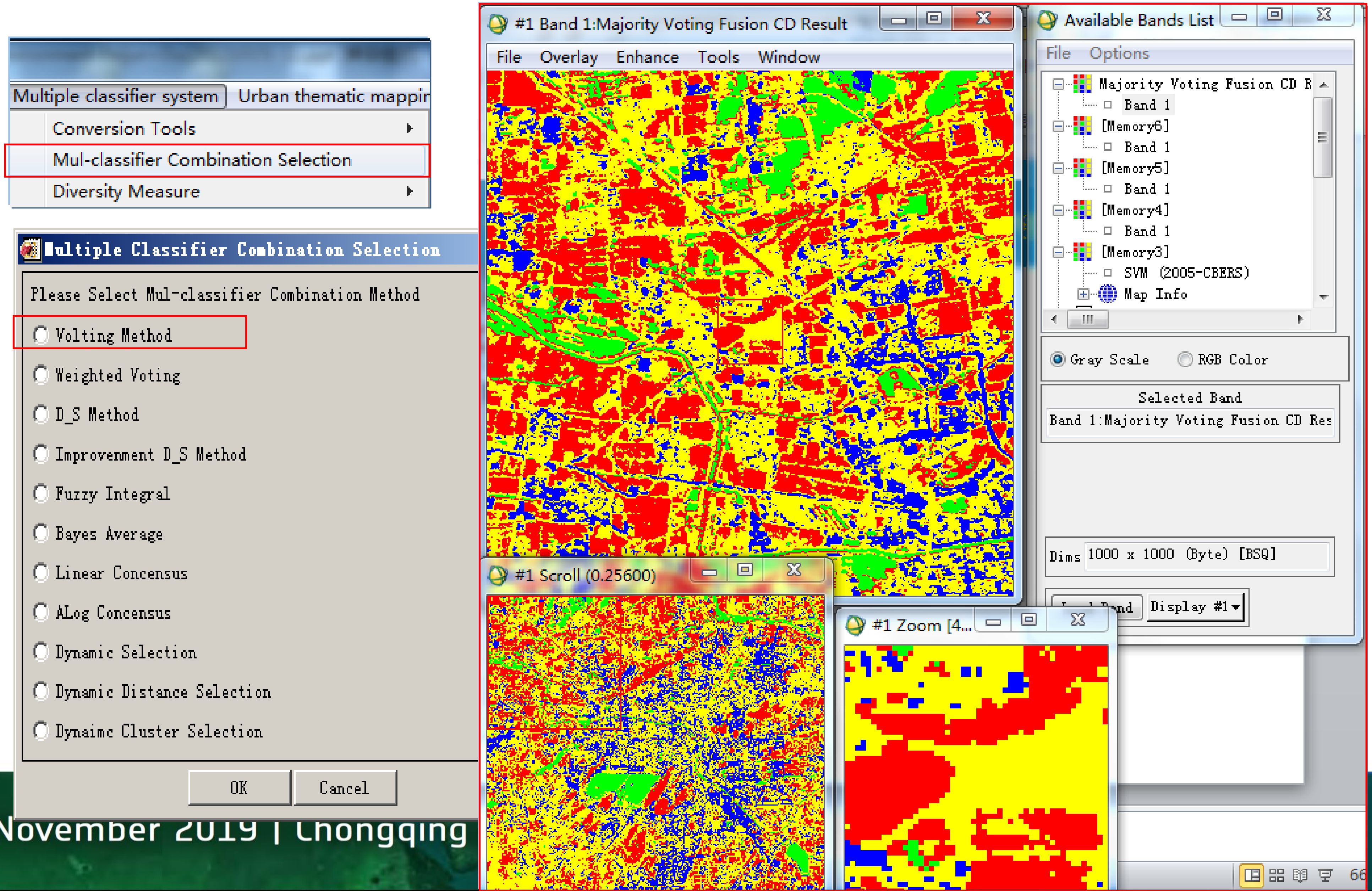

Topographic Radar Window Help Multiple classifier system Urban thematic mapping Change Detection


Spectral Map Vector Topographic Radar Window Help Multiple classifier system Urban thematic mapping Change Detection
ENVI ROI To Weka ROI
ENVI Image To Weka Image
Weka Classification To Envi Classification
Weka Classification Rule To Envi Classification Rule
Probability Transform
Conversion Tools
Mul-classifier Combinati
Diversity Measure
Multiple Classifier Combination Selection
Please Select Mul-classifier Combination Method
Volting Method
Weighted Voting
D_S Method
Improvement D_S Method
Fuzzy Integral
Bayes Average
Linear Concensus
ALog Concensus
Dynamic Selection
Dynamic Distance Selection
Dynaimc Cluster Selection
OK
Cancel



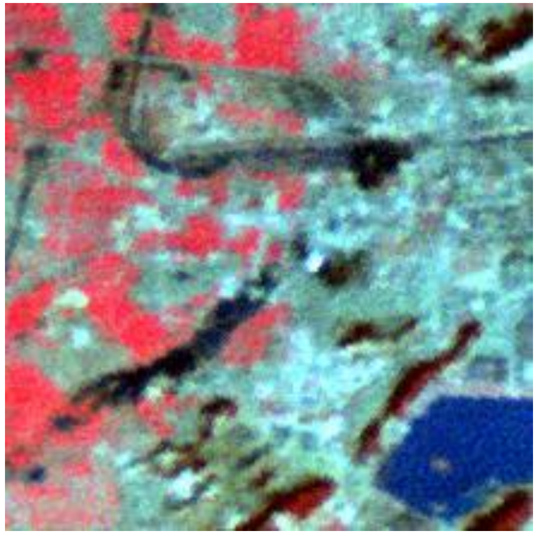
Weka GUI Chooser
Program Visualization Tools Help
Applications
Explorer
WEKA
The University of Waikato
Waikato Environment for Knowledge Anal
Version 3.7.7
(c) 1999 - 2012
The University of Waikato
Hamilton, New Zealand
Weka Explorer
Preprocess Classify Cluster Associate Select attributes Visualize
Open file... Open URL... Open DB... Generate... Undo Edit... Save...
Filter
Choose None
Current relation
Relation: None
Instances: None
Attributes
All
Status
Welcome to the Weka Explorer
Log
x 0
打开
查看: Used image
2001train.arff
2005whole.arff
Adaboost_RF_roi_set_1_of_1_test_1_of_1.arff
Adaboost_RT_roi_set_1_of_1_test_1_of_1.arff
Baging_REPTree_2005_roi_set_1_of_1_test_1_of_1.arff
J482005_roi_set_1_of_1_test_1_of_1.arff
NiveBayes_roi_set_1_of_1_test_1_of_1.arff
roi_set_1_of_1_test_1_of_1.arff
whole2011.arff
wtrain2005.arff
Invoke options dialog
Note:
Some file formats offer additional options which can be customized when invoking the options dialog.
最近使用的项目
桌面
我的文档
计算机
网络
文件名: C:\Users\WolfA\Desktop\龙计划3\Used image
文件类型: Arff data files (*.arff)
打开
取消


Weka KnowledgeFlow Environment
Design
DataSources
ArffLoader
C45Loader
CSVLoader
DatabaseLoader
JSONLoader
LibSVMLoader
MatlabLoader
SerializedInstanc
SVMLightLoader
TextDirectoryLoad
XRFFLoader
DataSinks
ArffSaver
C45Saver
CSVSaver
DatabaseSaver
JSONSaver
LibSVMSaver
MatlabSaver
SerializedInstanc
SVMLightSaver
XRFFSaver
Filters
Classifiers
bayes
functions
lazy
meta
AdaBoostM1
AdditiveRegres
AttributeSelec
Bagging
Classification
CostSensitiveC
CVParameterSel
FilteredClassi
LogitBoost
MultiClassClas
MultiClassClas
Untitled1
ArffLoader
dataSet
Training SetMaker
trainingSet
ClassAssigner
trainingSet
Bagging
batchClassifier
Prediction Appender
testSet
testSet
ArffLoader2
dataSet
TestSetMaker
testSet
ClassAssigner2
ArffSaver
Status
Log
Component
Parameters
Time
Status
[KnowledgeFlow]
0:2:7
Welcome to the Weka Knowledge Flow

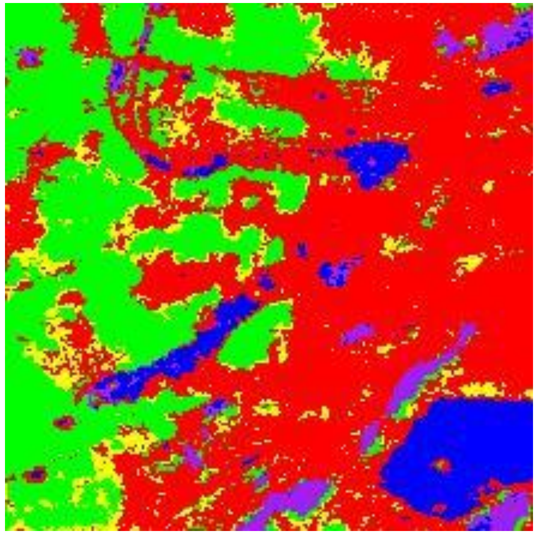


Multiple classifier system
Urban thematic mappin
Conversion Tools
Mul-classifier Combination Selection
Diversity Measure
Multiple Classifier Combination Selection
Please Select Mul-classifier Combination Method
Volting Method
Weighted Voting
D_S Method
Improvement D_S Method
Fuzzy Integral
Bayes Average
Linear Concensus
ALog Concensus
Dynamic Selection
Dynamic Distance Selection
Dynaimc Cluster Selection
OK
Cancel
#1 Band 1:Majority Voting Fusion CD Result
File
Overlay
Enhance
Tools
Window
#1 Scroll (0.25600)
#1 Zoom [4...
Available Bands List
File
Options
Majority Voting Fusion CD R
Band 1
[Memory6]
Band 1
[Memory5]
Band 1
[Memory4]
Band 1
[Memory3]
SVM (2005-CBERS)
Map Info
Gray Scale
RGB Color
Selected Band
Band 1:Majority Voting Fusion CD Res
Dims 1000 x 1000 (Byte) [BSQ]
Display #1

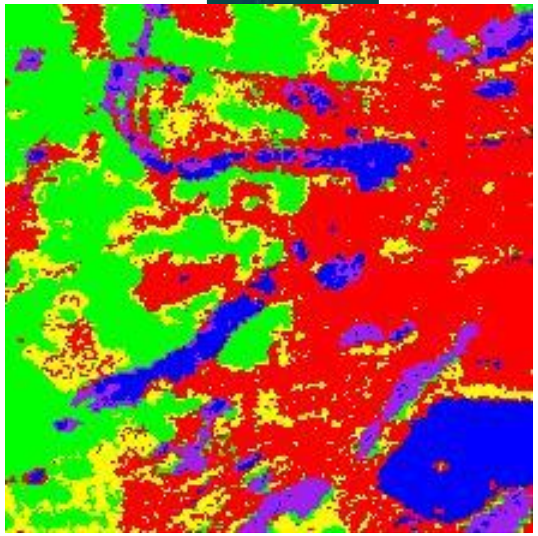
BJ-1 PAN and MS images



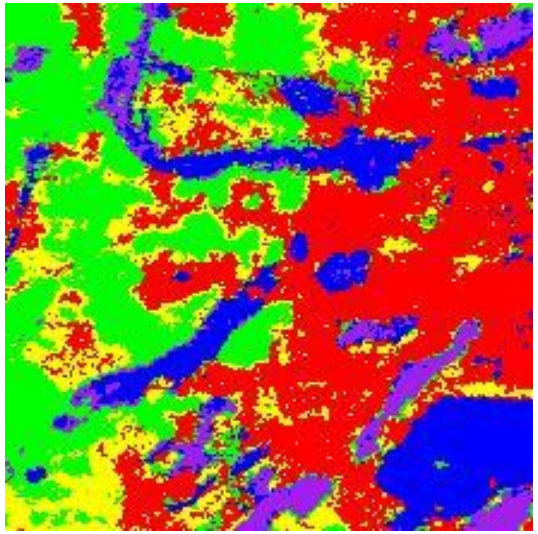
(a) Multispectral image (b) Panchromatic image



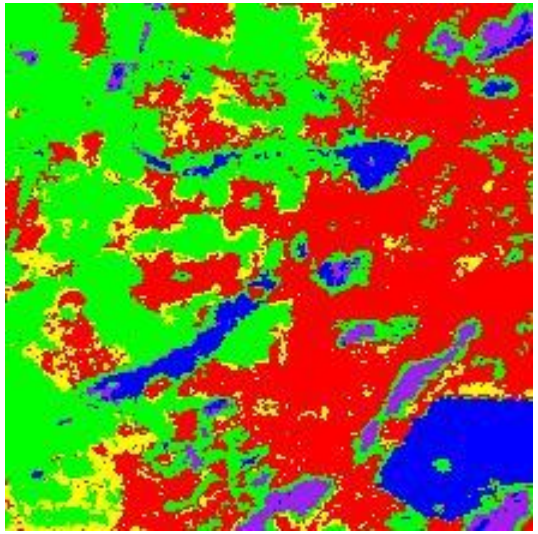
MLC



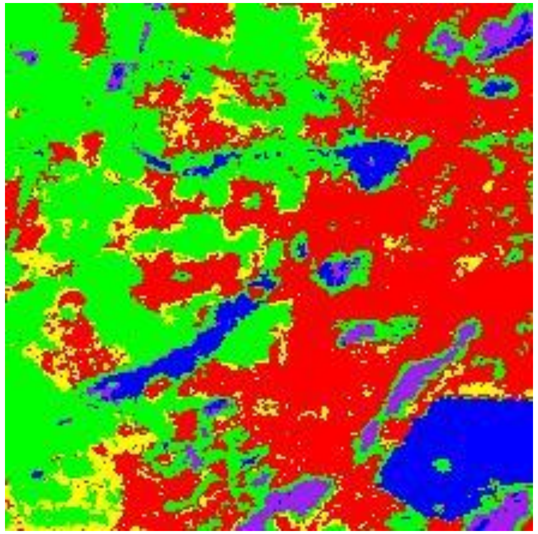
SVM



BPNN



RBFNN



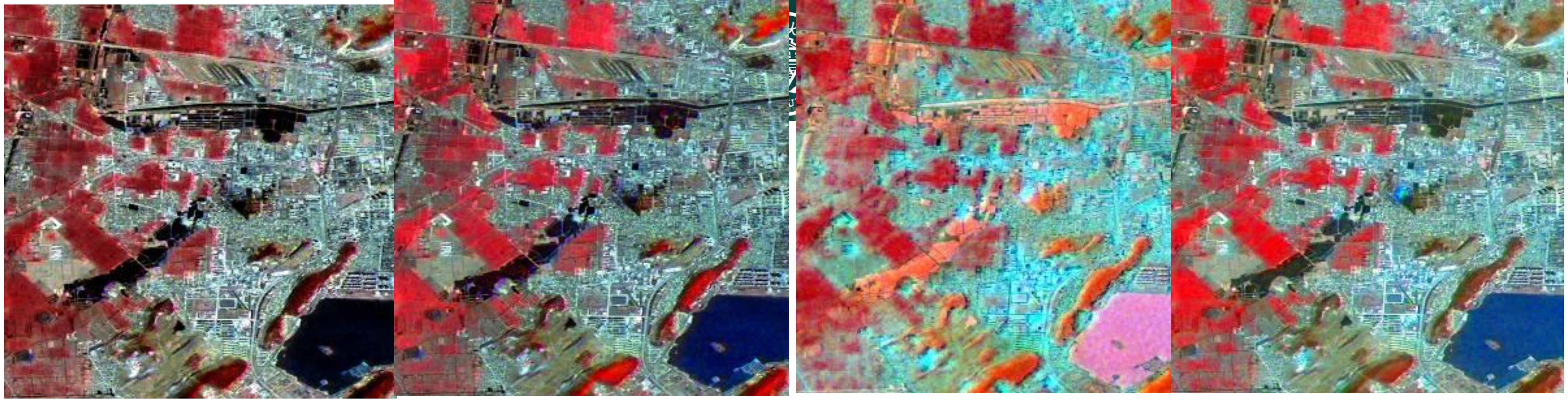
DTC

	OA (%)	Kappa
MLC	90.2423	0.8495
SVM	86.1821	0.7964
BPNN	88.1467	0.8244
RBFNN	89.3910	0.8370
DTC	88.2122	0.8230

	BPNN	RBFNN	DTC
Base classifier	88.1467	89.3910	88.2122
25% Bagging	88.6051	88.4741	81.7944
50% Bagging	88.6228	89.5874	81.7289
75% Bagging	88.2954	89.7184	80.3536
100% Bagging	88.8847	90.0458	81.4669
Boosting	90.2423	90.1768	88.2122

	OA	Kappa
MV	90.3078	0.8513
D-S	90.4388	0.8532
FI	90.2423	0.8499

MLC+BPNN+DTC



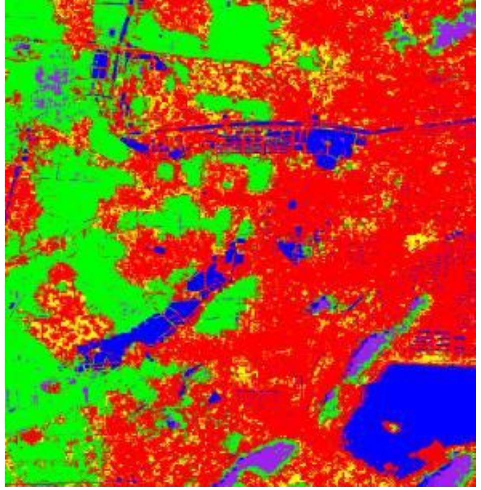
(a) IHS (b) Brovey (c) PCA (d) Gram-Shmidt

	OA (%)	Kappa
MLC	92.0019	0.8925
SVM	92.2201	0.8964
BPNN	88.0635	0.8430
RBFNN	85.5429	0.8094
DTC	92.2685	0.8966

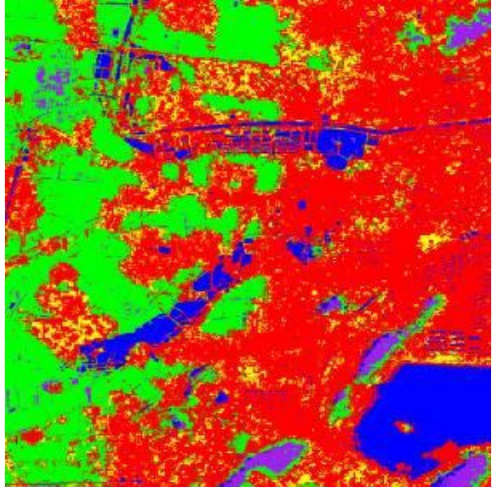
	BPNN	RBFNN	DTC
Base classifier	88.0635	85.5429	92.2685
25% Bagging	90.6689	84.7067	91.6142
50% Bagging	90.0267	83.4828	91.4687
75% Bagging	89.5540	83.4707	91.8686
100% Bagging	88.8997	84.4644	91.9292
Boosting	89.2874	86.1003	92.0625

	OA	Kappa
MV	92.9593	0.9059
D-S	92.9593	0.9059
FI	93.1774	0.9087

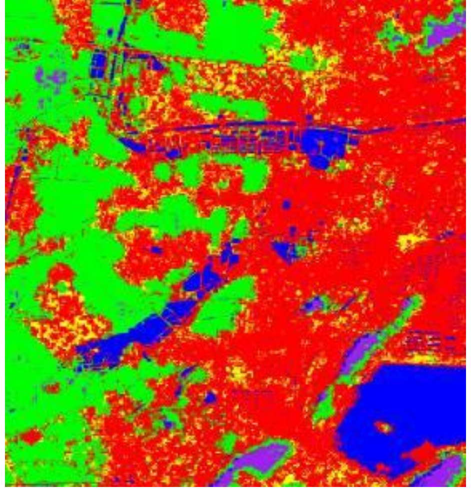
MLC+SVM+DTC



MV



D-S



FI

MLC+SVM+DTC

	OA (%)	Kappa
MLC	92.0019	0.8925
SVM	92.2201	0.8964
BPNN	88.0635	0.8430
RBFNN	85.5429	0.8094
DTC	92.2685	0.8966

	OA	Kappa
MV	92.9593	0.9059
D-S	92.9593	0.9059
FI	93.1774	0.9087

urban land cover classification based on multi-temporal CBERS imagery

Multi-temporal and multi-scale remote sensing data used are

CBERS-01 CCD image (patch=371, row=62) on March 31, 2001,

CBERS-02 CCD images (patch=371, row=62) on March 18, 2005, April 11, 2007 and

CBERS-02 IRMSS image (patch=371, row=62) on April 13, 2007. The region of interest is urban area of Xuzhou city, including four districts: Jiuli, Gulou, Yunlong, Quanshan.

Category system
Current Land Use Classification (GB/T 21010-2007)

How was the classification system established

Classification methods
Classification conducted by using three method OOC,MLC and SVM

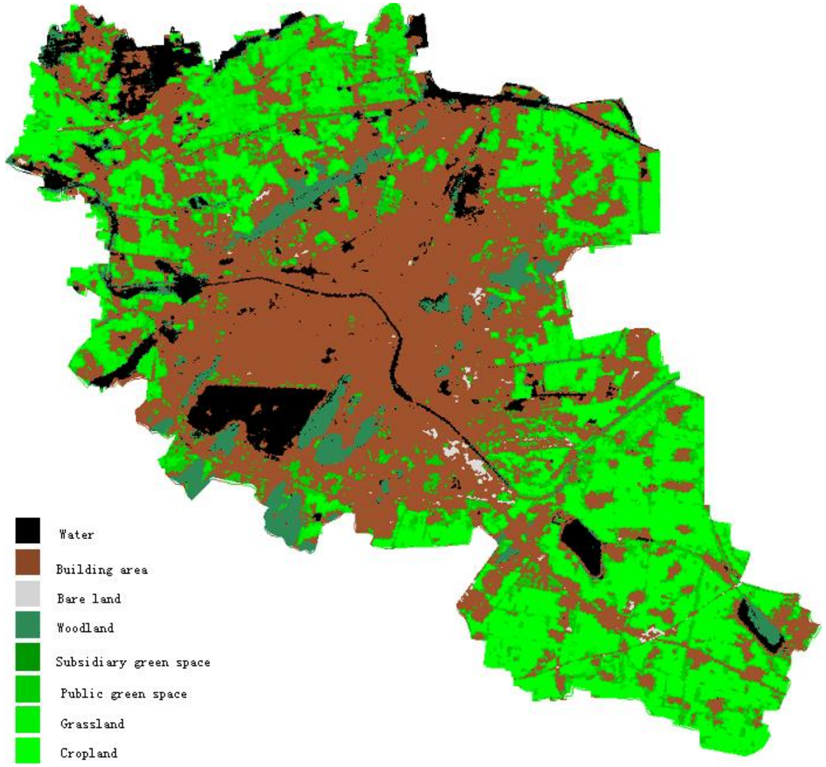
Which classifier was chosen for land use/cover

Landscape analysis
Class and landscape metric calculated (Fragstat user guide)

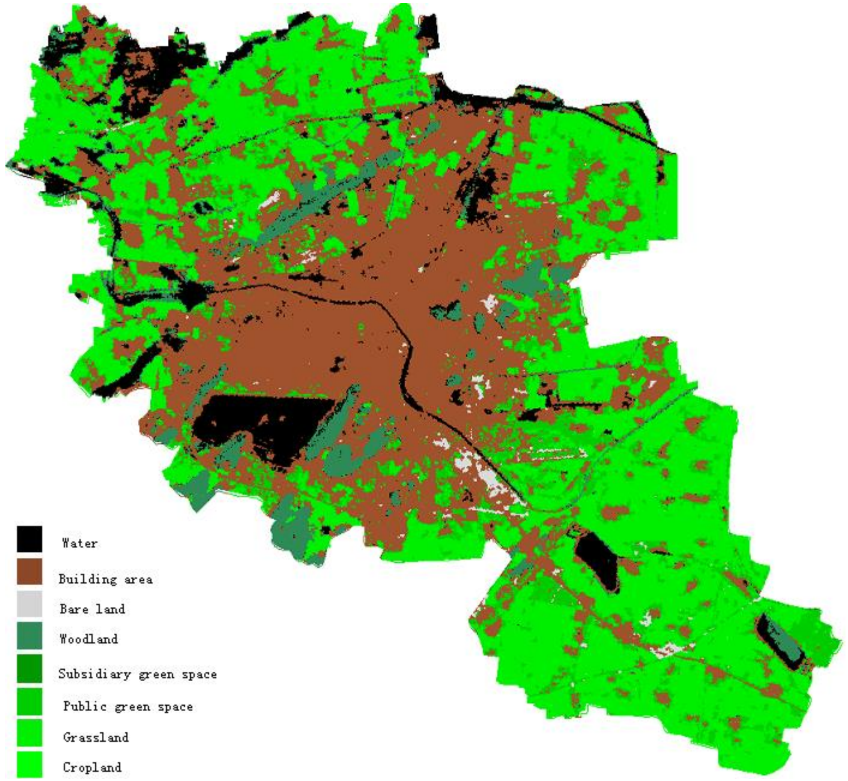
How have urban landscape pattern change during the last 6 years

