



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

Peijun Du

Nanjing University

dupjrs@126.com, peijun@nju.edu.cn

Content

- 1 Urban remote sensing
- 2 Technical flow of urban mapping
- 3 Urban extent mapping
- 4 Urban land cover/land use mapping
- 5 Urban thematic mapping
- 6 ISA estimation and mapping
- 7 Change detection
- 8 Conclusions and Advances

Content

1 Urban remote sensing

2 Technical flow of urban mapping

3 Urban extent mapping

4 Urban land cover/land use mapping

5 Urban thematic mapping

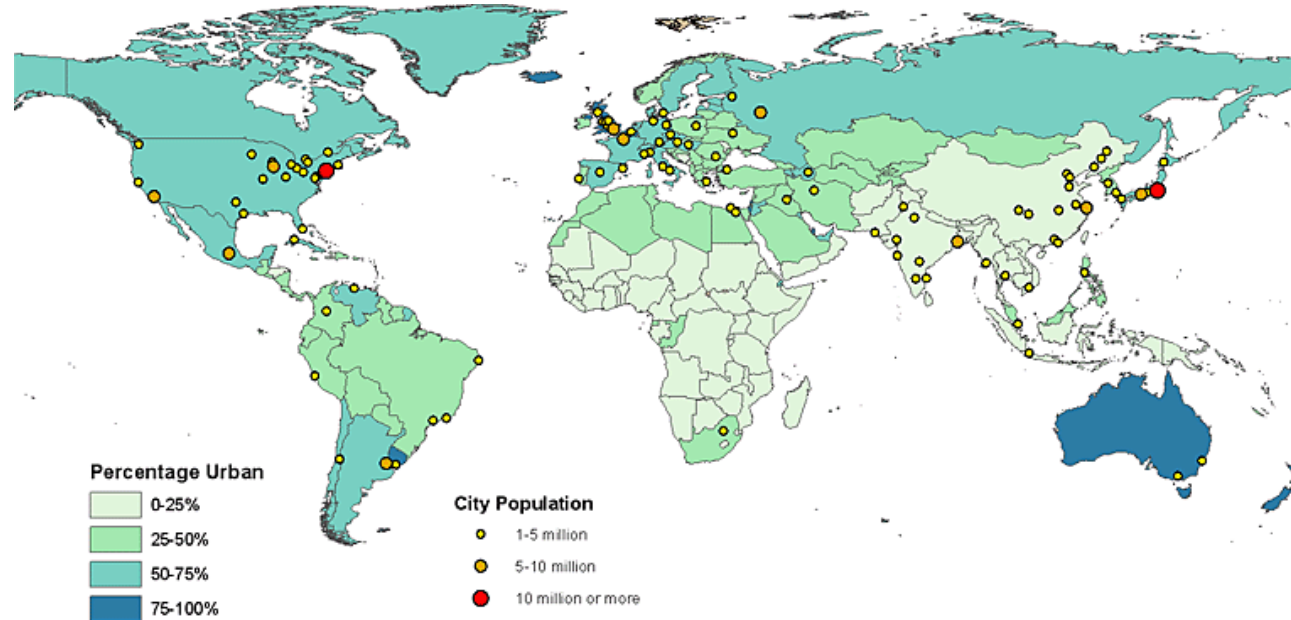
6 ISA estimation and mapping

7 Change detection

8 Conclusions and Advances

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.