Multi-scale analysis
Urban pattern change analyzed by CCD and IRMSS

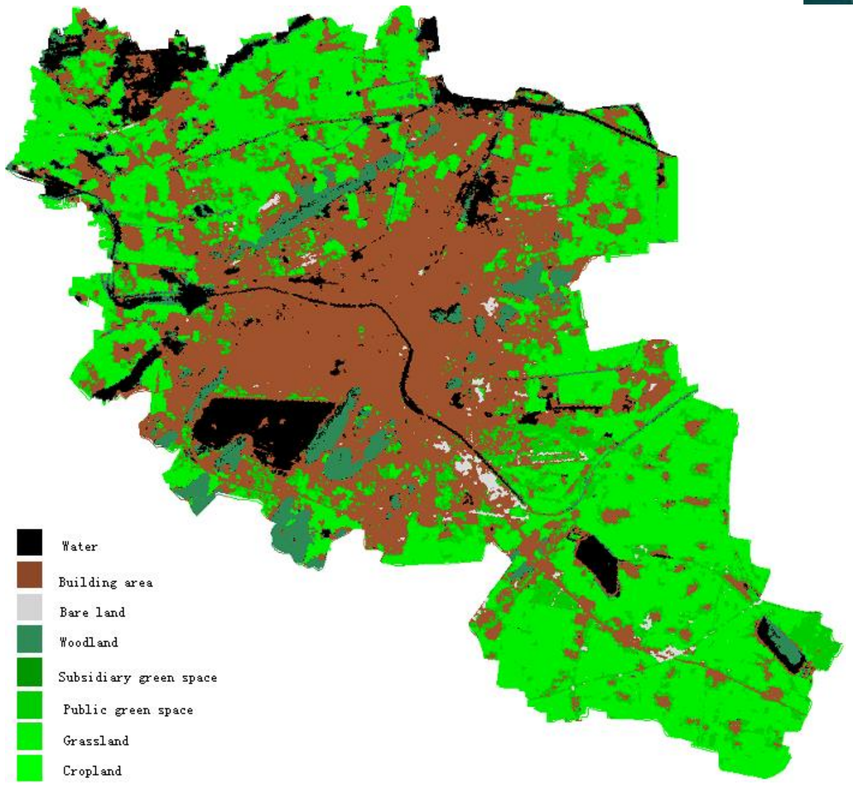
What's the difference and relationship between CCD and IRMSS

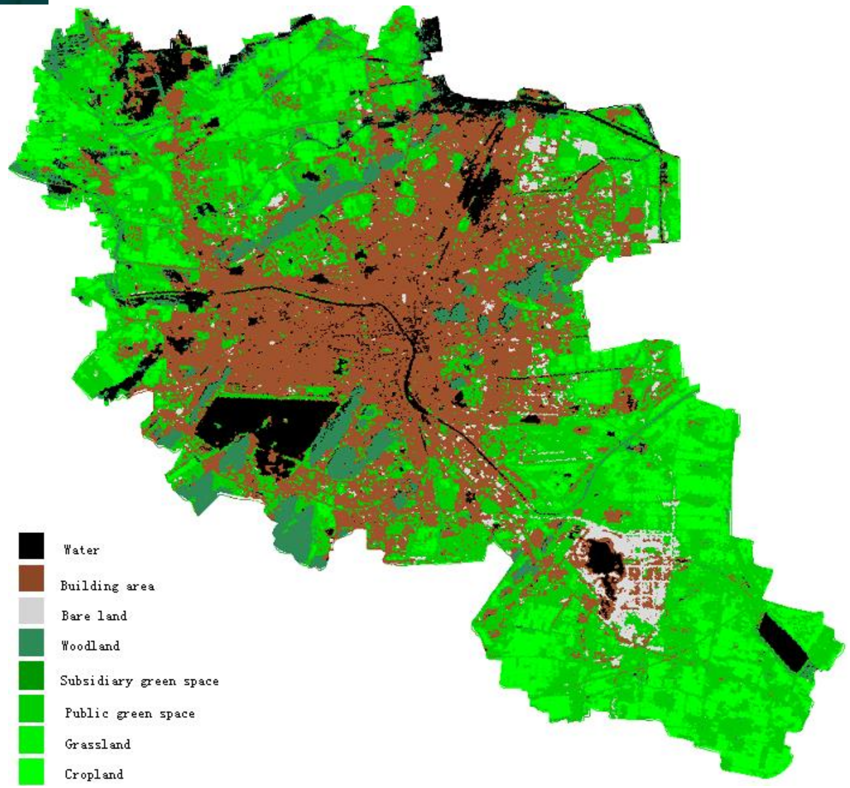


Land cover map in 2001 (CCD)



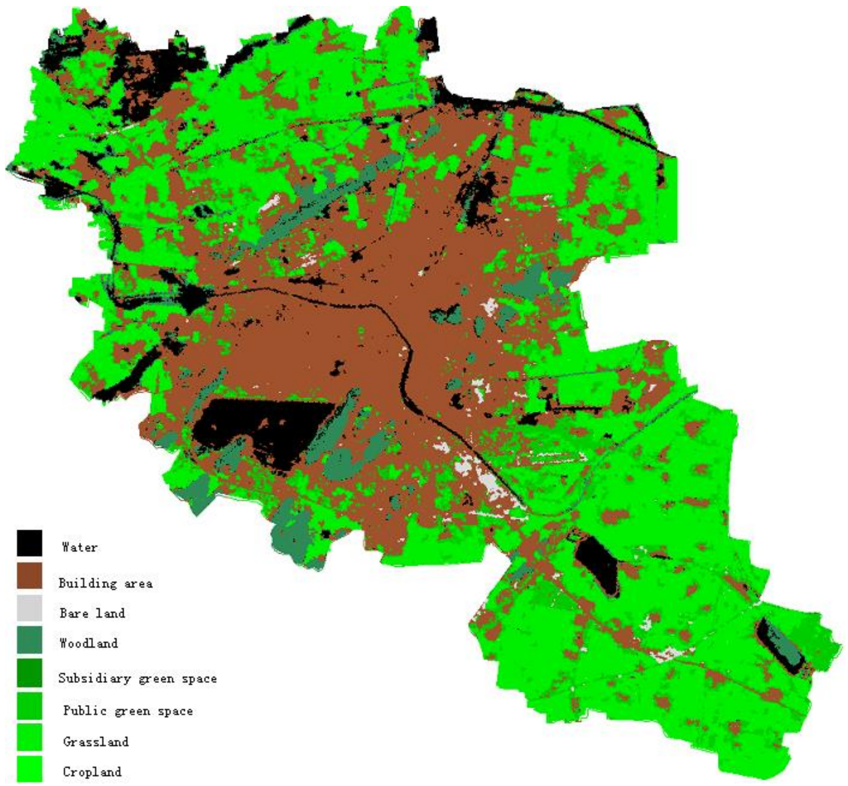
Land cover map in 2005 (CCD)

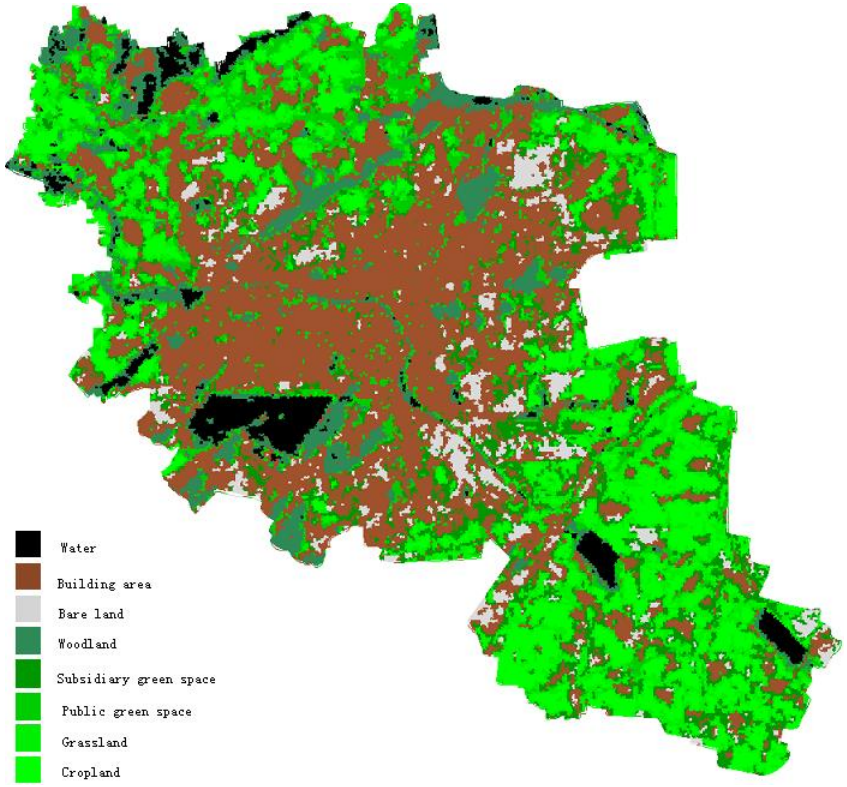




Land cover map in 2005 (CCD)

Land cover map in 2007 (CCD)

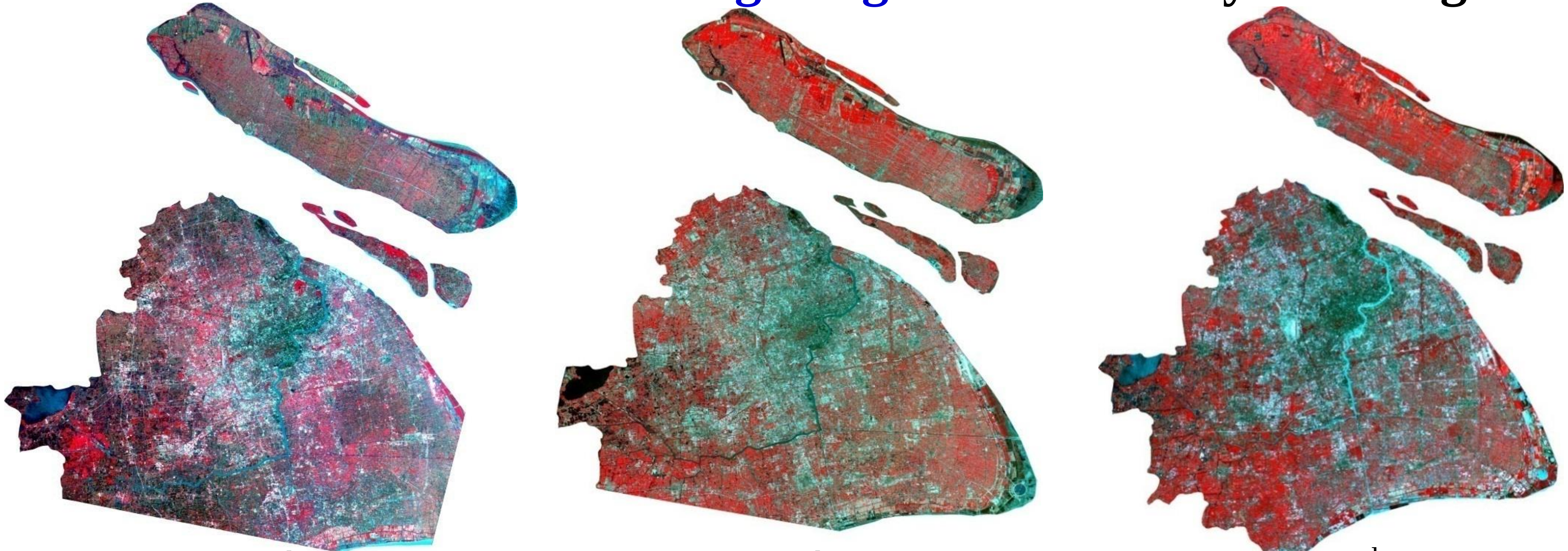




Land cover map in 2005 (CCD)

Land cover map in 2005 (IRMSS)

Quantifying spatio-temporal change of urban land cover/use using BJ-1 and CBERS remote sensing images: A case study of Shanghai



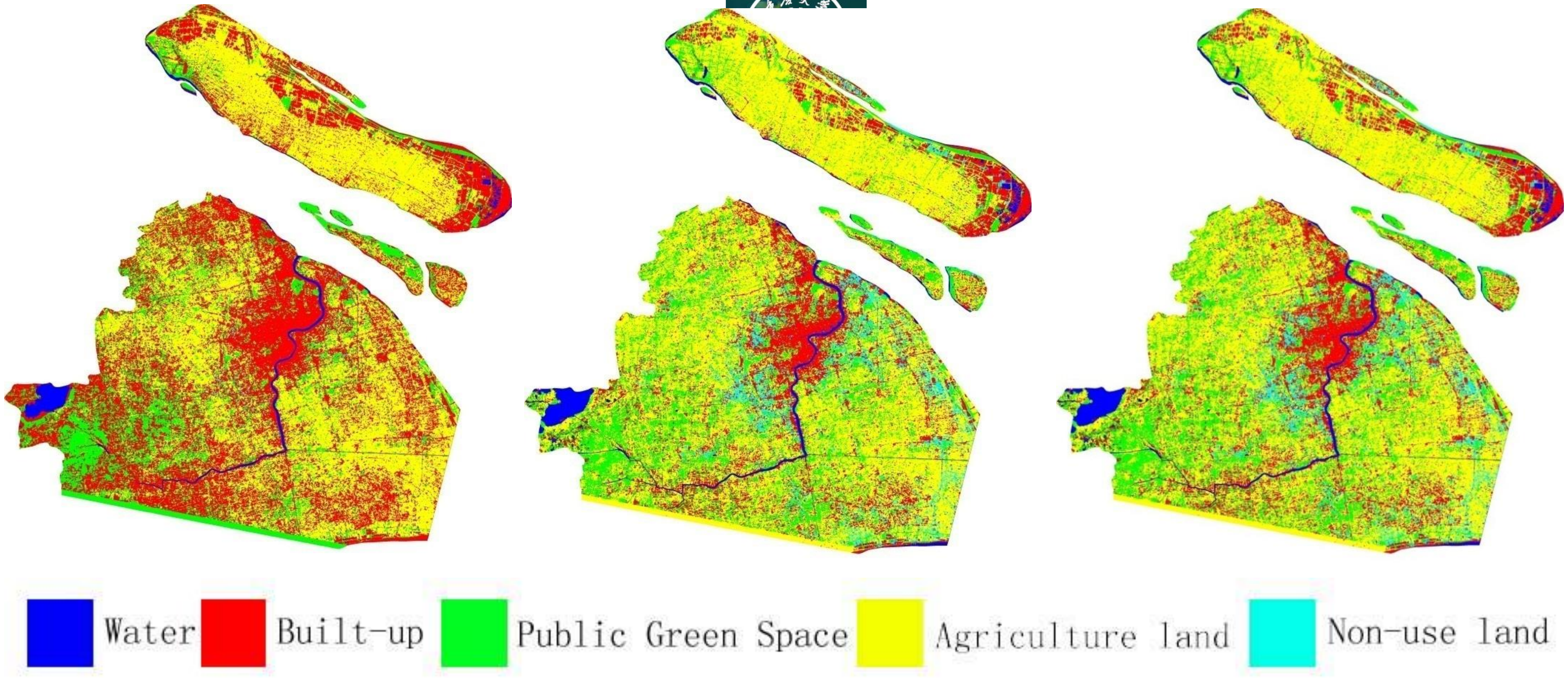
Jun 5th,2002
CBERS 01/02
(R:NIR, G:Red, B: Green)

Apr 28th,2005
CBERS 01/02
(R:NIR, G:Red, B: Green)

May 11th,2009
BJ-1
(R:NIR, G:Red, B: Green)

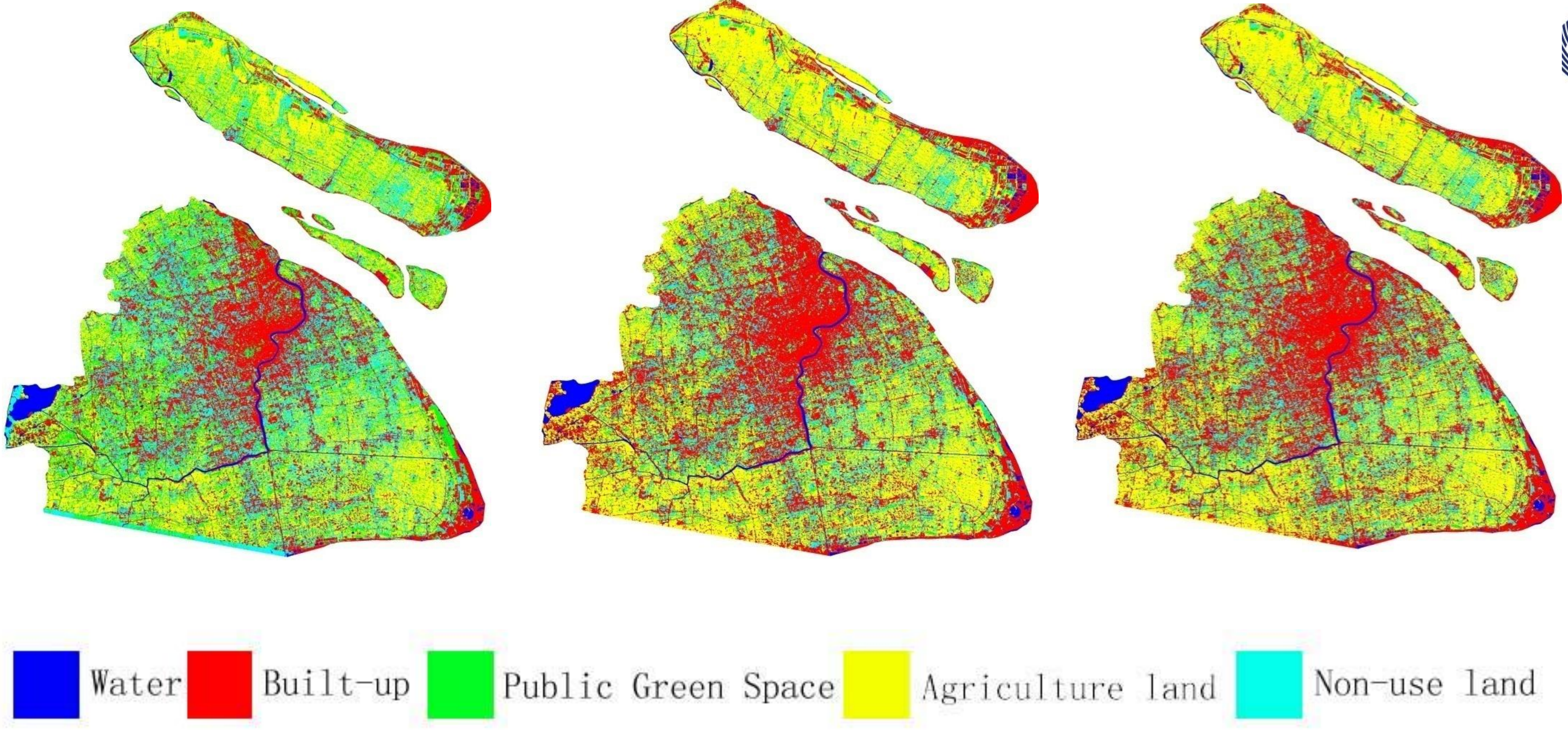
Land cover classification: Maximum likelihood classifier

Support Vector Machine with two different Kernel functions(RBF and Polynomial)



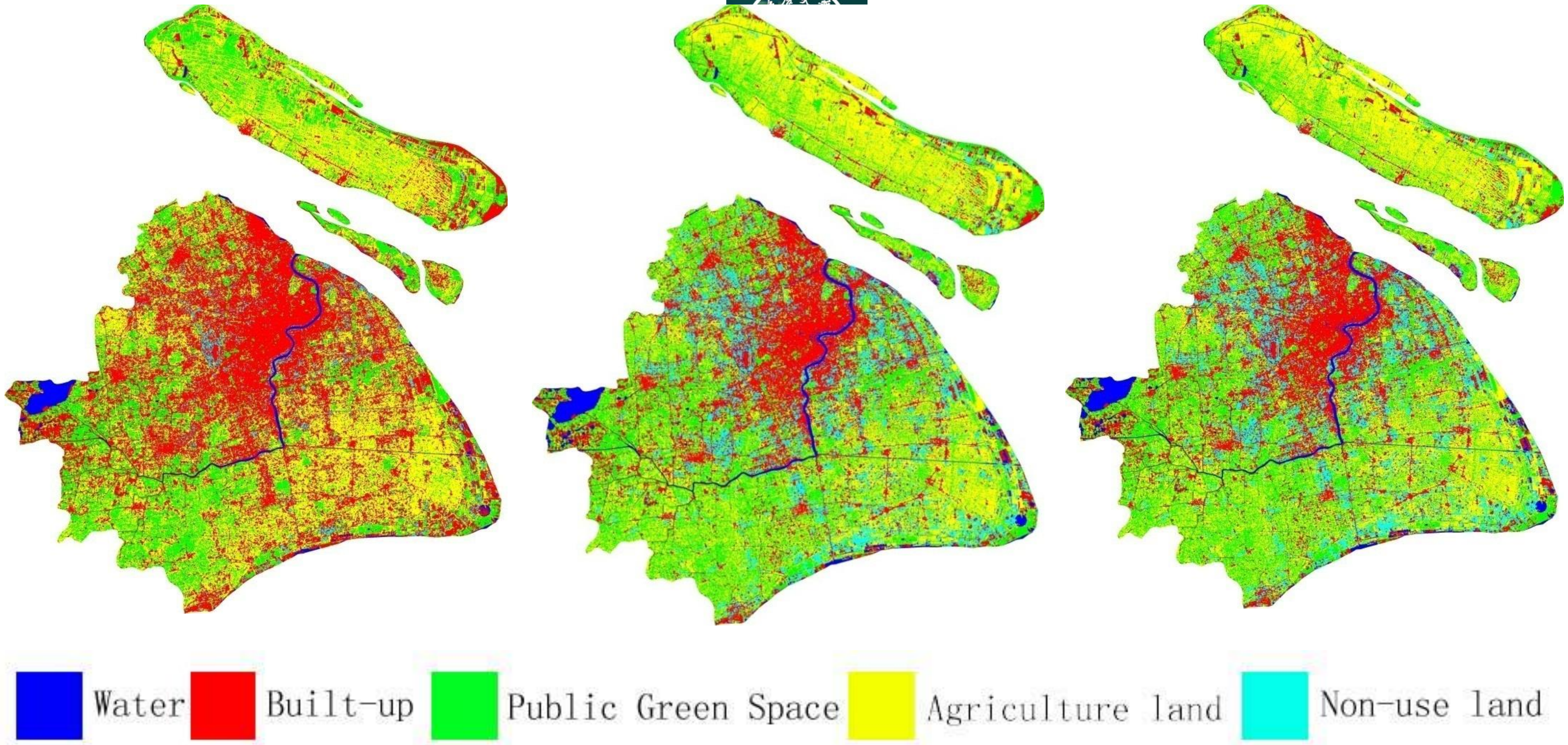
(a) MLC (b) SVM-RBF (c) SVM-Polynomial

Classifications Results of 2002



(a) MLC (b) SVM-RBF (c) SVM-Polynomial

Classifications Results of 2005



(a) MLC (b) SVM-RBF (c) SVM-Polynomial

Classifications Results of 2009

Accuracy assessment

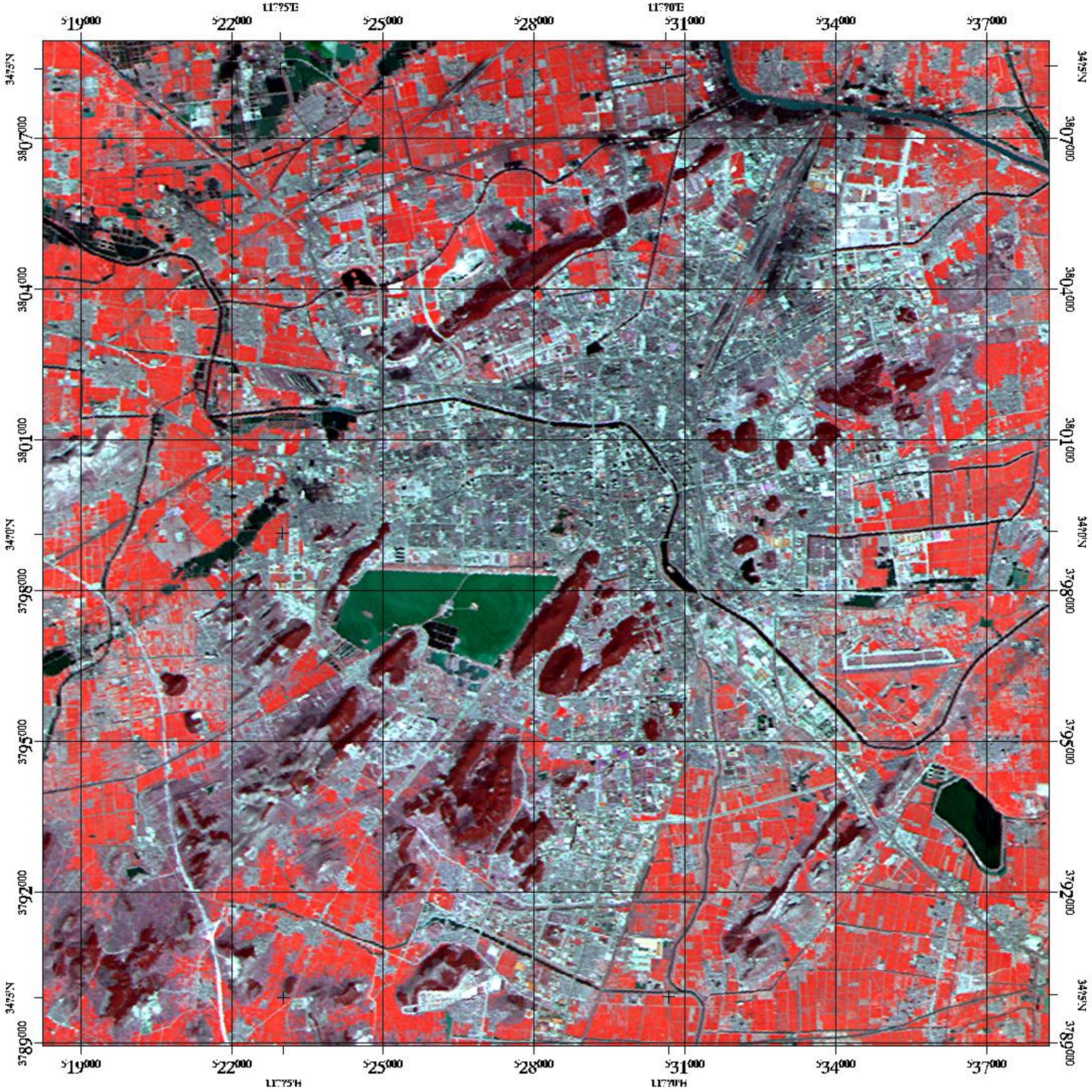
	2002			2005			2009		
	MLC	RBF	POL	MLC	RBF	POL	MLC	RBF	POL
OA	80.3960	87.5428	87.6238	76.8046	79.6920	79.4033	79.5026	88.4220	88.5077
Kappa	0.7543	0.8439	0.8452	0.7109	0.7455	0.7419	0.7413	0.8540	0.8550

The accuracy of SVM is higher than MLC

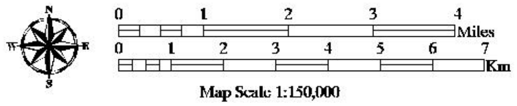
The accuracy of two kernel functions :RBF and Pol is similar

The SVM is too time-consuming, may be 5-10 minutes

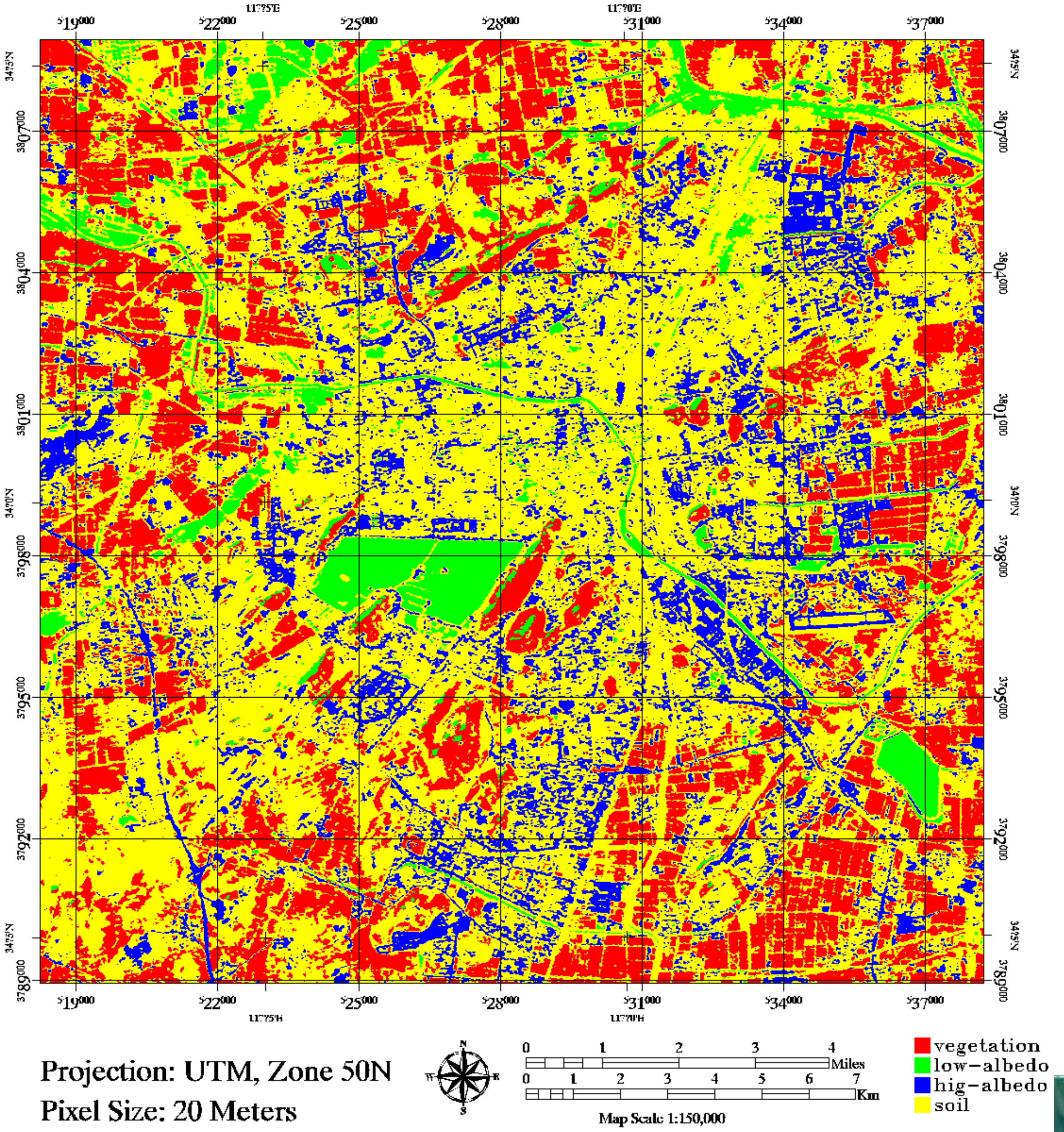
Classification Map of Xuzhou,China



Projection: UTM, Zone 50N
Pixel Size: 20 Meters
Datum: WGS-84
Ellipsoid: WGS_1984



Classification Map of Xuzhou,China



Projection: UTM, Zone 50N
Pixel Size: 20 Meters
Datum: WGS-84
Ellipsoid: WGS_1984

Content

Vegetation:

- Accuracy of derived layers will be highly de pendent on the spectral differences of the targeted vegetation types
- Attributes such as biomass, leaf area index, and structural complexity have been
estimated in forest environments – more work is needed in urban environments to
determine whether these are achieved given t he mix of species
- Maybe assessed using ratio's of re (chlorophyll absorption), near infrared (cellular structure) or mid-infrared (water absorption) reflectance

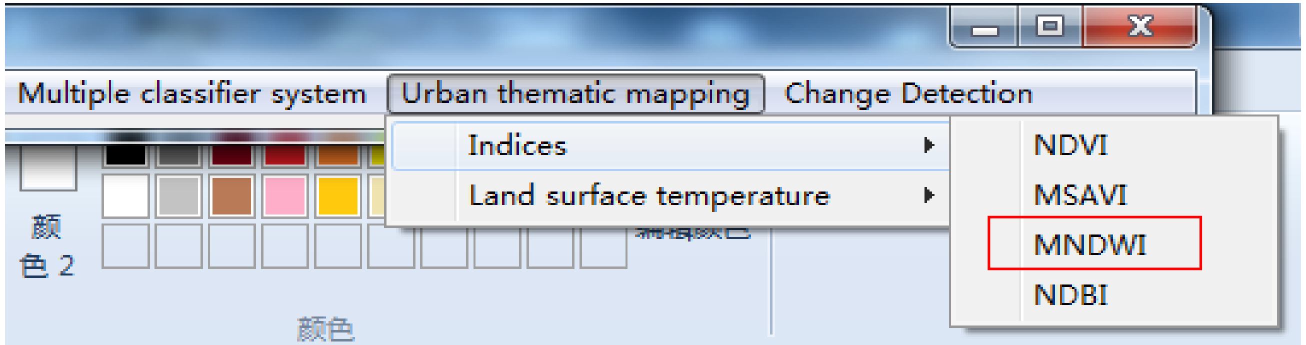
Mapping methods:

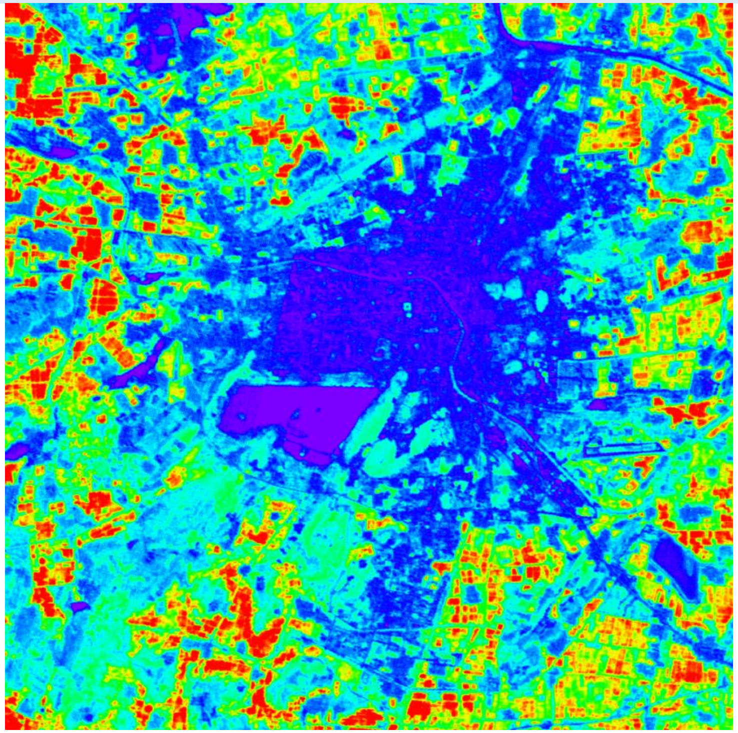
- Vegetation index (RVI, DVI, NDVI, GEMI, MSAVI, GEMI)
- Classification
- Spectral mixture analysis

Land surface temperature(LST)

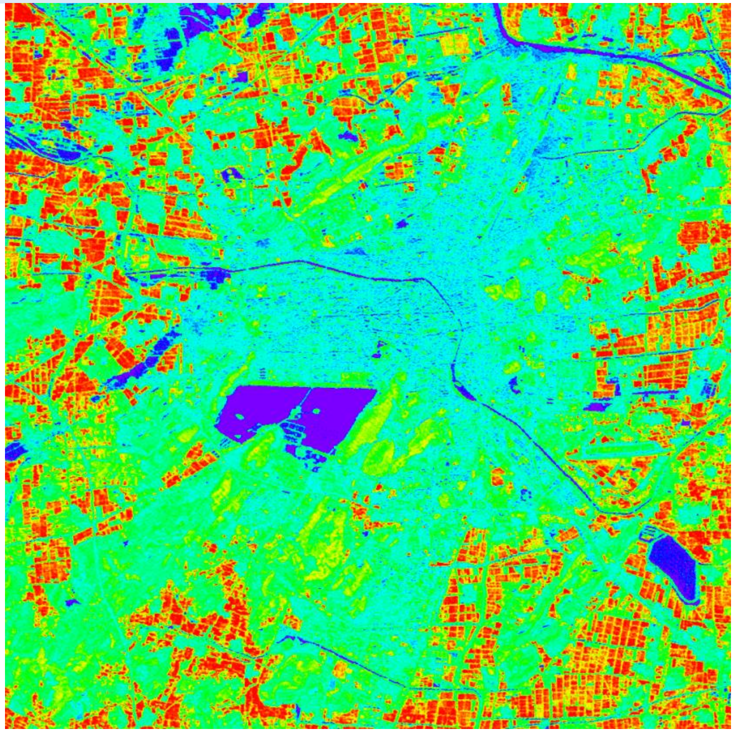
- Key parameter in the surface energy budget and controlled by the complex interplay of topography, incoming radiation, atmospheric processes, as well as by the soil moisture distribution and the different land covers and vegetation types.

- plays significant roles in urban heat island, climate change, vegetation ecology and environmental monitoring in the studies of urban thermal environment and dynamics

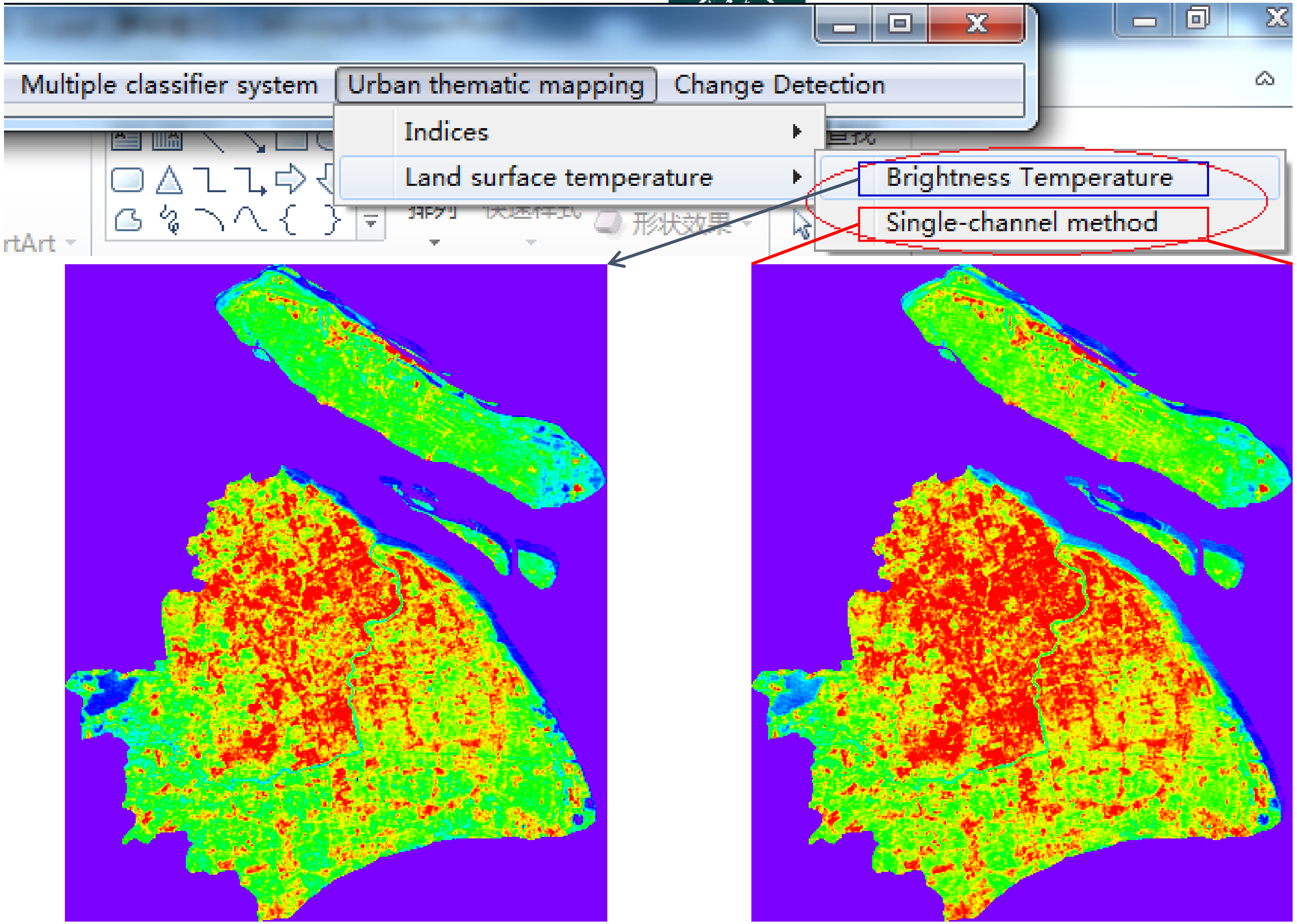




CBERS2001



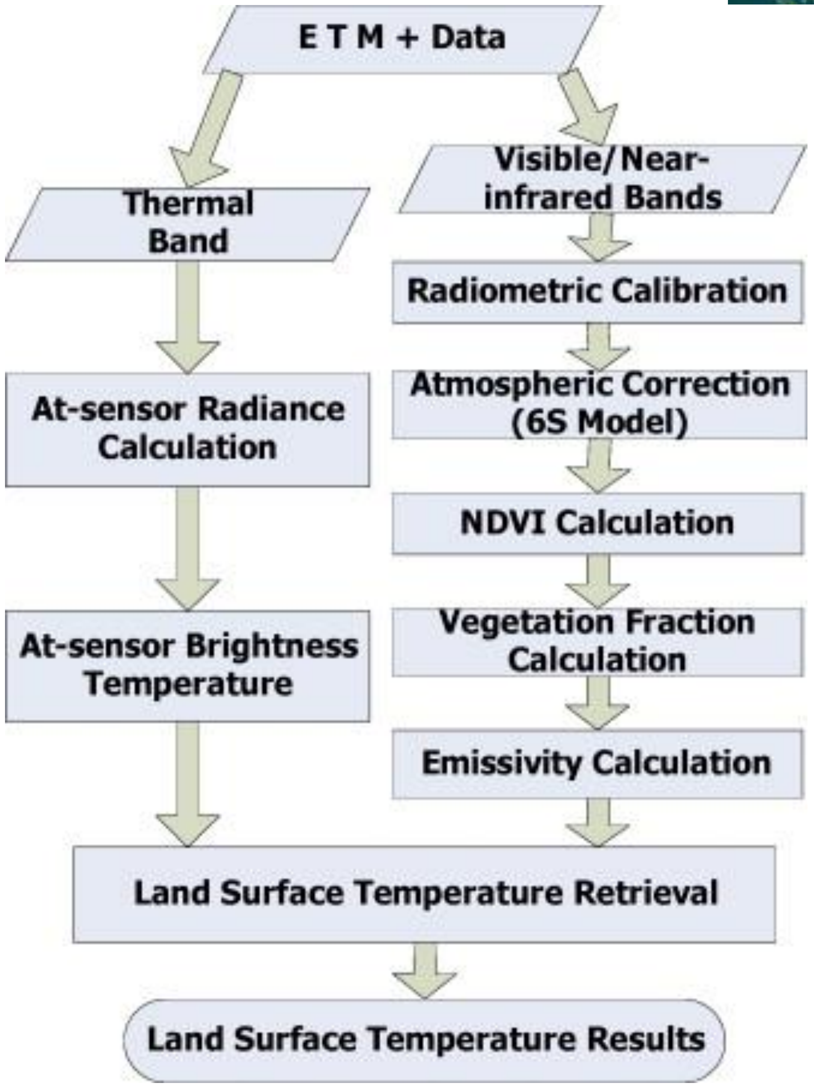
CBERS2005


Multiple classifier system
Urban thematic mapping
Change Detection
Indices
Land surface temperature
Brightness Temperature
Single-channel method

HJ1-B
IRS

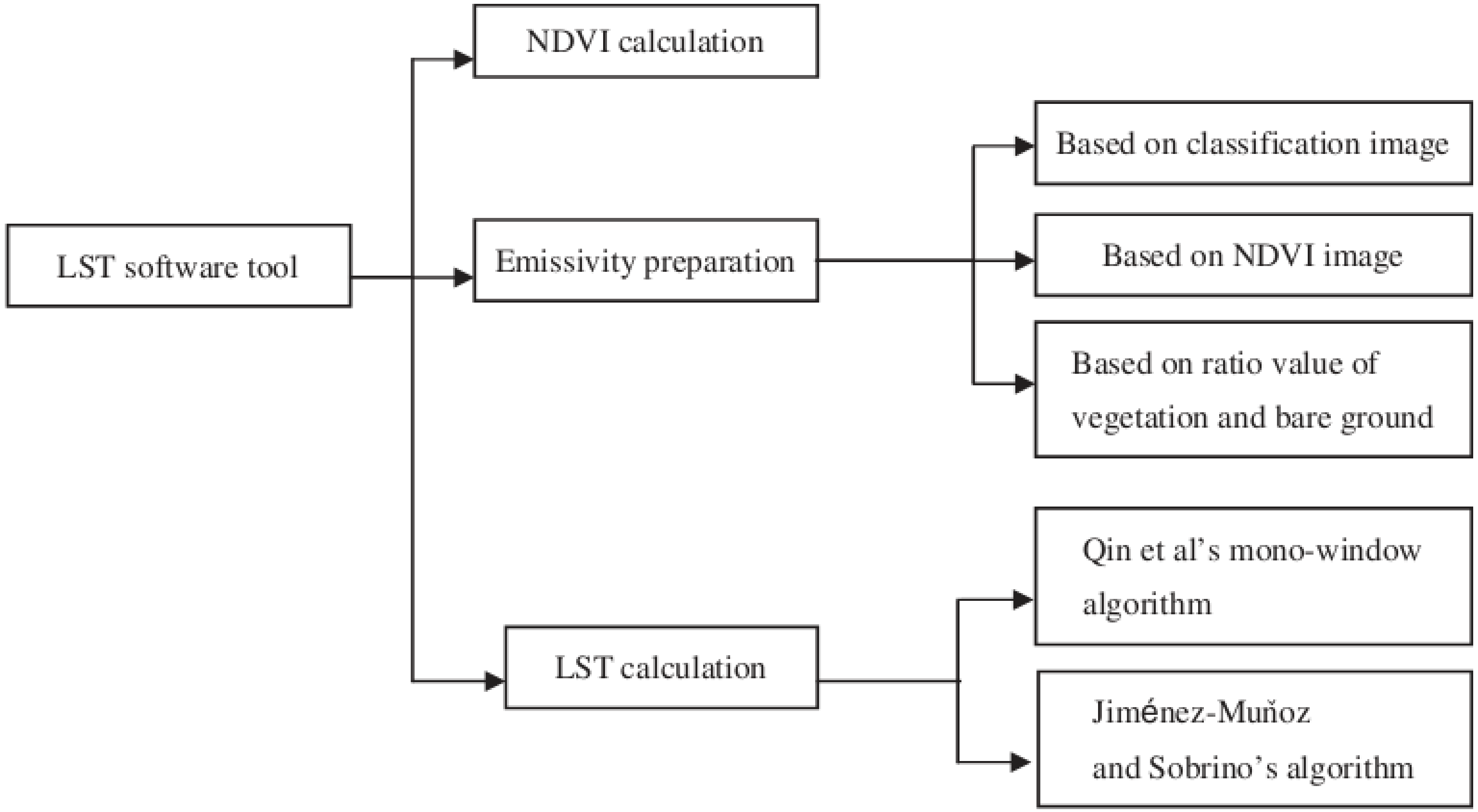
LST retrieval methods:

- Mono-window algorithm (MWA), Single channel algorithm (SMA) for single thermal band (TM/ETM+, HJ-1)
- Split-window algorithm (SWA) for multiple thermal bands (MODIS)
- Temperature and Emissivity Separation algorithm (TES) for ASTER



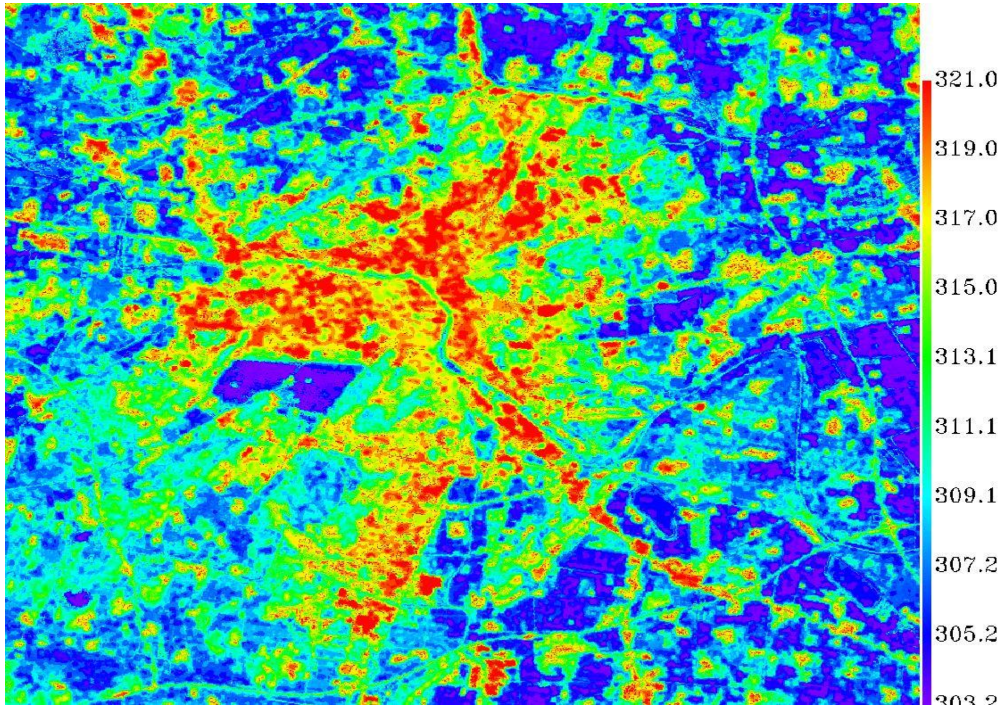
Qin et al. Geothermal area detection Using Landsat ETM+ thermal infrared Data and its mechanistic analysis- A case Study in Tengchong, China. JAG, 2011

Flow Chart of LST Retrieval (Landsat ETM+).

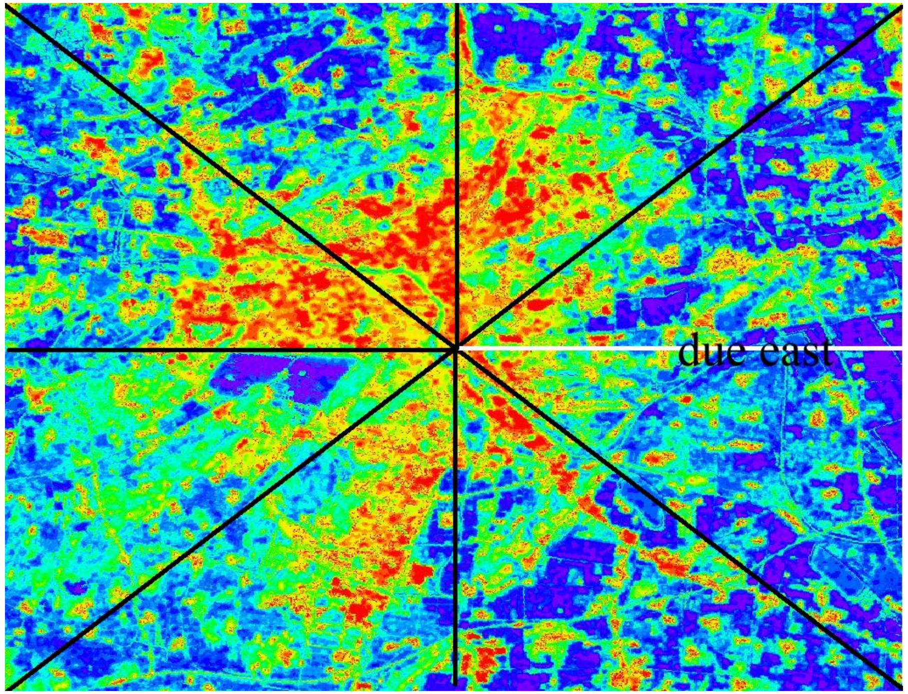


Zhang et al. A C++ program for retrieving land surface temperature from the data of Landsat TM/ETM+ band6. Computer & Geoscience, 2006

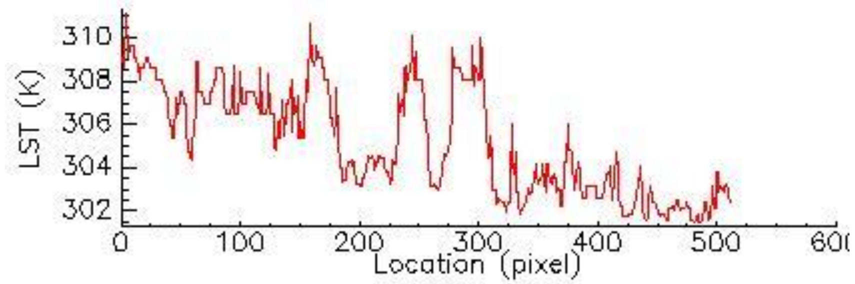
Land cover classification and LST retrieval using TM image(Xuzhou)

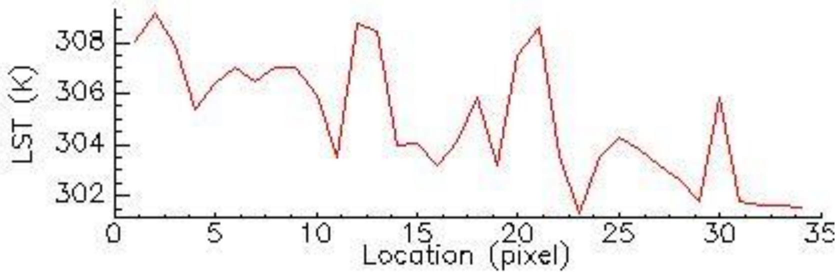


MWA

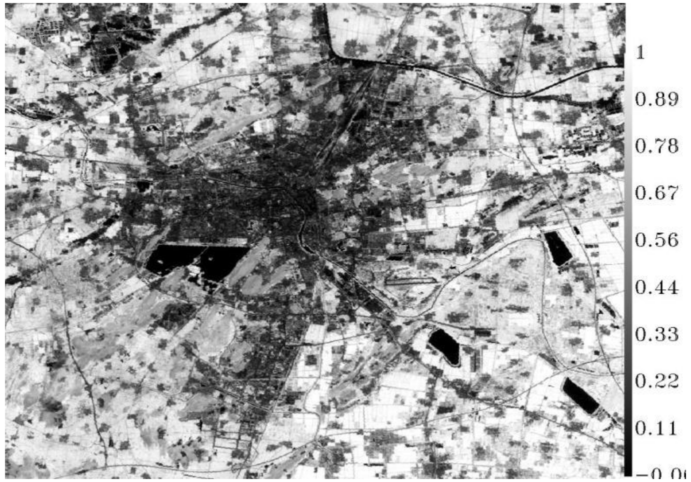


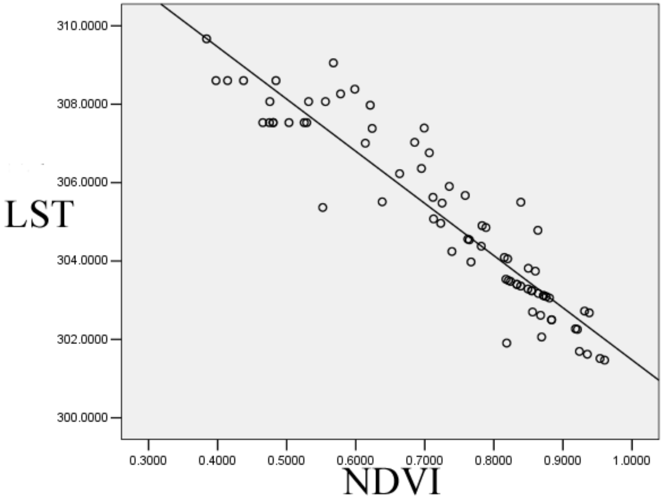
SCA

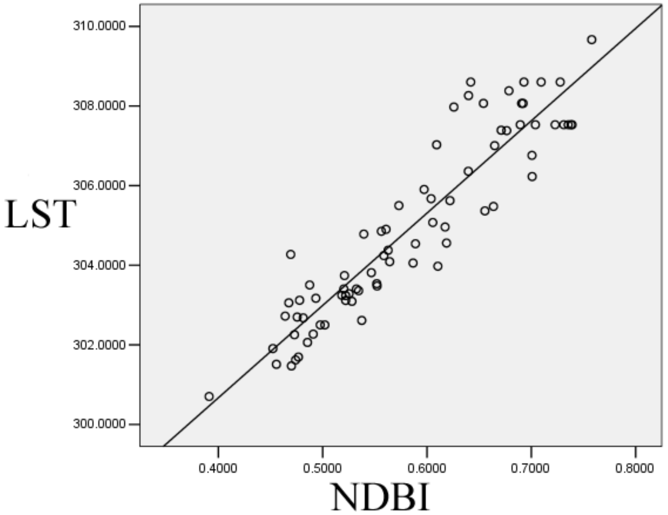




Transection derived from LST data at 60m and 900m scales

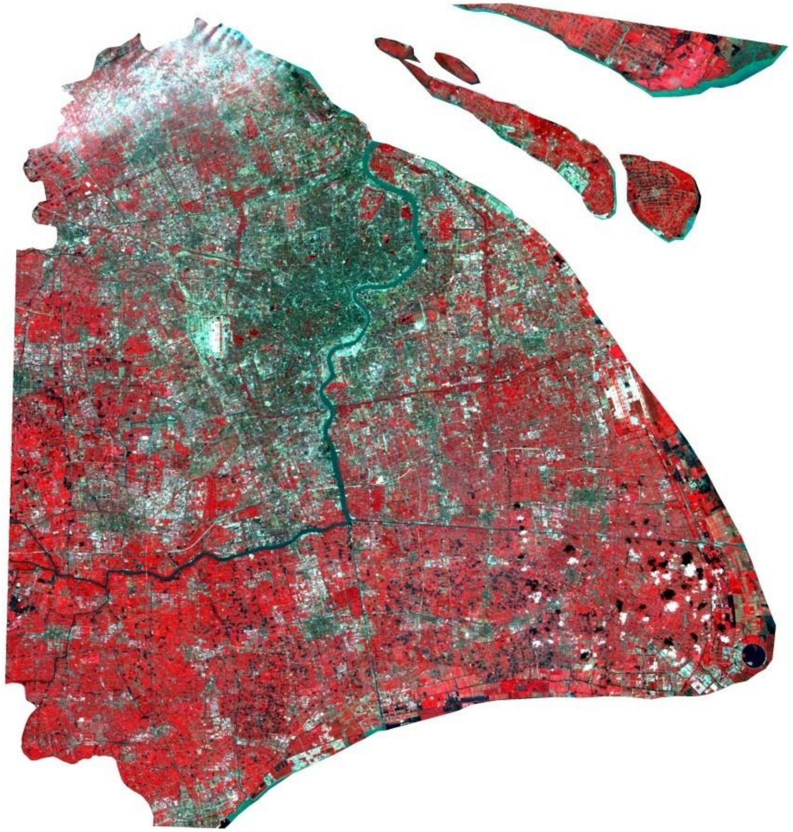




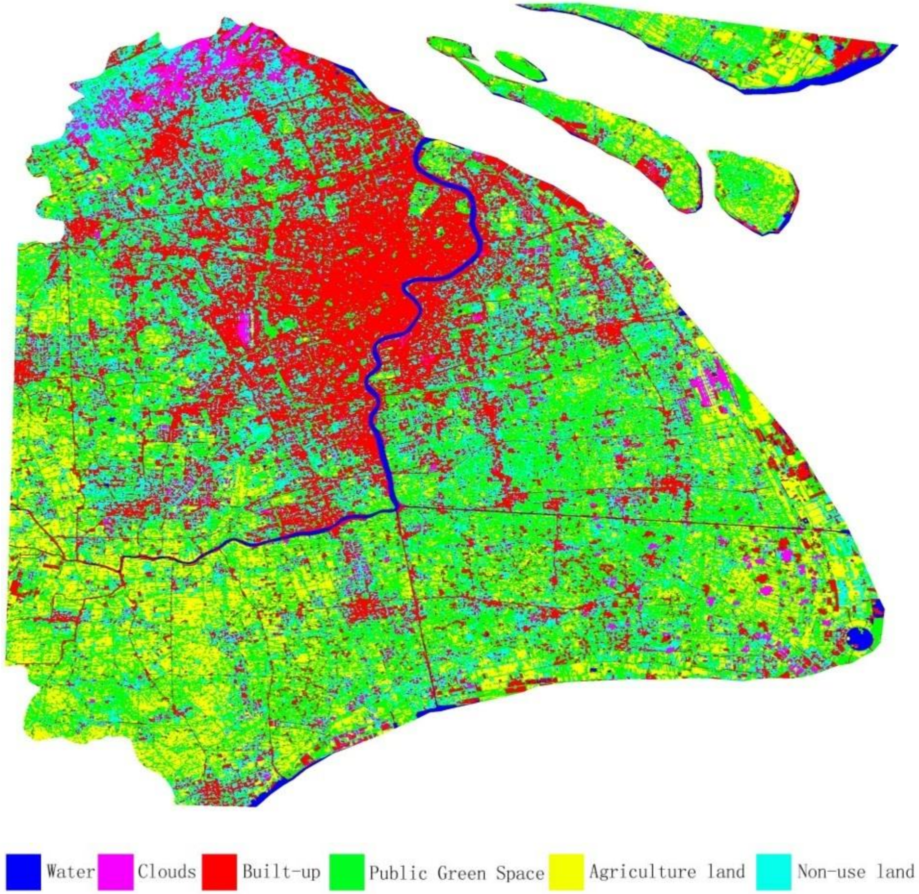


NDVI,NDBI, and their relationship between LST

Land cover classification and LST retrieval using HJ-1 image (Shanghai)



HJ-1 Multspectral Image(2009.10.24)
(R: band 4, G: band 3, B: band 2)



SVM-RBF classification

Public Green Space

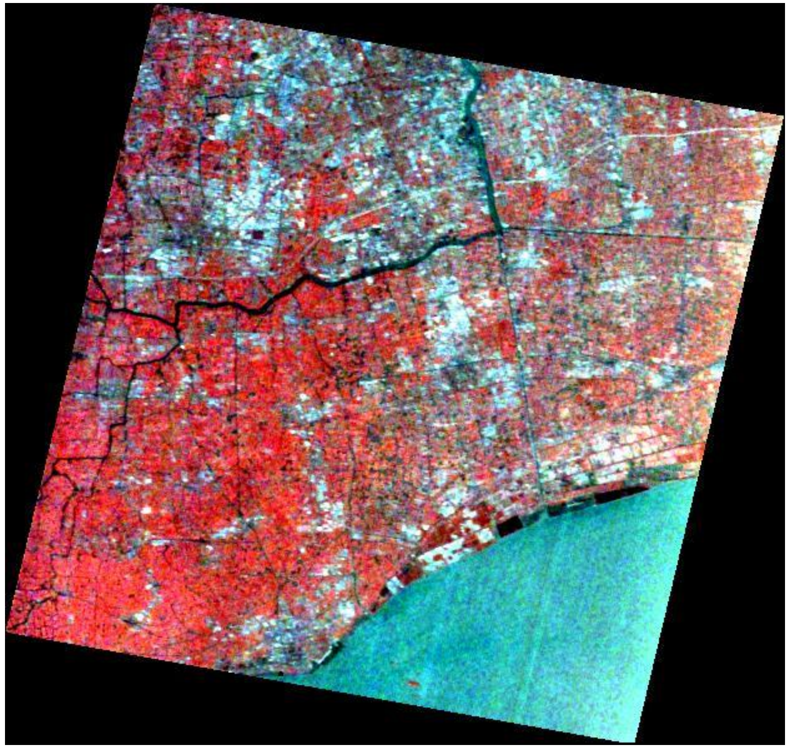
Lake in Century Park

NO	Longitude	Latitude	Ground Truth	Classification Result
1	121°24'57"	31°13'17"	Grass	4
2	121°26'31"	31°13'28"	Platanus	3
3	121°28'08"	31°14'06"	Granite	5
4	121°28'12"	31°14'14"	Pine	4
5	121°28'55"	31°14'33"	Built-up areas	3
6	121°28'52"	31°14'27"	Marble	5
7	121°28'57"	31°14'25"	Built-up areas	3
8	121°29'07"	31°14'27"	Built-up areas	3
9	121°29'07"	31°14'28"	Road	3
10	121°32'41"	31°12'54"	Poplar, willow	5
11	121°32'42"	31°12'57"	Lake water	1
12	121°36'15"	31°11'54"	Bamboo, pine	5
13	121°36'16"	31°11'38"	Buildings	3
14	121°35'12"	31°20'12"	Wasteland	6
15	121°36'00"	31°19'24"	Unused land	3
16	121°35'58"	31°19'08"	New road	4
17	121°35'53"	31°19'02"	Wasteland	6
18	121°35'46"	31°18'28"	Factory	3
19	121°36'09"	31°18'03"	New Buildings	6
20	121°36'41"	31°18'12"	Greenhouse	5

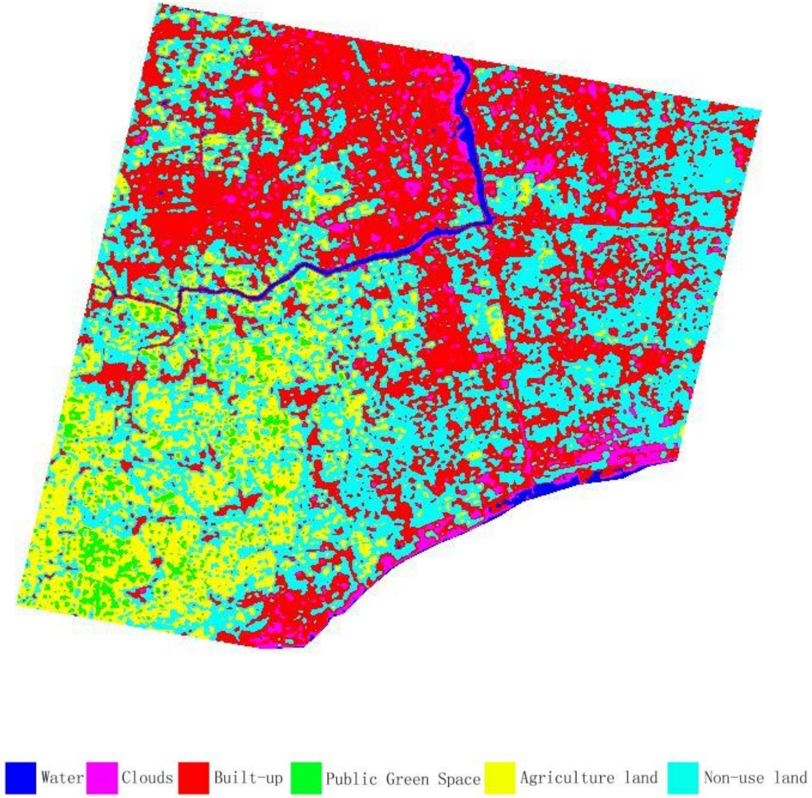
Buildings

Non-use land

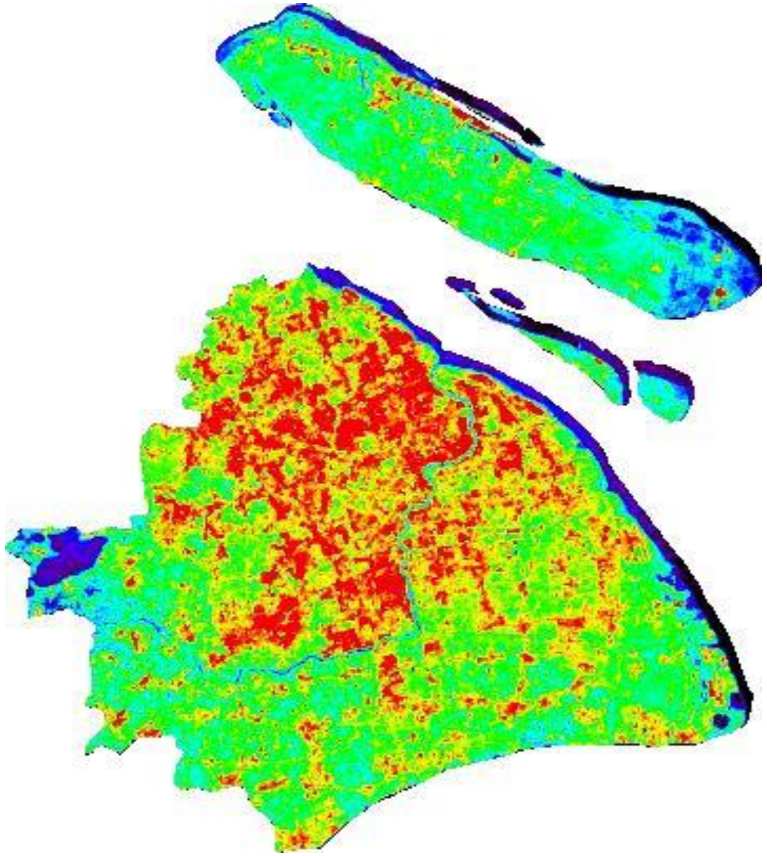
ground truth



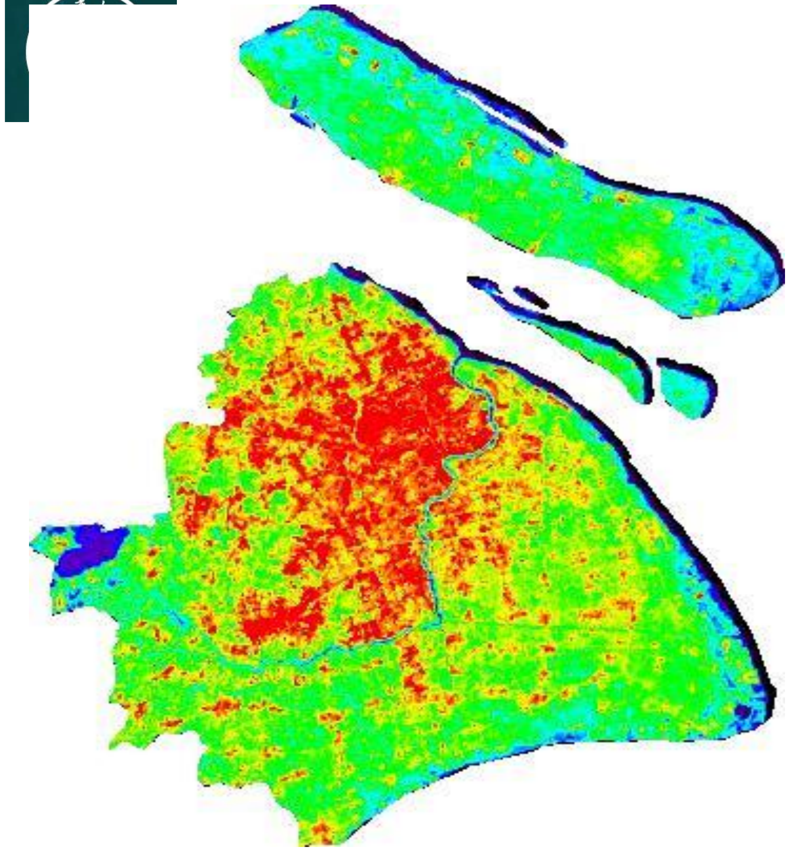
HJ-1 Hyperspectral Image(2009.05.01)
R: band 88, G: band 28, B: band 18



SAM Classification

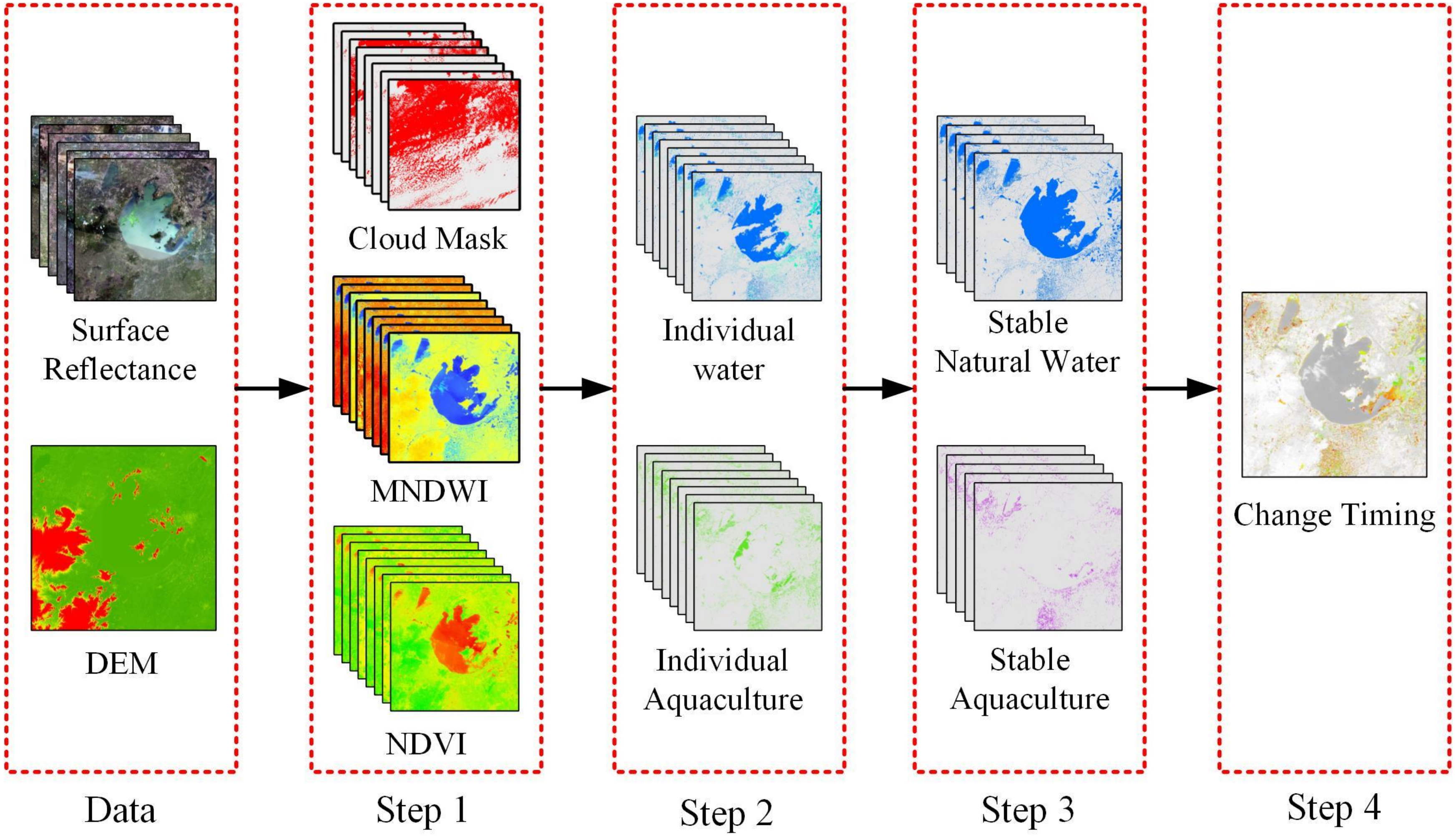


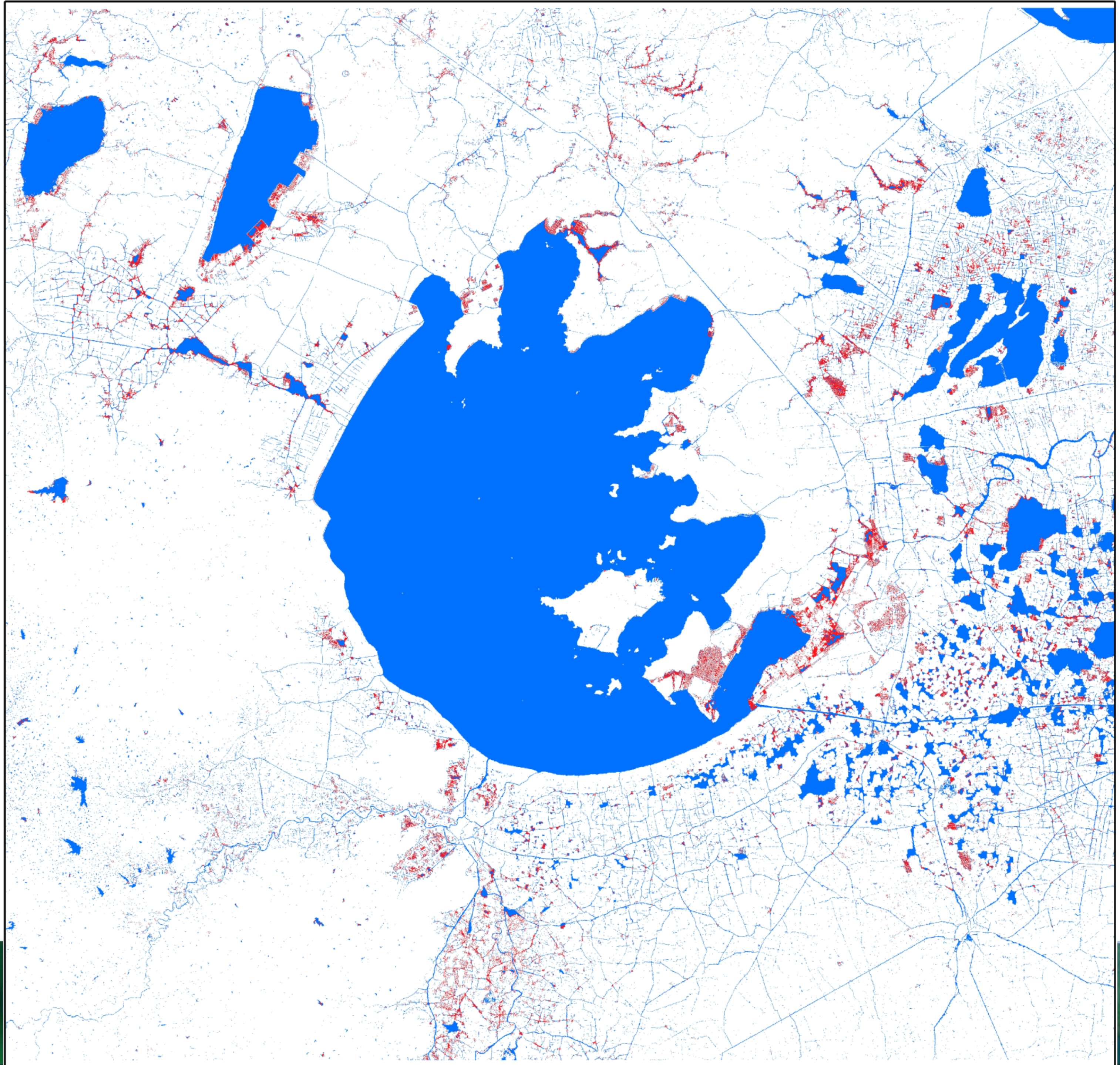
(a) 2009.10.21



(b) 2009.05.01

LST result by modified mono-window algorithm
from TIR image of HJ-1


Cloud Mask
Surface
Reflectance
MNDWI
DEM
NDVI
Individual
water
Individual
Aquaculture
Stable
Natural Water
Stable
Aquaculture
Change Timing
Data
Step 1
Step 2
Step 3
Step 4



18–23 Novem

Content

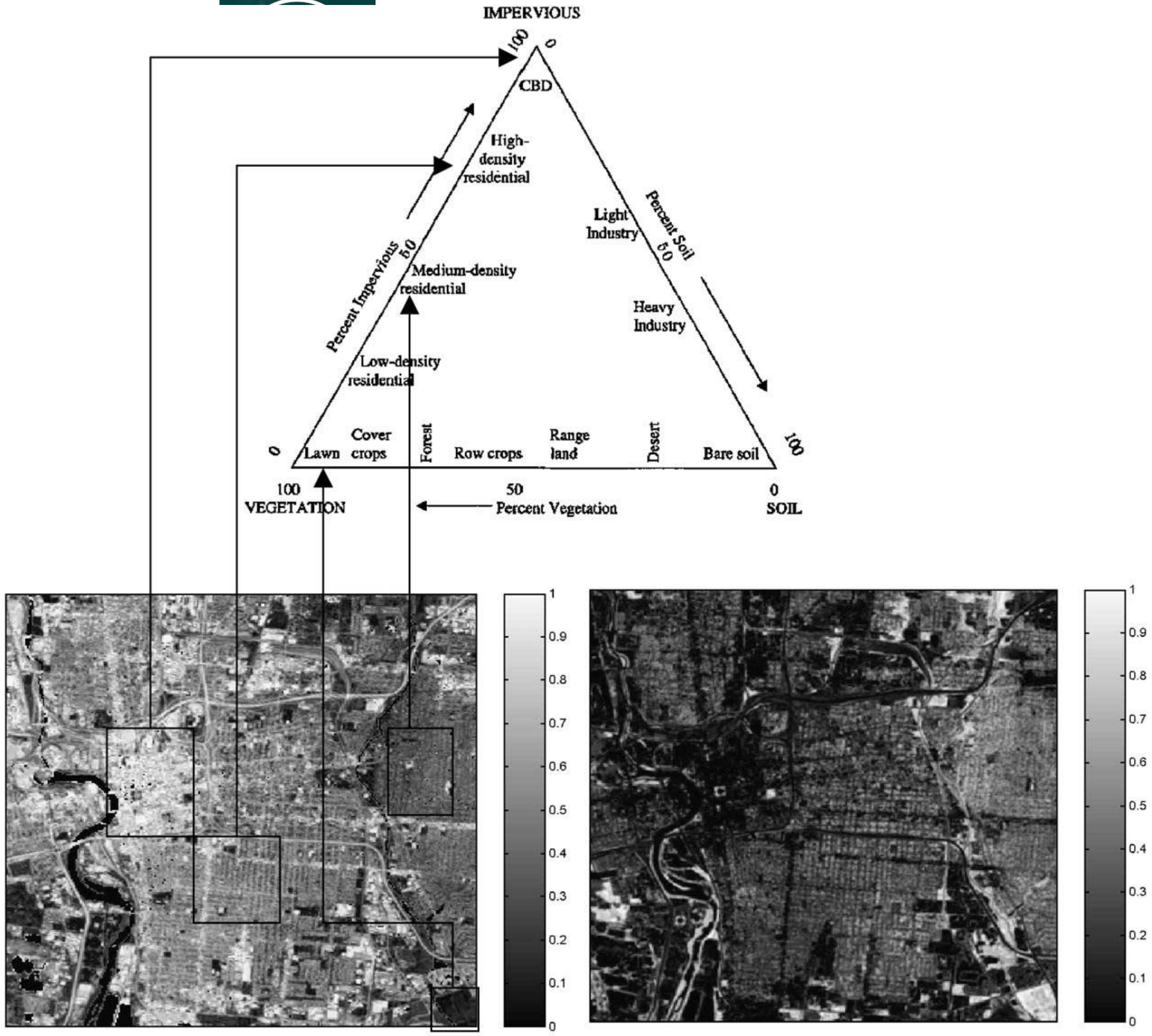
Impervious surfaces are anthropogenic features through which water cannot infiltrate into the soil, such as roads, driveways, sidewalks, parking lots, rooftops, and so on.

- Field survey with GPS
- Manual digitizing from hard-copy maps or RS imagery
- Image classification
- Spectral mixture analysis

Qihao Weng, Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sensing of Environment 117 (2012) 34–49

Vegetation – impervious surface-soil (V-I-S) model

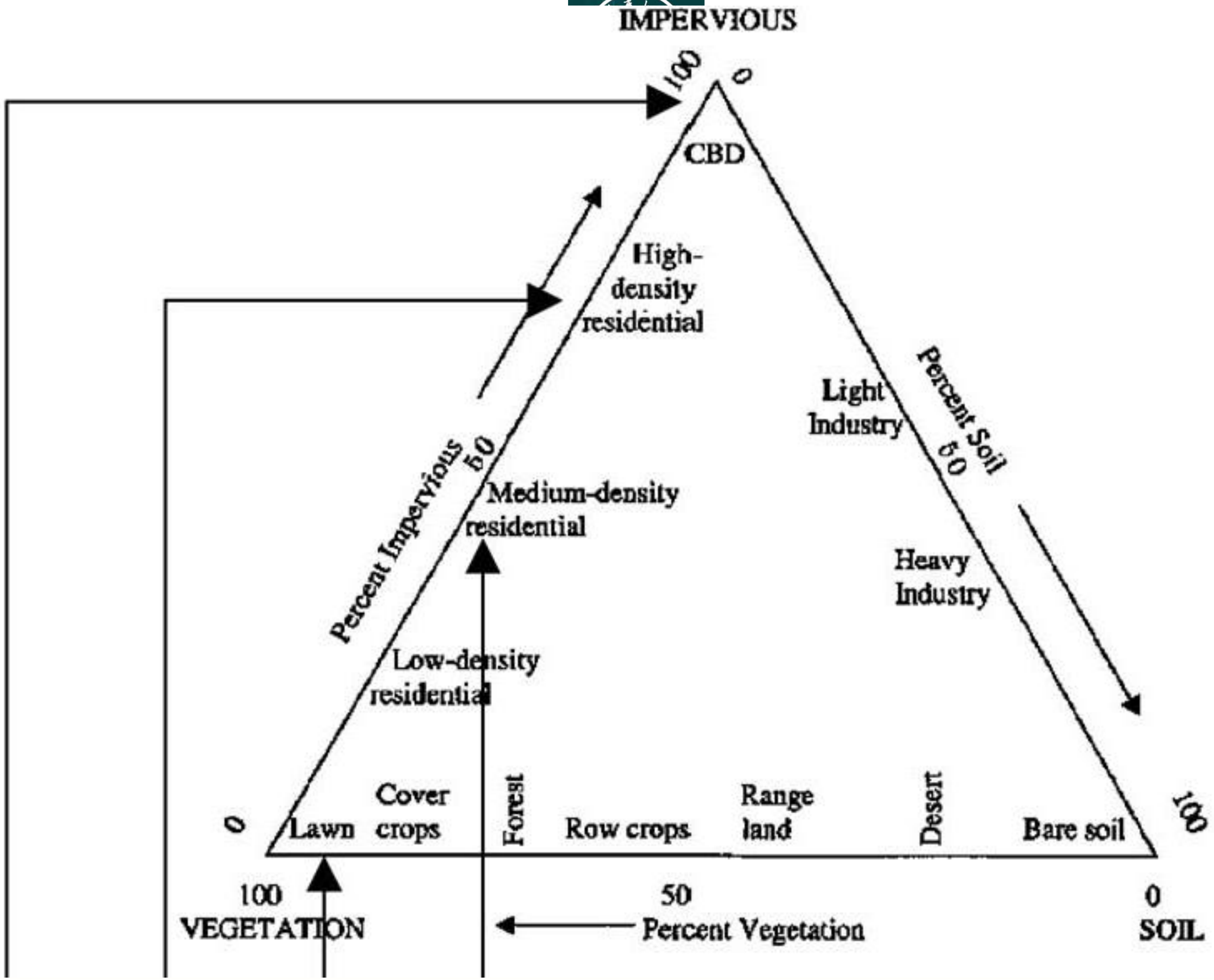
(Ridd, 1995)



Fraction image of impervious surface

Fraction image of vegetation

Changshan Wu,
Alan T. Murray.
Remote Sensing of Environment 84 (2003) 493–505

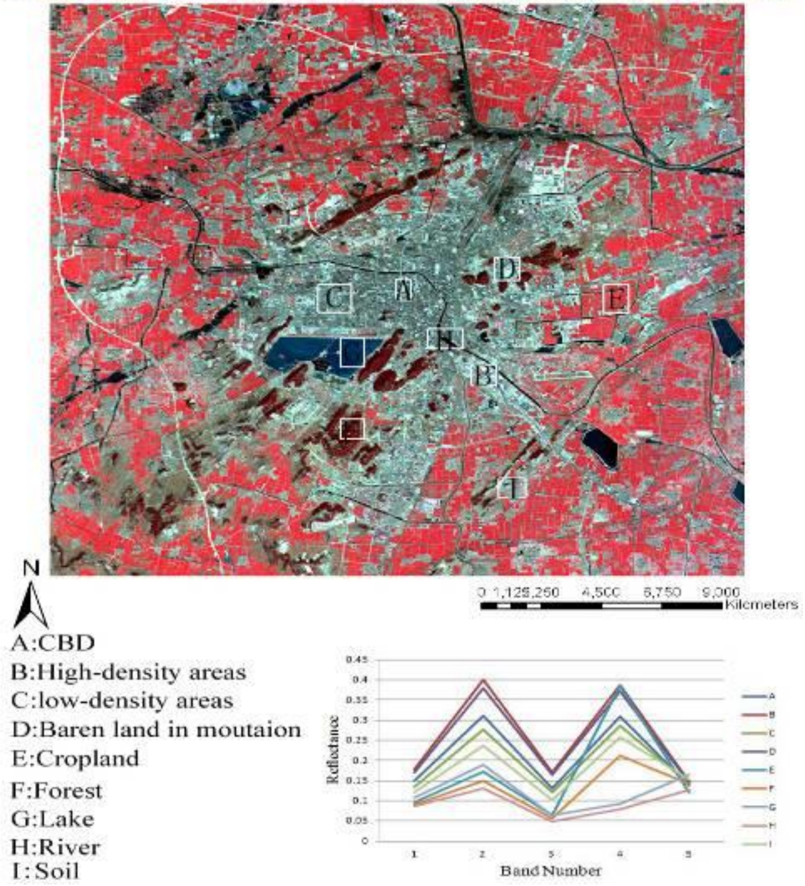

IMPERVIOUS
100
0
CBD
High-density residential
Light Industry
Percent Soil
50
Percent Impervious
50
Medium-density residential
Heavy Industry
Low-density residential
0
Lawn
Cover crops
Forest
Row crops
Range land
Desert
Bare soil
100
100
VEGETATION
50
Percent Vegetation
0
SOIL

Extracting Impervious surface based on spectral mixture analysis

- Image preprocessing
- Endmember extraction
- Abundance estimation by spectral mixture model
- Impervious surface estimation.

Spectral mixture Models: Linear SMM, ANN (SOM, MLP)

The Flase Color Image of the Study Area
(CBERS 02B-R:Band4, G:Band3, B:Band 2)

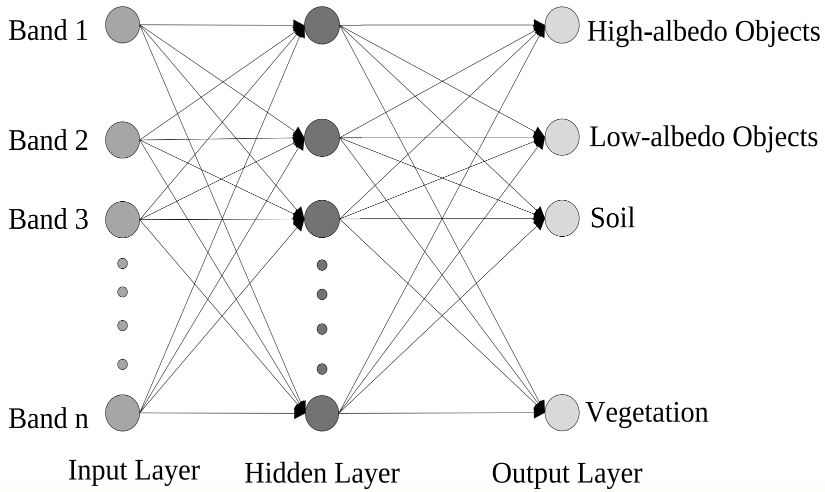


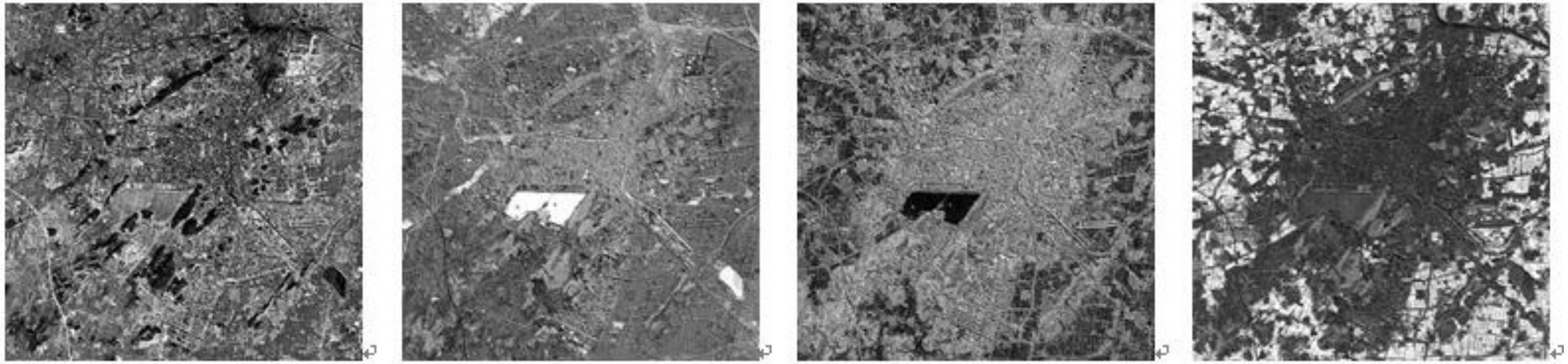
Linear spectral Mixture Model (LSMM)

$$\mathrm{R}_b = \sum_{i=1}^{n} f_{i,b} R_{i,b} + e_b$$

$$\sum_{i=1}^{n} f_i = 1 \qquad f_i > 0$$

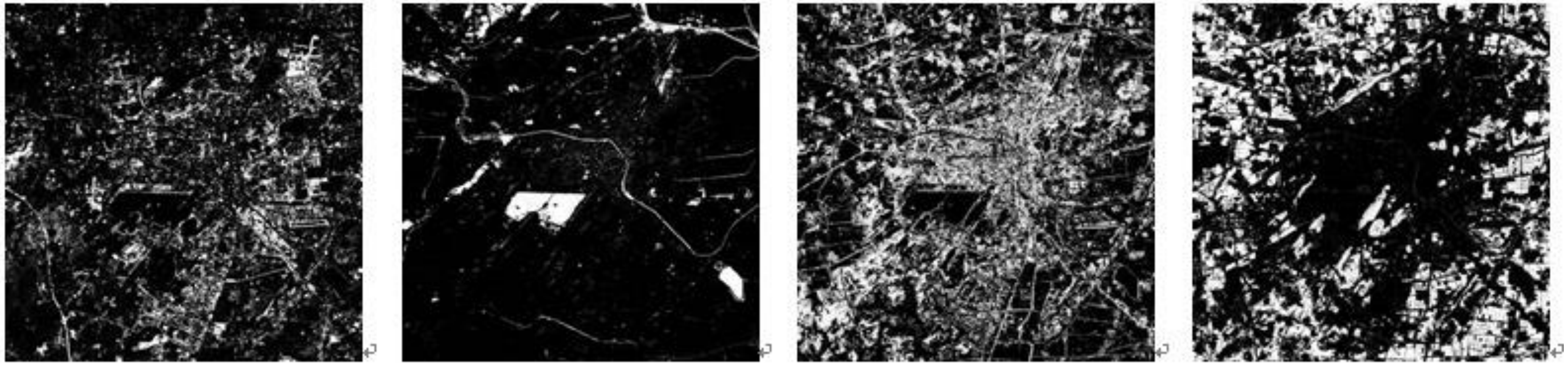
MLP neural network





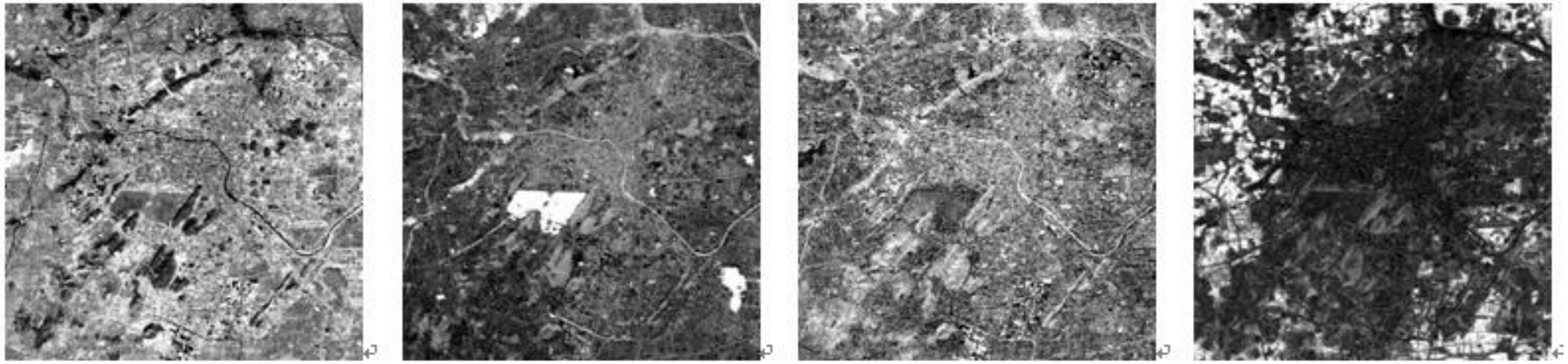
High-albedo Low-albedo Soil Vegetation

(a) 2005 CBERS LSMM four fraction images



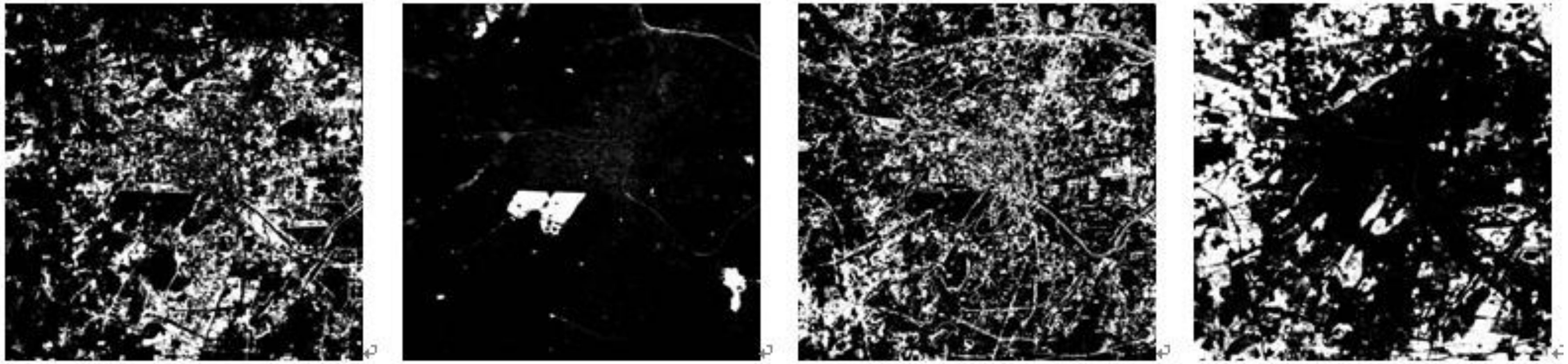
High-albedo Low-albedo Soil Vegetation

(b) 2005 CBERS MLP four fraction images



High-albedo Low-albedo Soil Vegetation

(c) 2009 HJ-1 LSMM four fraction images



High-albedo Low-albedo Soil Vegetation

(d) 2009 HJ-1 MLP four fraction images

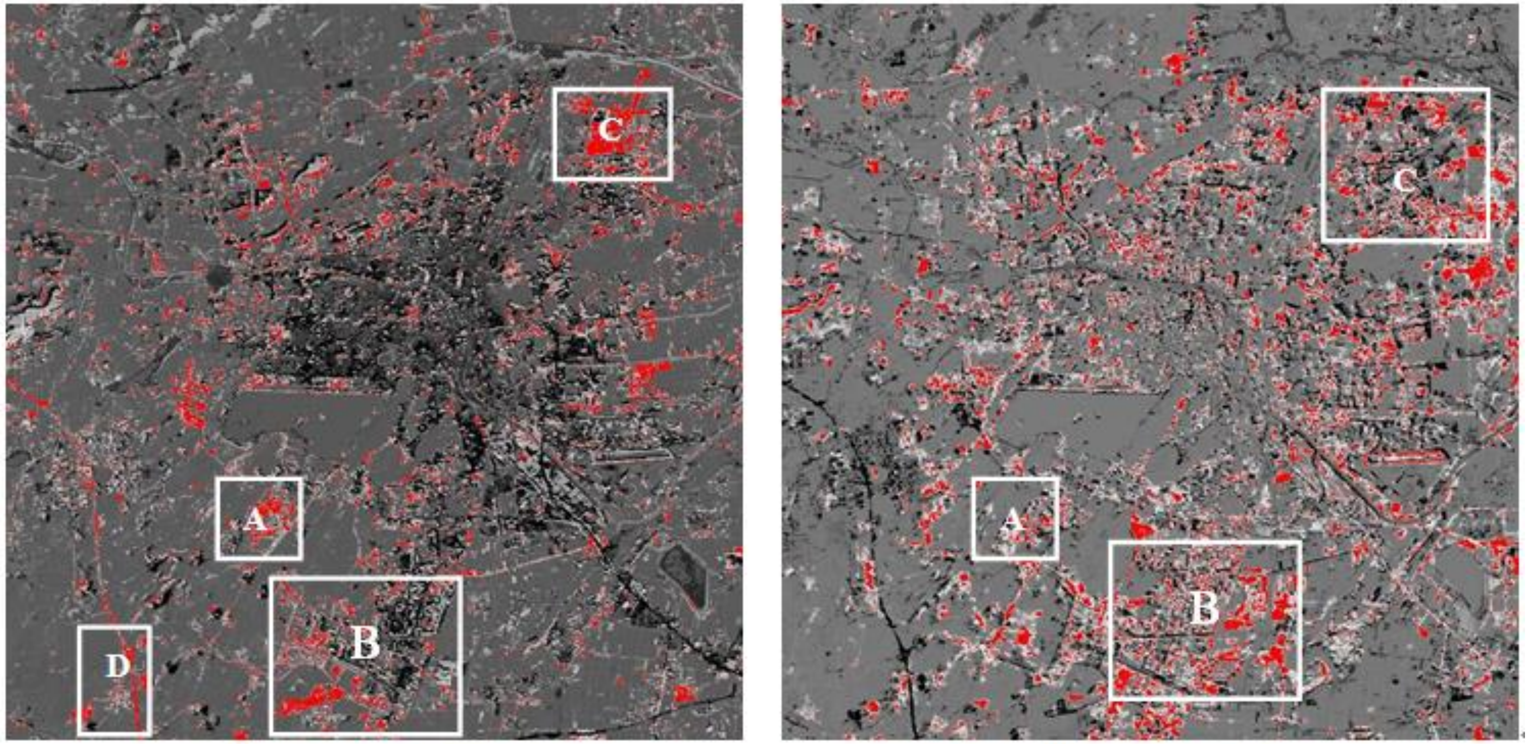
0 1

SE , RMSE and R^2 results of accuracy assessment

	RMSE	SE	R^2
2005-LSMM	0.153	0.131	0.693
2005-MLP	0.122	0.107	0.818
2009-LSMM	0.149	0.127	0.683
2009-MLP	0.147	0.126	0.735

(a) 2001 CBERS image (b) 2005 CBERS image (c) 2009 HJ-1 image

Figure 5. Impervious surface area results using MLP.

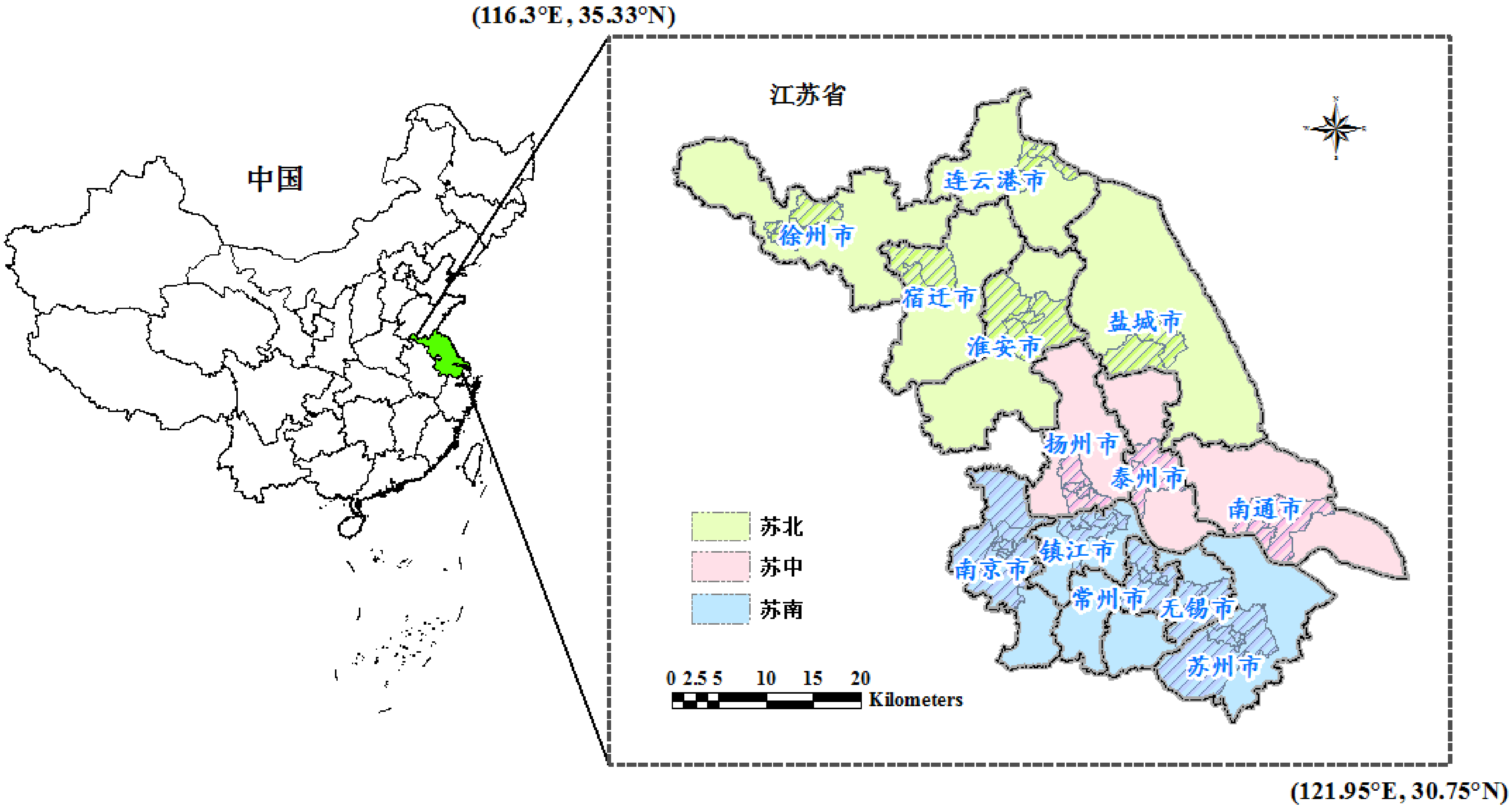


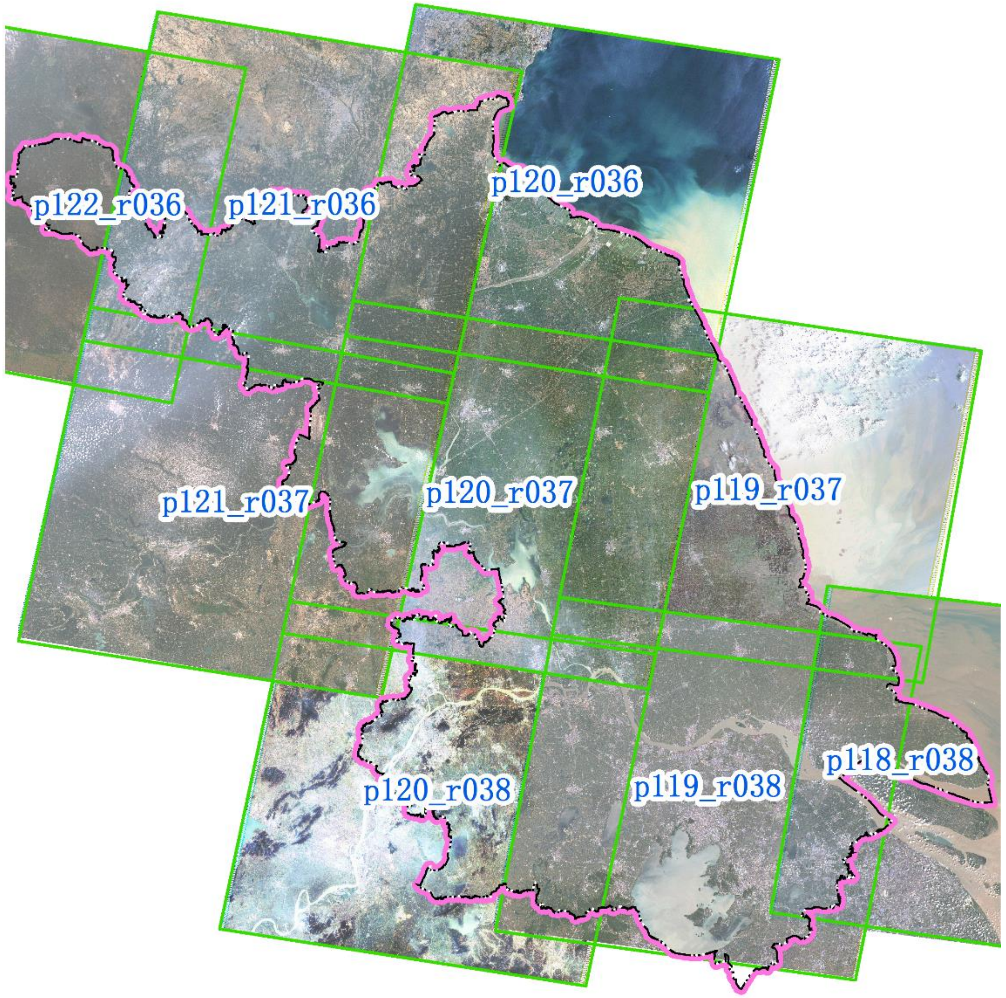
(a) growth area from 2001 to 2005 (b) growth area from 2005 to 2009

A: Nanhu New Campus of CUMT. B: Tongshan New District, C: Northern Industry land, D: Round-the-City Freeway

Unchange Change

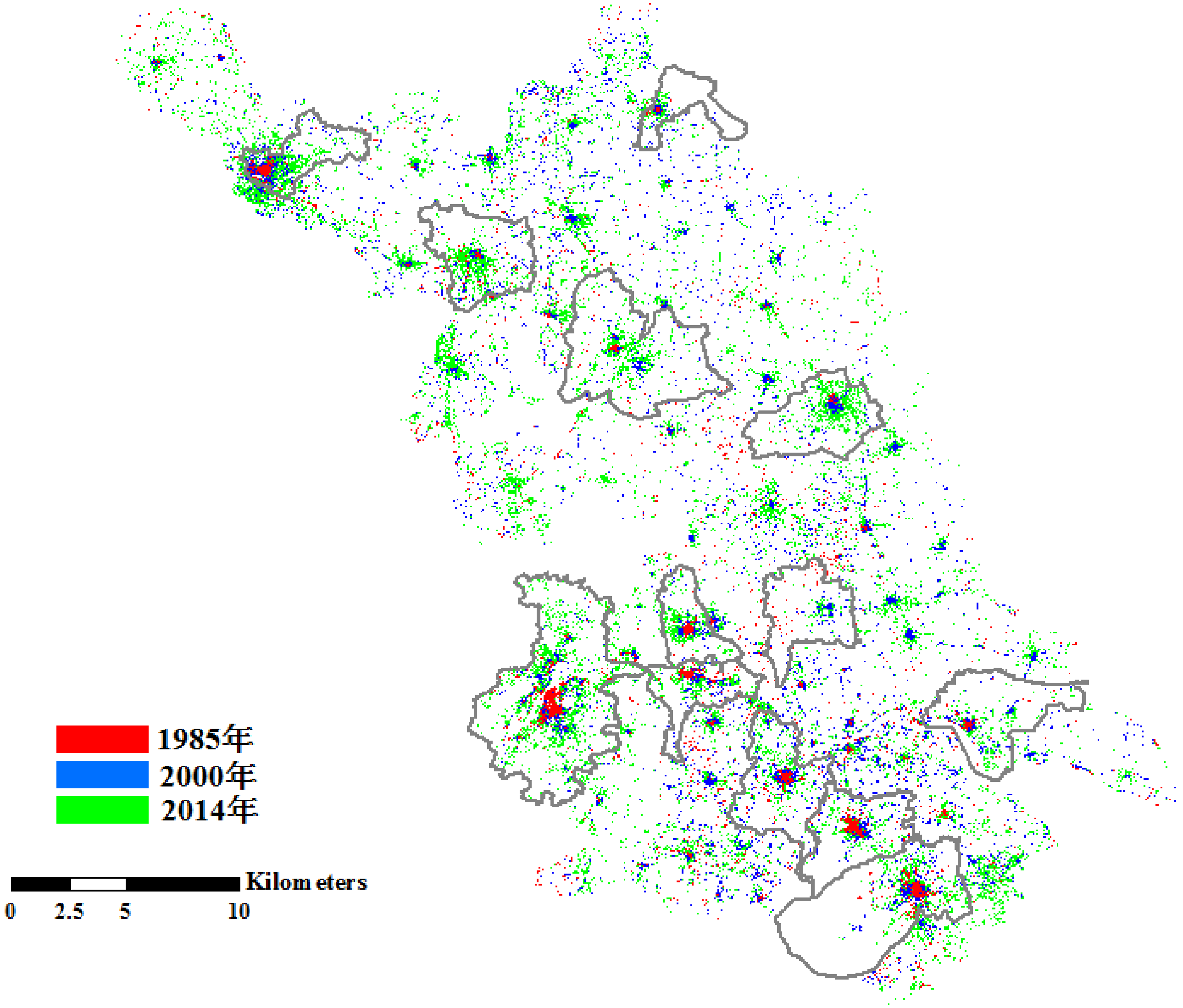
Figure 6. Impervious surface growth area.

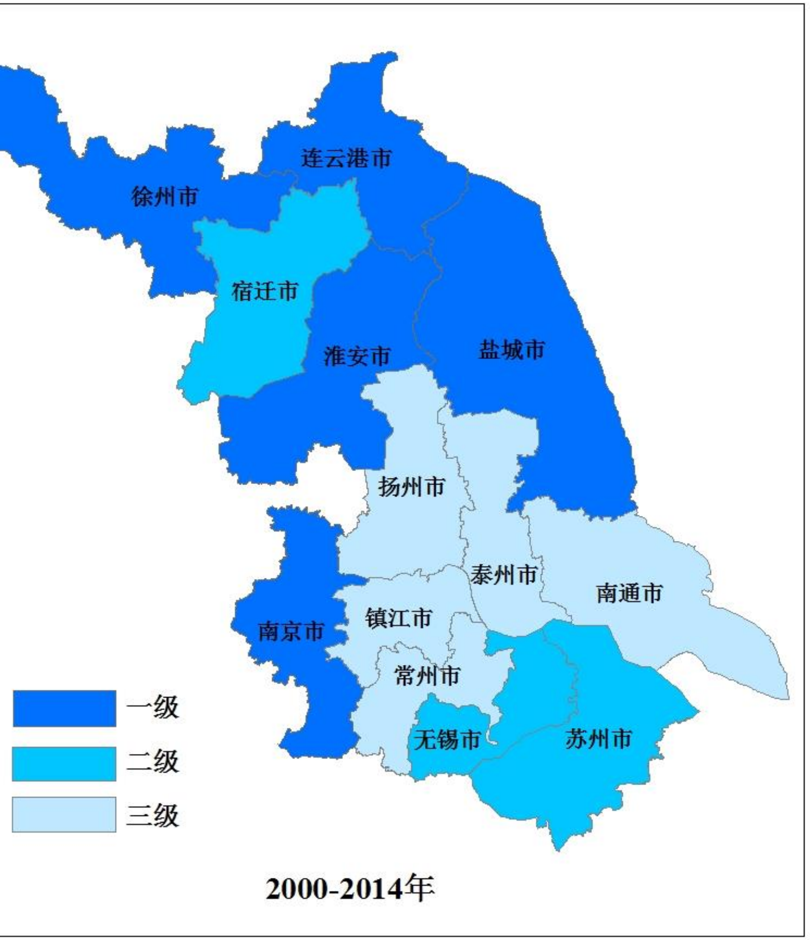

(116.3°E, 35.33°N)
中国
江苏省
连云港市
徐州市
宿迁市
盐城市
淮安市
扬州市
泰州市
南通市
镇江市
南京市
常州市
无锡市
苏州市
苏北
苏中
苏南
0 2.5 5 10 15 20
Kilometers
(121.95°E, 30.75°N)

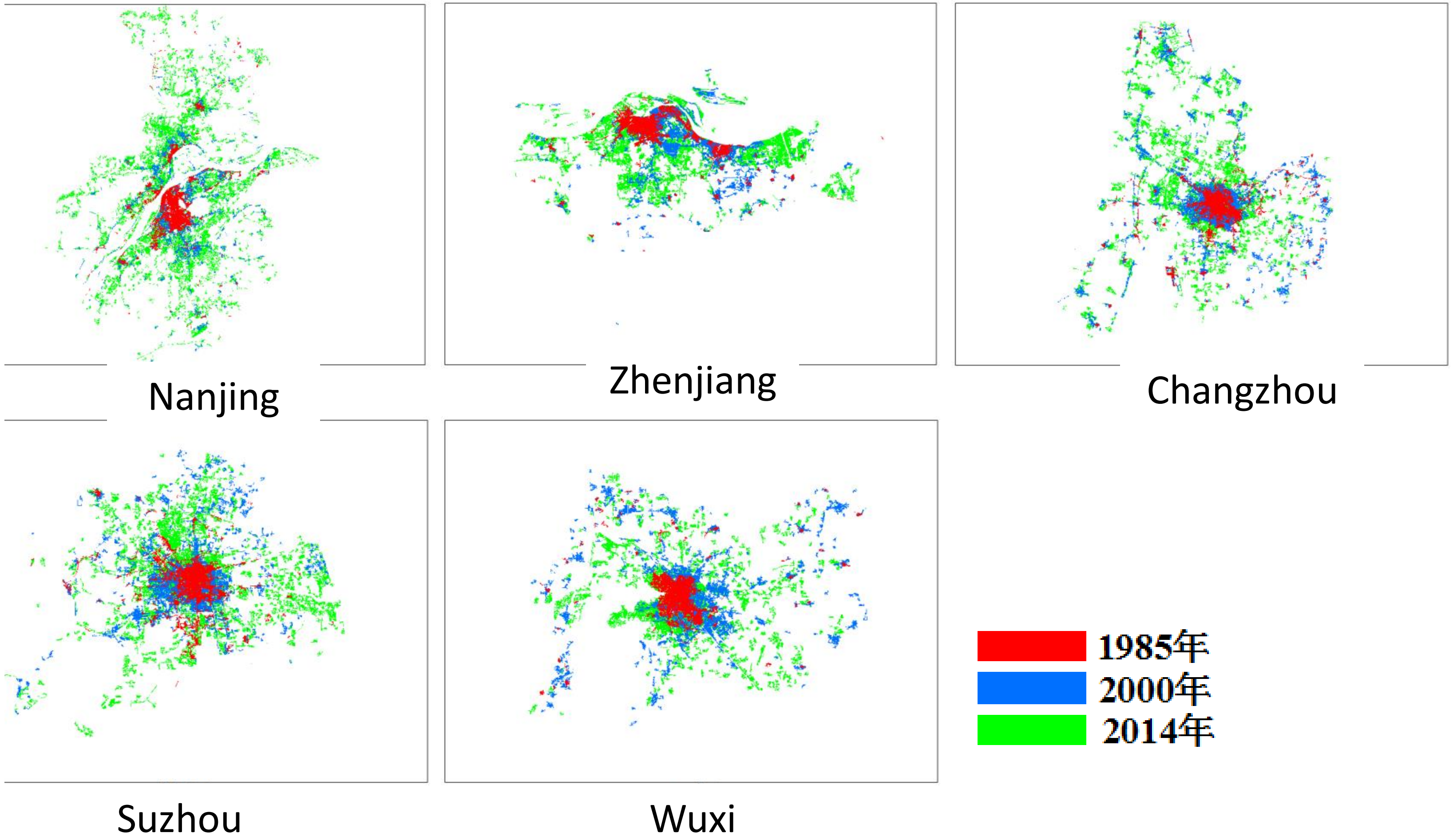


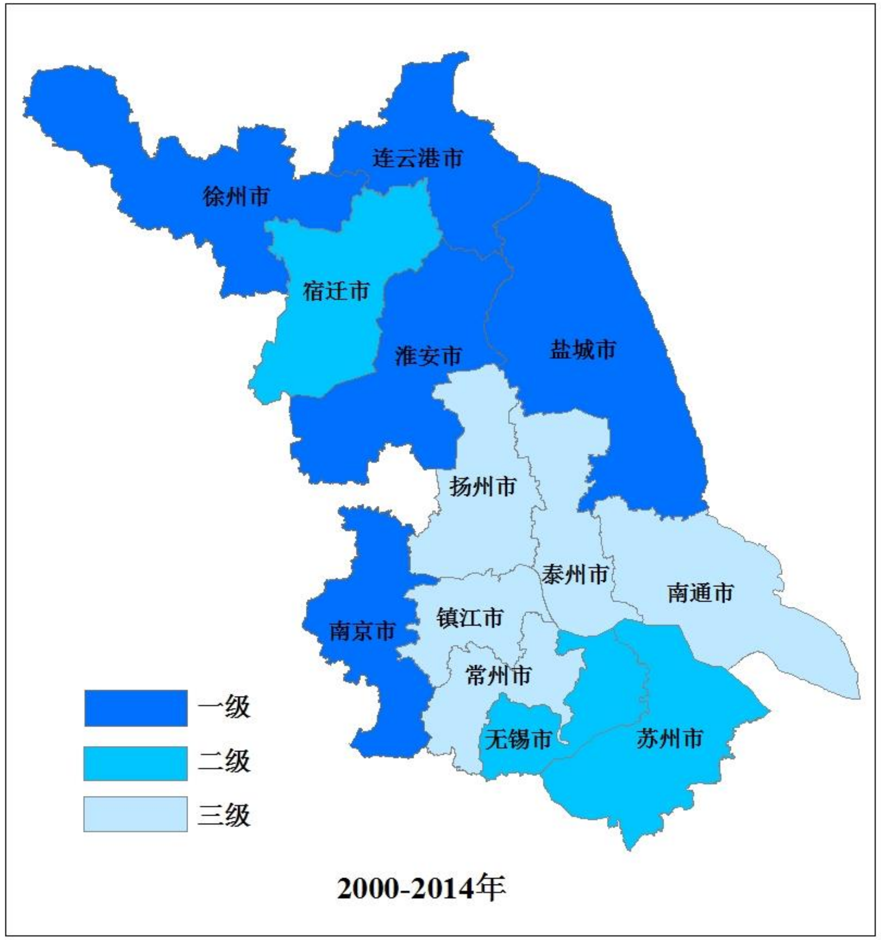
data：

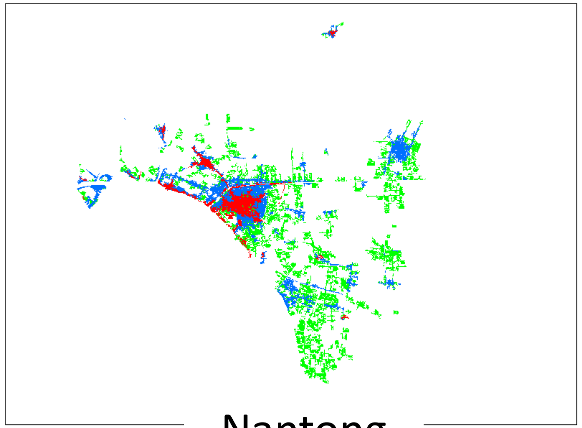
1985, Landsat 5 TM
2000, Landsat 7 ETM+
2014, Landsat 8 OLI


1985年
2000年
2014年
Kilom eters
0
2.5
5
10

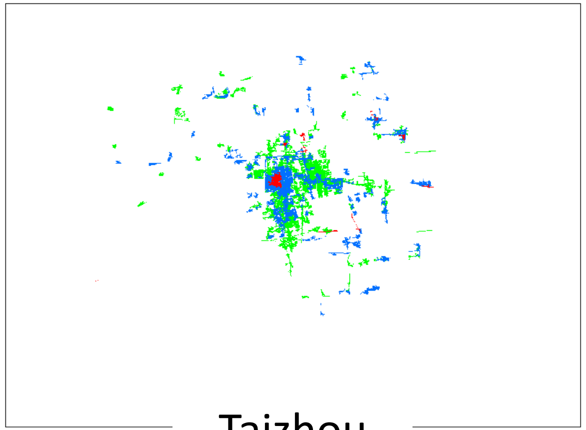

连云港市
徐州市
宿迁市
淮安市
盐城市
扬州市
泰州市
南通市
镇江市
南京市
常州市
无锡市
苏州市
一级
二级
三级
2000-2014年


Nanjing
Zhenjiang
Changzhou
Suzhou
Wuxi
1985年
2000年
2014年

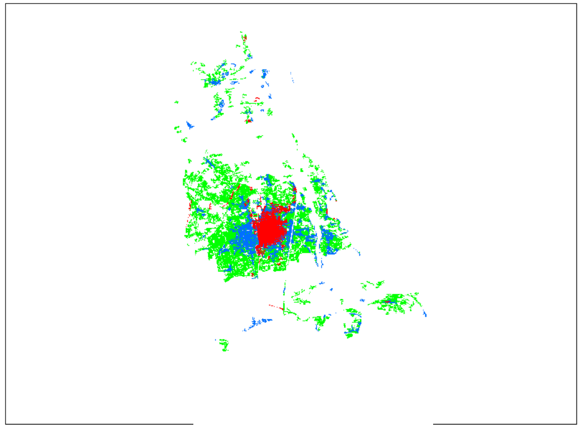




Nantong

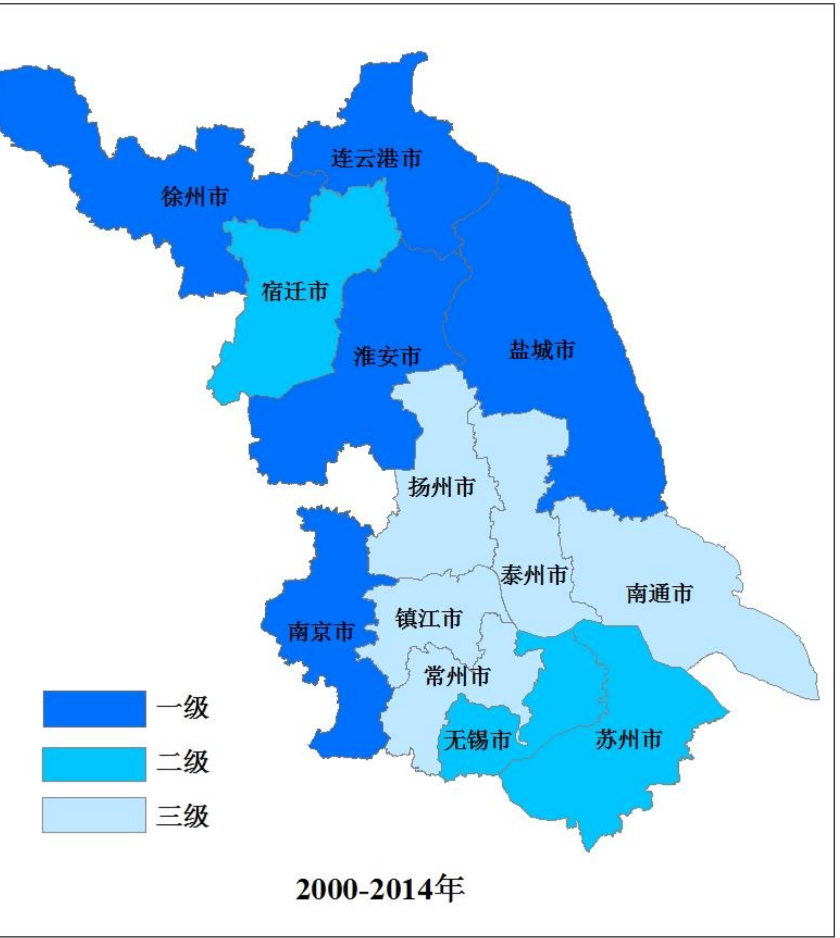


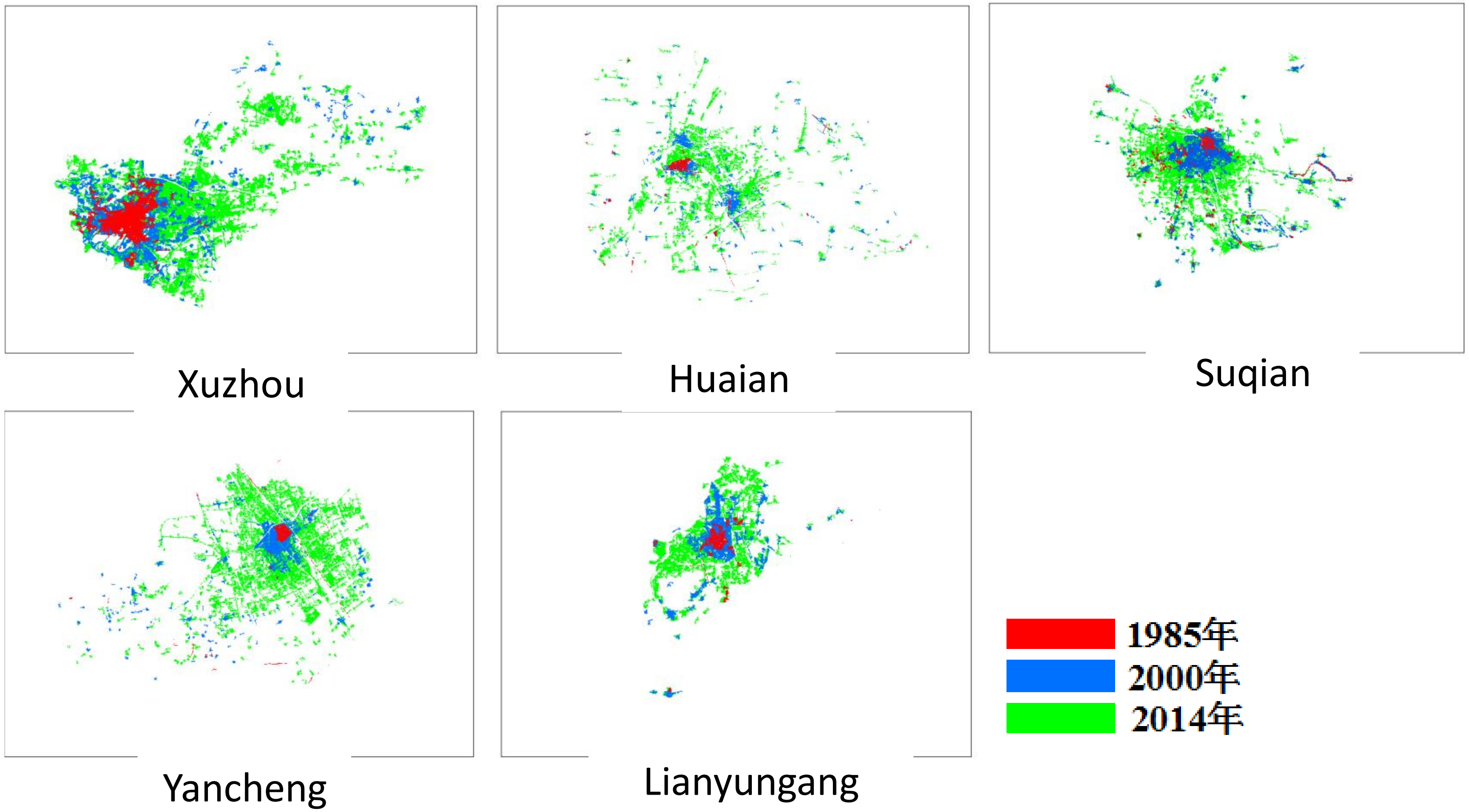
Taizhou



Yangzhou

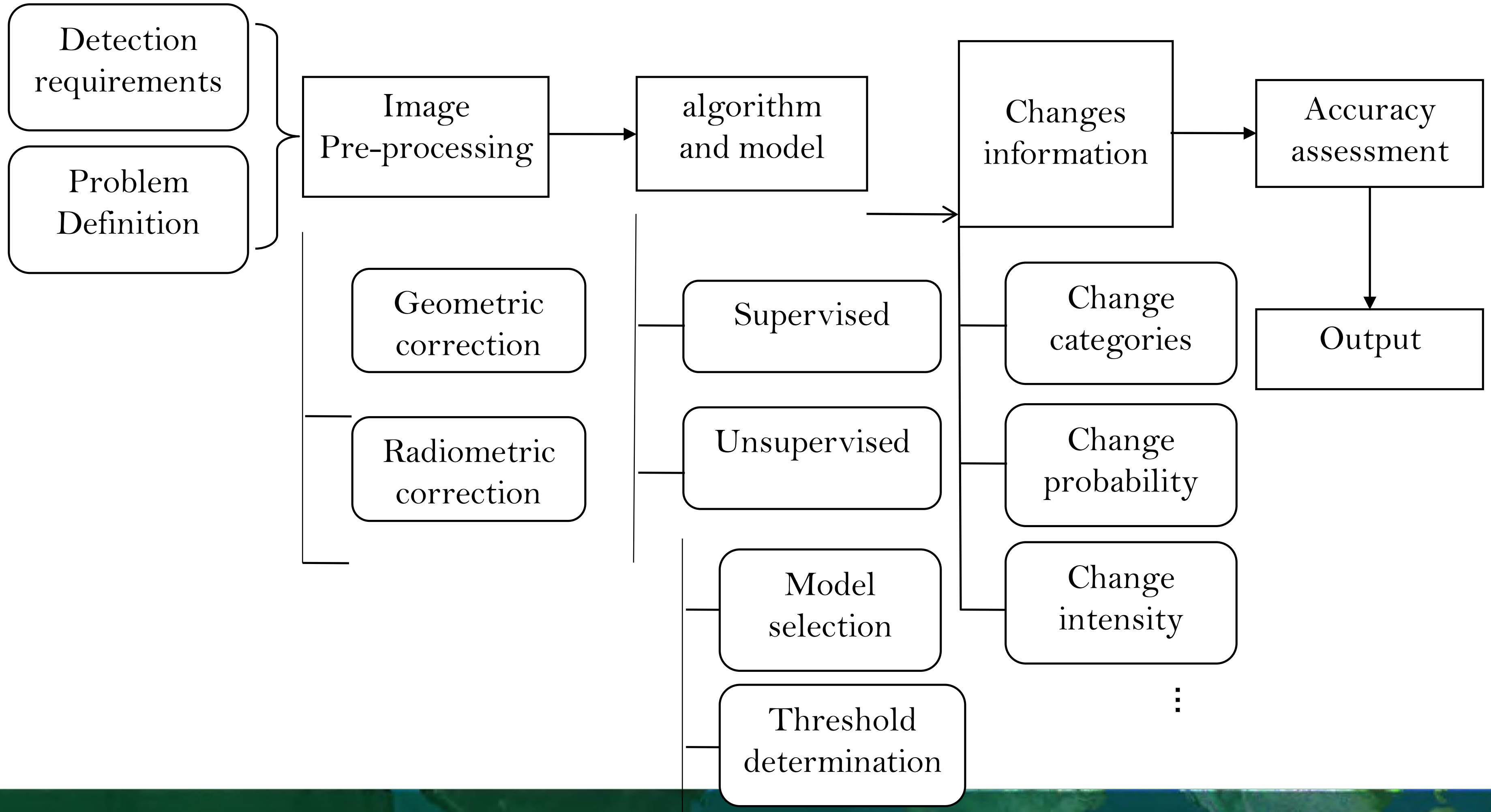
1985年
2000年
2014年


连云港市
徐州市
宿迁市
淮安市
盐城市
扬州市
泰州市
南通市
镇江市
南京市
常州市
无锡市
苏州市
一级
二级
三级
2000-2014年


Xuzhou
Huaian
Suqian
Yancheng
Lianyungang
1985年
2000年
2014年

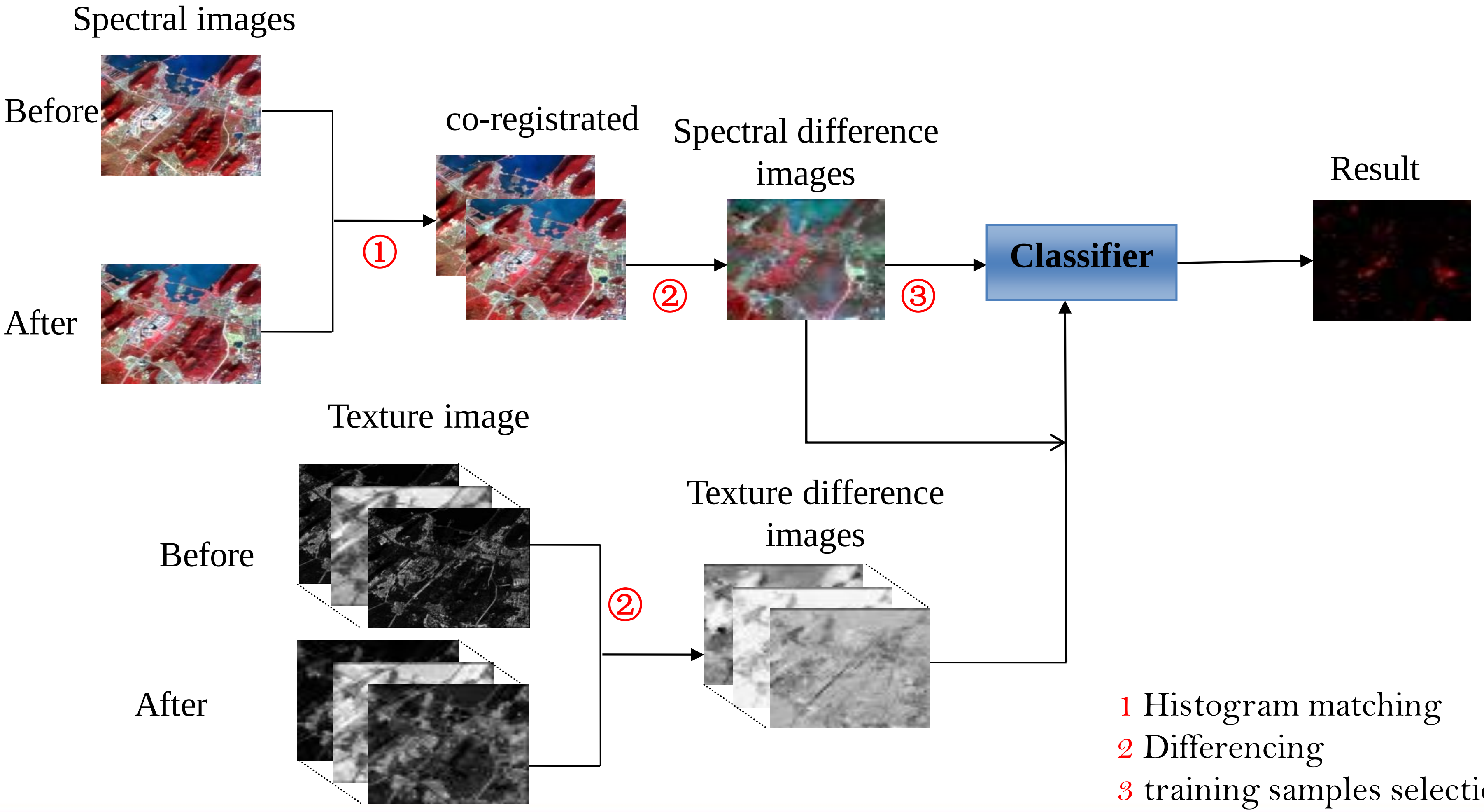
Content

Change detection tries to identify changes in the probability distribution of a stochastic process or time series.



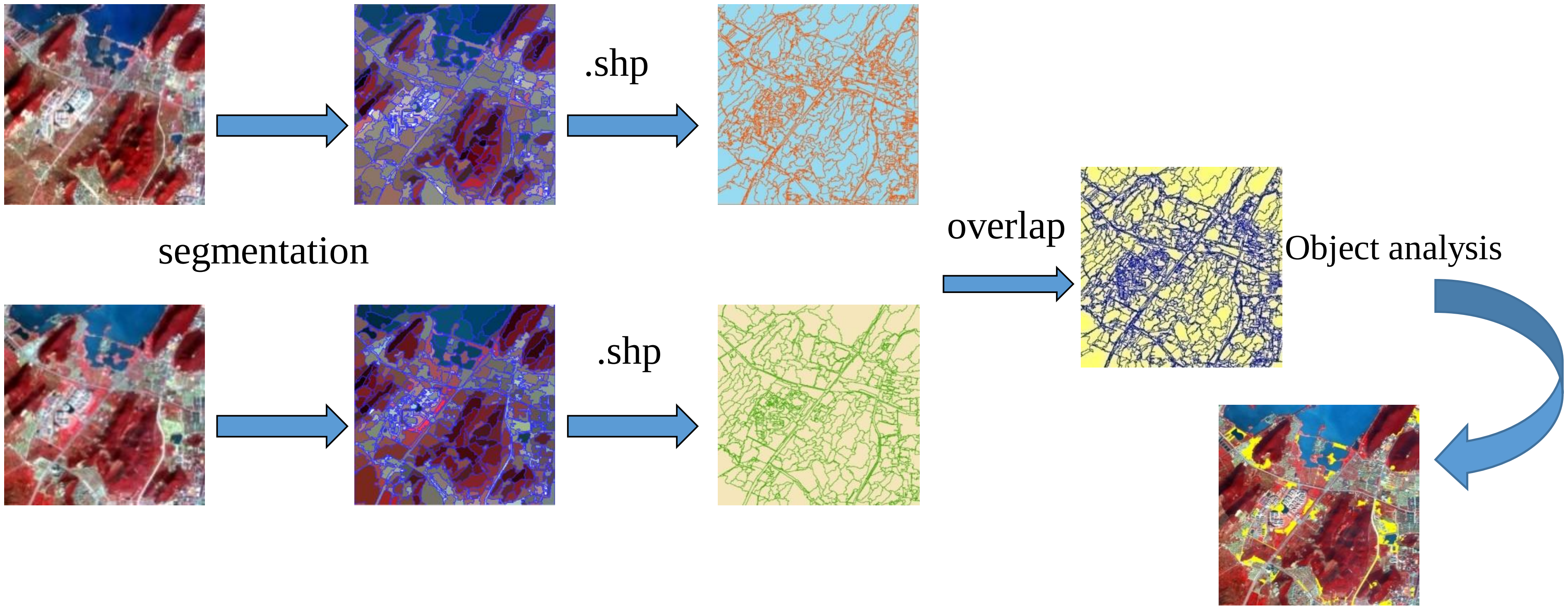
Unsupervised change detection/data			Single band	Multiple bands	
			Panchromatic, SAR, one band/feature of MS/HRS image	**Medium-low multiple spectral image**	**Hyperspectral /Ultraspectral image**
Binary detection	Image algebra	Difference	√		
		Ratio	√		
		Regression analysis	√		
		Distance or similarity measure	√		
	Image transform			√	√
	Image Clustering		√	√	√
Multi-class detection	Change Vector Analysis			√	√
	Image transform			√	√
	iterative weight multivariable			√	√
	Polar coordinate system			√	√
	Image Clustering		√	√	√

Supervised: classifier-based (multiple features)



1 Histogram matching
2 Differencing
3 training samples selection

Supervised: object oriented-based



Information fusion techniques for change detection from multi-temporal remote sensing images

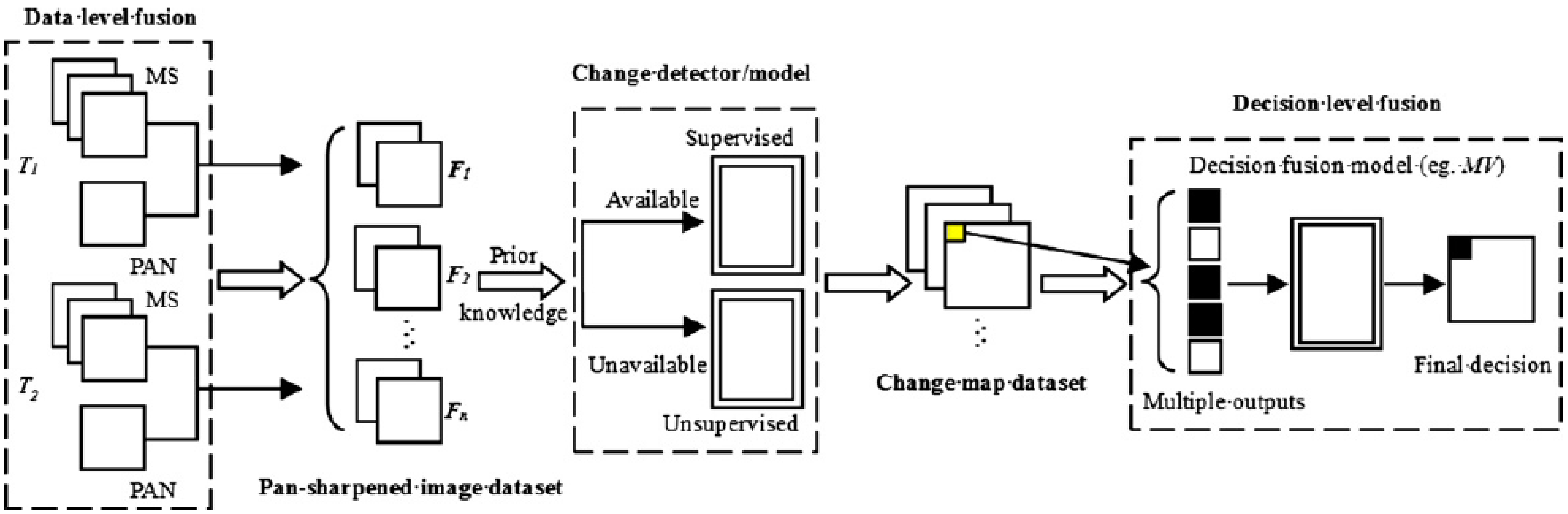


Fig. 1. Flowchart of the proposed change detection procedure based on information fusion techniques.

Peijun Du, Sicong Liu, Junshi Xia, Yindi Zhao. Information Fusion 14 (2013) 19–27

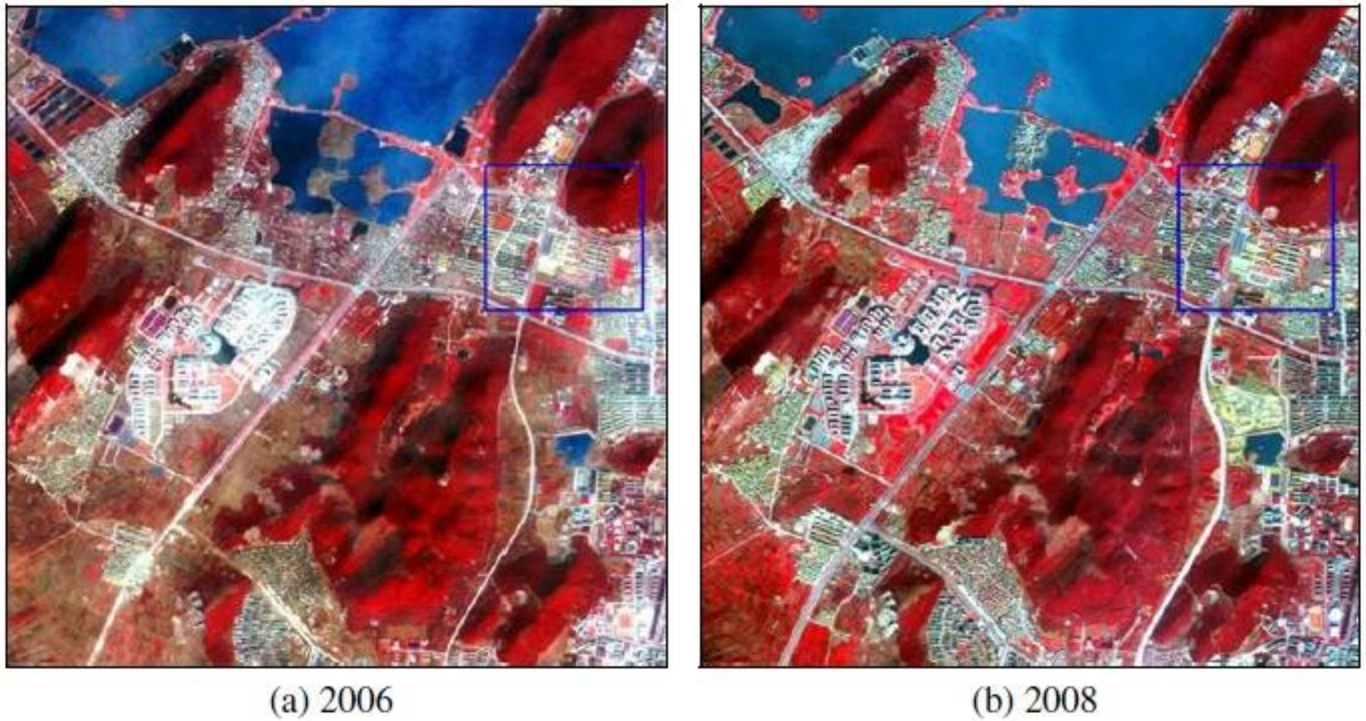
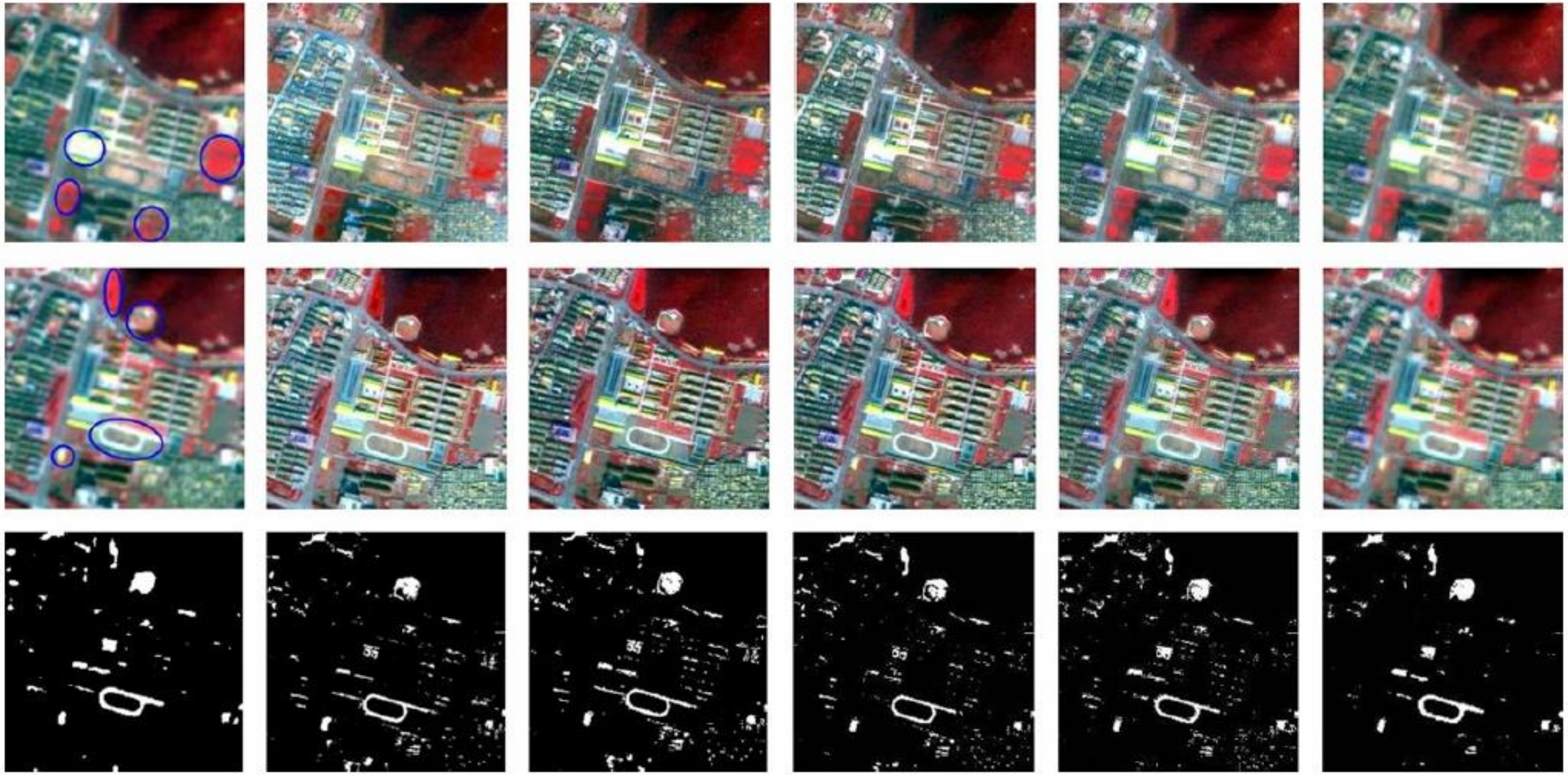
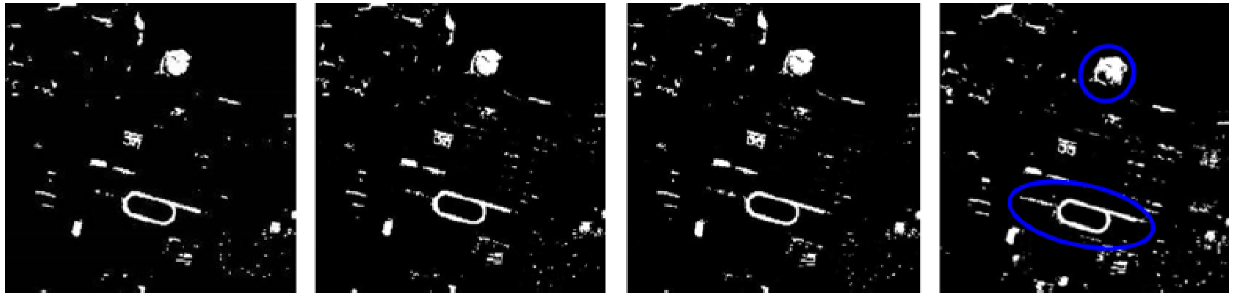


Fig. 6. False composite images of ALOS pan-sharpened data over the study area.



(a) Original *MS* (b) *GIHS* (c) *GS* (d) *PCA* (e) *HPF* (f) *WT*



(a) *MV* (b) *DS* (c) *FI* (d) PCA

Fig. 8. Change detection results from decision level fusion strategy.

Table 4
Accuracy and errors of change detection results from different fusion strategy.

Dataset and fusion	Fusion method	Overall accuracy (%)	Kappa coefficient	Omission ratio (%)	Commission ratio (%)	Omission errors	Commission errors	Overall errors
Second stage-decision level fusion	*MV*	89.44	0.7828	17.39	7.56	687	**267**	**954**
	FI	89.37	0.7820	16.35	8.68	**646**	314	960
	D–S	89.36	0.7817	16.38	8.68	647	314	961
First stage-data level fusion	*PCA*	88.29	0.7599	17.62	9.99	696	361	1057
	GIHS	88.33	0.7598	19.11	8.56	755	**299**	**1054**
	GS	88.22	0.7587	16.91	10.77	**668**	396	1064
	HPF	87.63	0.7458	19.27	10.04	761	356	1117
	WT	87.11	0.7340	21.67	9.05	856	308	1164
Original *MS* data	–	84.72	0.6851	23.75	12.80	938	442	1380

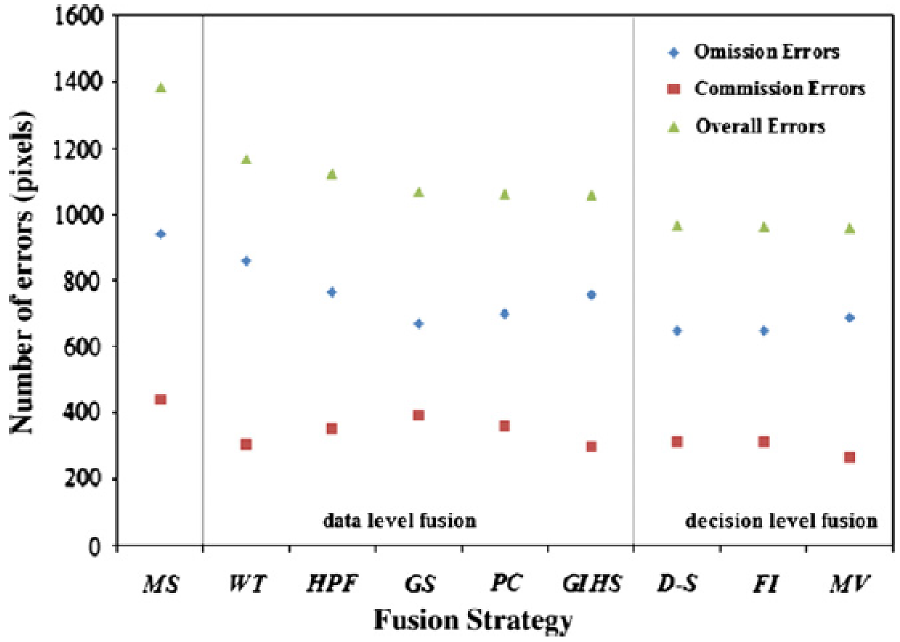


Fig. 9. Errors of change detection from different fusion strategies.

Fusion of Difference Images for Change Detection

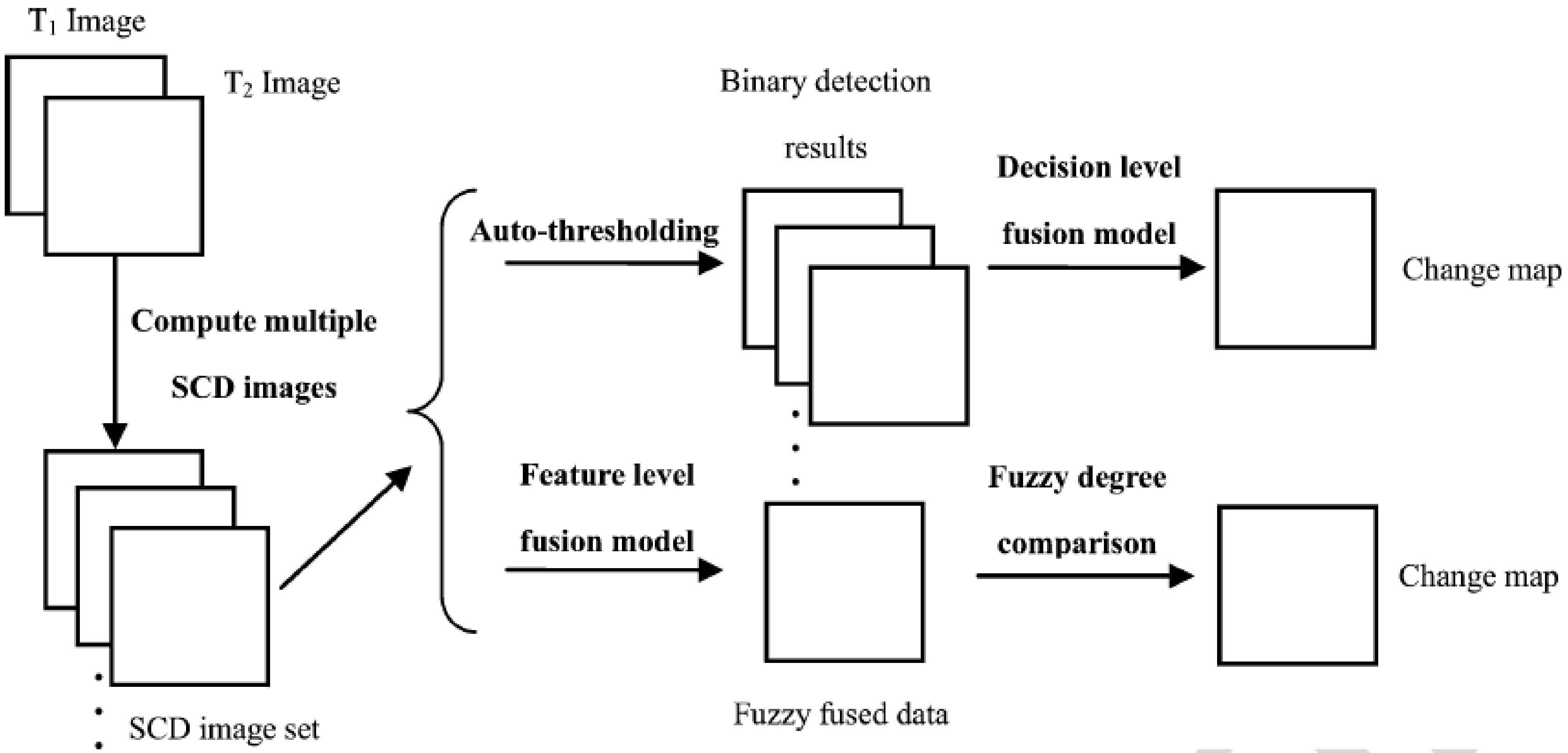
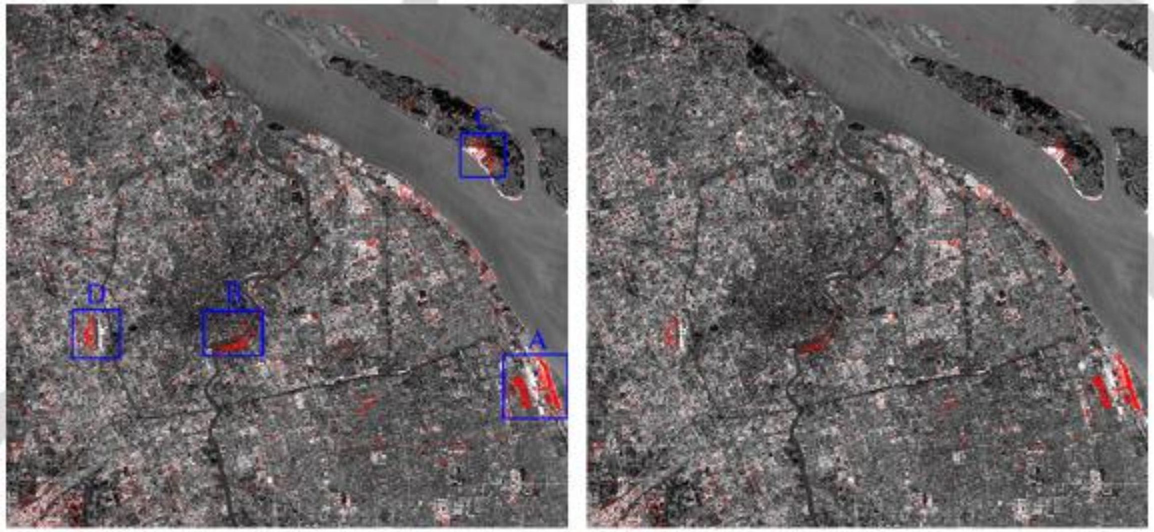


Fig. 1. Flowchart of the fusion procedure aimed at fusing multiple spectral change difference (SCD) images.

Peijun Du, *Sicong Liu, Paolo Gamba, Kun Tan, and Junshi Xia. IEEE J-STARS, 2012*

Fig. 2. False color composites of 2005 and 2009 CBERS images for the first test site (Shanghai). (a) 2005; (b) 2009.

(a) (b)



(a) (b)

Fig. 3. Change detection results (in red) for the Shanghai test site using two level fusion schemes: (a) feature level fusion; (b) decision level fusion using Majority Voting. In blue the areas highlighted in Fig. 4: A-Pudong International Airport; B-Expo Park of World Expo 2010, C-Jiangnan Shipyard located in Changxing Island, and D-Hongqiao International Airport.

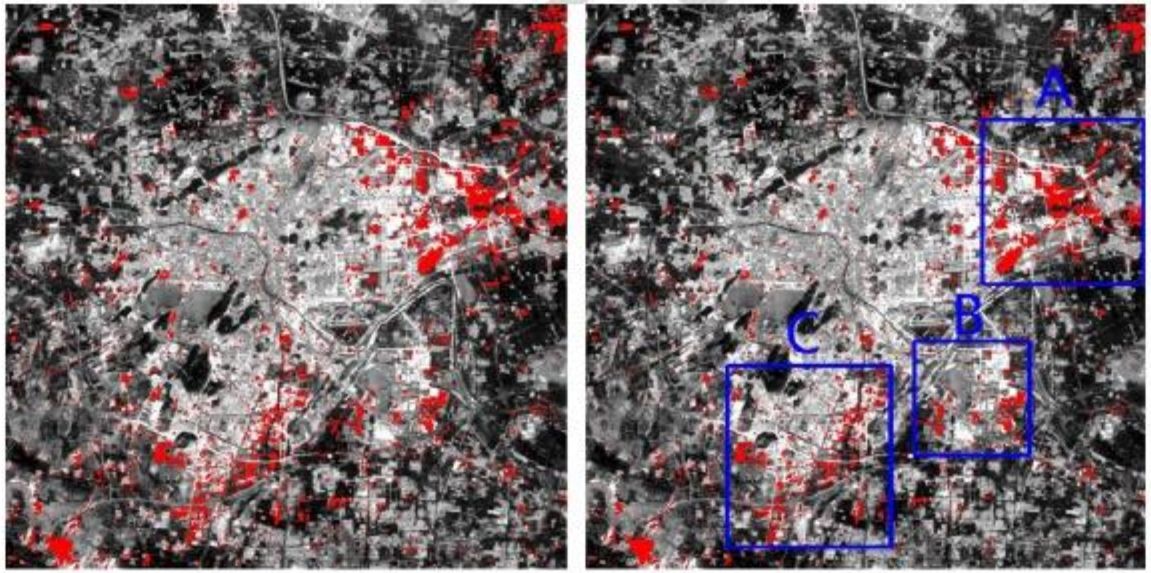
TABLE III

ACCURACY VALUES FOR THE SHANGHAI TEST SITE

Fusion Level	Fusion Method	*Overall Accuracy (%)*	*Kappa*	*Omission (%)*	*Commission (%)*
Single SCD Image	Y_{SD}	87.04	0.7353	23.34	6.01
	Y_{SR}	86.74	0.7292	23.71	6.36
	Y_{AD}	88.35	0.7617	22.84	3.19
	Y_{ED}	88.68	0.7704	16.82	8.63
	Y_{CST}	88.96	0.7751	19.74	5.10
Feature Level	*FS*	91.43	0.8268	11.39	7.61
Decision Level	*MV*	90.74	0.8014	19.30	4.76
	DS	90.71	0.8010	19.82	4.06
	FI	91.04	0.8075	19.26	3.96

(a) (b)

Fig. 5. False color composite images of the secon
HJ-1/B data; (b) 2011 HJ-1/A data.



(a) (b)

Fig. 6. Change detection results (in red) in the Xuzhou test site using two level fusion schemes: (a) feature level fusion; (b) decision level fusion using Majority Voting. In blue the areas highlighted in Fig. 7: A- Xuzhou Economic Development Zone, B- anew district of Xuzhou, C- Tongshan new area.

TABLE V
ACCURACY VALUES FOR THE XUZHOU TEST SITE

Fusion Level	Fusion Method	*Overall Accuracy (%)*	*Kappa*	*Omission (%)*	*Commission (%)*
Single SCD Image	Y_{SD}	87.32	0.7265	18.11	16.61
	Y_{SR}	86.70	0.7233	10.17	22.42
	Y_{AD}	88.96	0.7620	15.78	14.42
	Y_{ED}	87.99	0.7386	19.28	14.19
	Y_{CST}	90.52	0.7938	15.78	10.57
Feature Level	*FS*	92.12	0.8307	7.99	13.29
Decision Level	*MV*	91.91	0.8219	13.75	9.38
	DS	92.11	0.8267	13.16	9.33
	FI	92.58	0.8355	13.51	8.91

Content

Conclusions:

- Urban mapping at different scales is an important direction of remote sensing applications
- Both qualitative mapping (urban extent, land cover/use) and quantitative mapping (LST, ISA percentage) are important
- Thematic mapping (water, vegetation, ISA) is useful.
- Chinese EO data are effective to urban mapping
- The potential use of Sentinel-2 and other satellites

Advances:

- Animations
- 3D mapping/ Virtual City
- Raster to Vector
- Novel algorithms
- Urban development modeling (CA, MAS, and so on.)
- Link urban mapping with environmental analysis
- and so on.

New data & sensors for urban area remote sensing

- SAR
- InSAR
- Airborne and terrestrial LiDAR
- VHR optical orbital and airborne sensors and data
- Hyperspectral sensors and data
- Thermal IR sensors and data
- UAVs and airborne sensors

Structure detection and characterization in urban areas

- Change detection techniques
- Classification algorithms
- Multitemporal analysis
- Feature extraction methods
- Calibration and correction approaches

Algorithms and techniques for remotely sensed data interpretation in urban areas

- Building extraction and reconstruction
- Road and road network extraction
- Vehicle detection and traffic monitoring
- Urban area extraction
- Land use and land cover mapping
- Data mining

Algorithms and techniques for urban area applications

- Urban modeling
- Urban area trend monitoring
- Urban heat island monitoring
- Urban atmosphere monitoring
- GIS & remote sensing data fusion

Urban climatology, geology, and geohazards

- Urban heat island effects
- Air quality assessment
- Subsidence
- Hydrology
- Earthquake/Volcanic/ falling, landslide and debris flow geological hazards/Coastal hazards
- Environmental monitoring (soil, groundwater contaminant)

RS applications to social science

- Applications to vital statistics
- RS and health
- RS and GIS applications to social science
- Applications to security and emergency
- Applications to "World Expo" and "Olympic Games"
- RS and GIS applications in archaeology

RS applications to urban planning and conservation

- Urban planning
- Transportation planning
- Digital city
- Urban conservation
- Urban simulation based on RS
- Cultural heritage

Urban development and growth pattern

- Urban development modeling
- Contributions to urban trajectory theory
- Detailed structure change
- Smart growth

Urban and peri-urban ecology

- Urban and peri-urban landscape ecology
- Urban and peri-urban ecological process modeling
- Comparative studies

Thank you for your attention

Welcome to Nanjing University

Contact me: dupjrs@126.com, peijun@nju.edu.cn