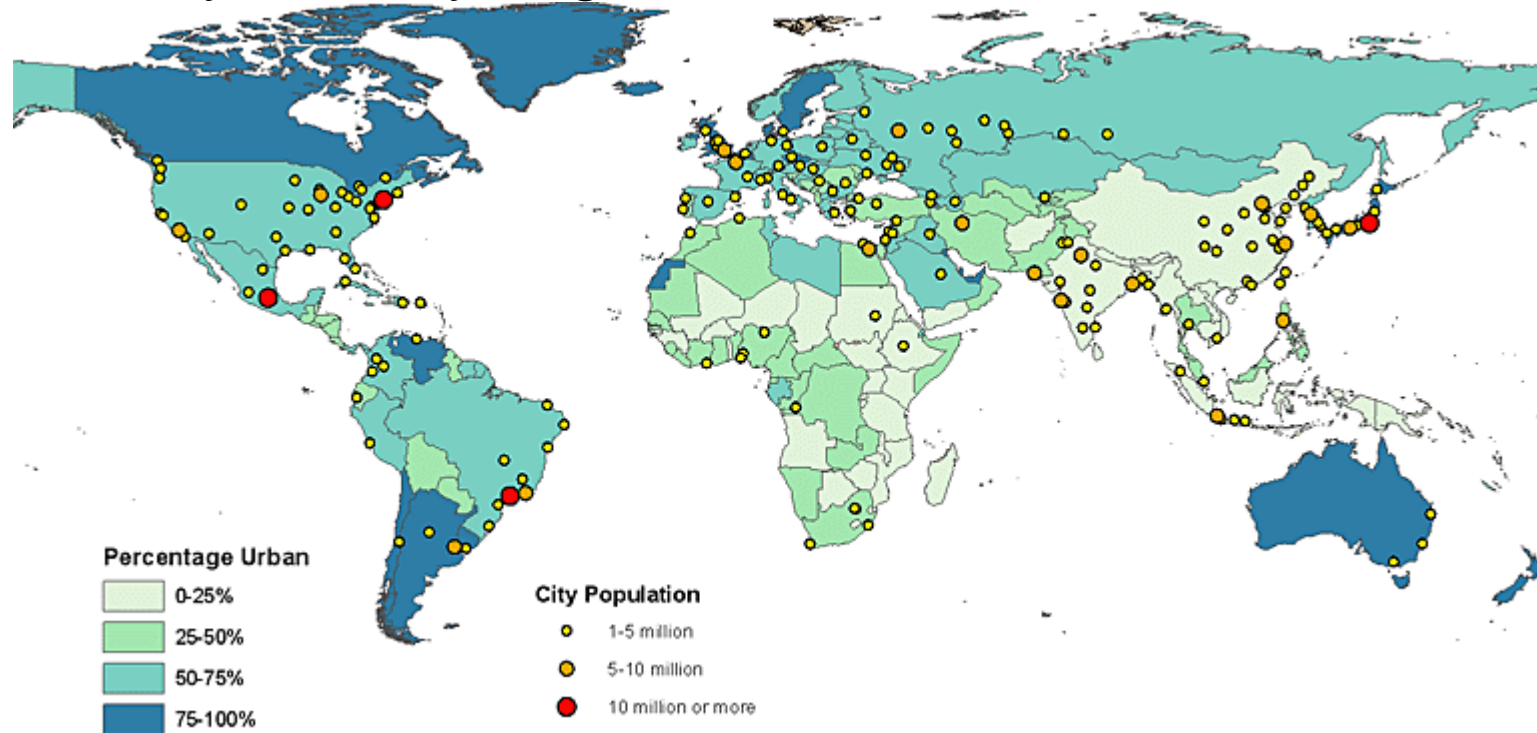


Percentage of urban population and agglomerations by size class, 1960

World Urbanization Prospects, the 2011 Revision

<http://esa.un.org/unpd/wup/index.html>

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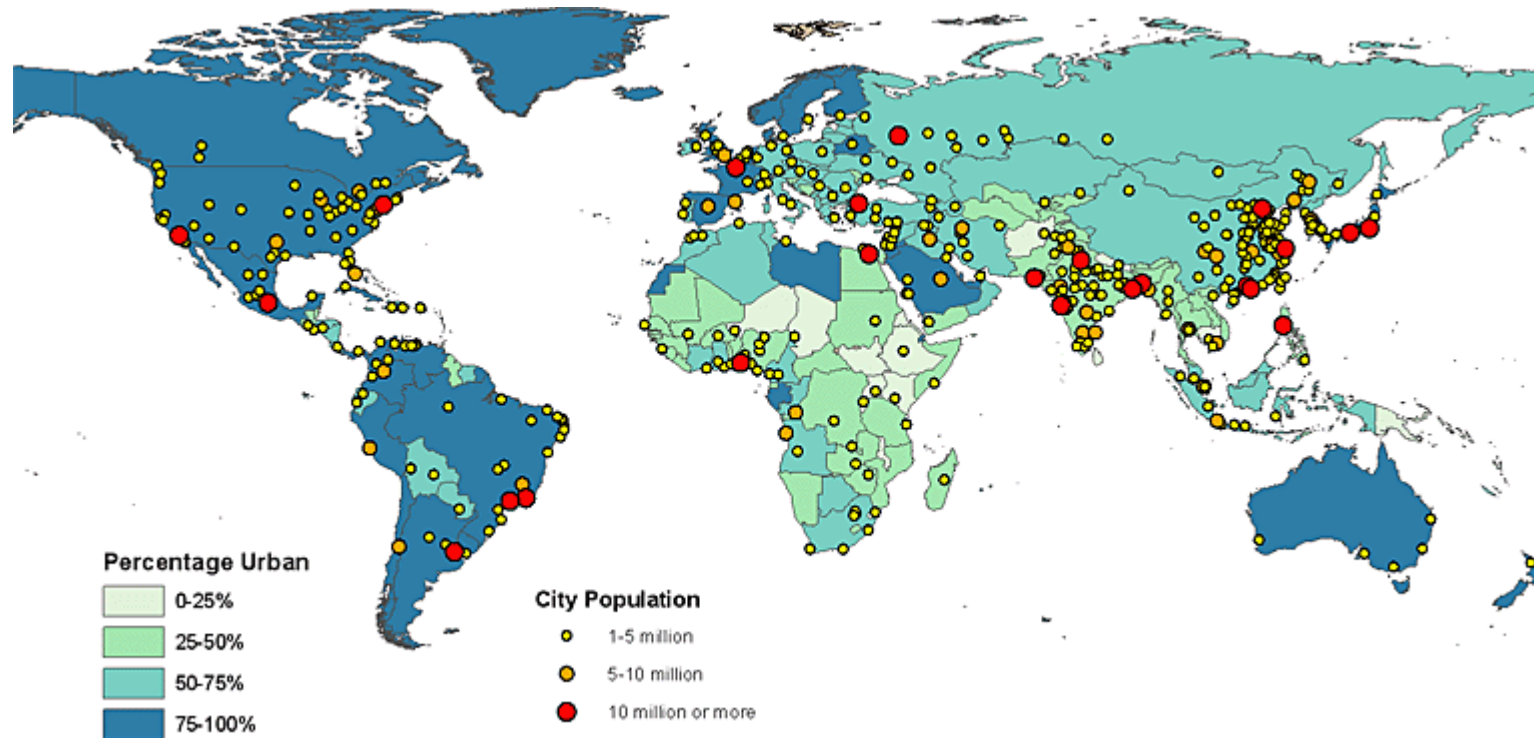


Percentage of urban population and agglomerations by size class, 1980

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.

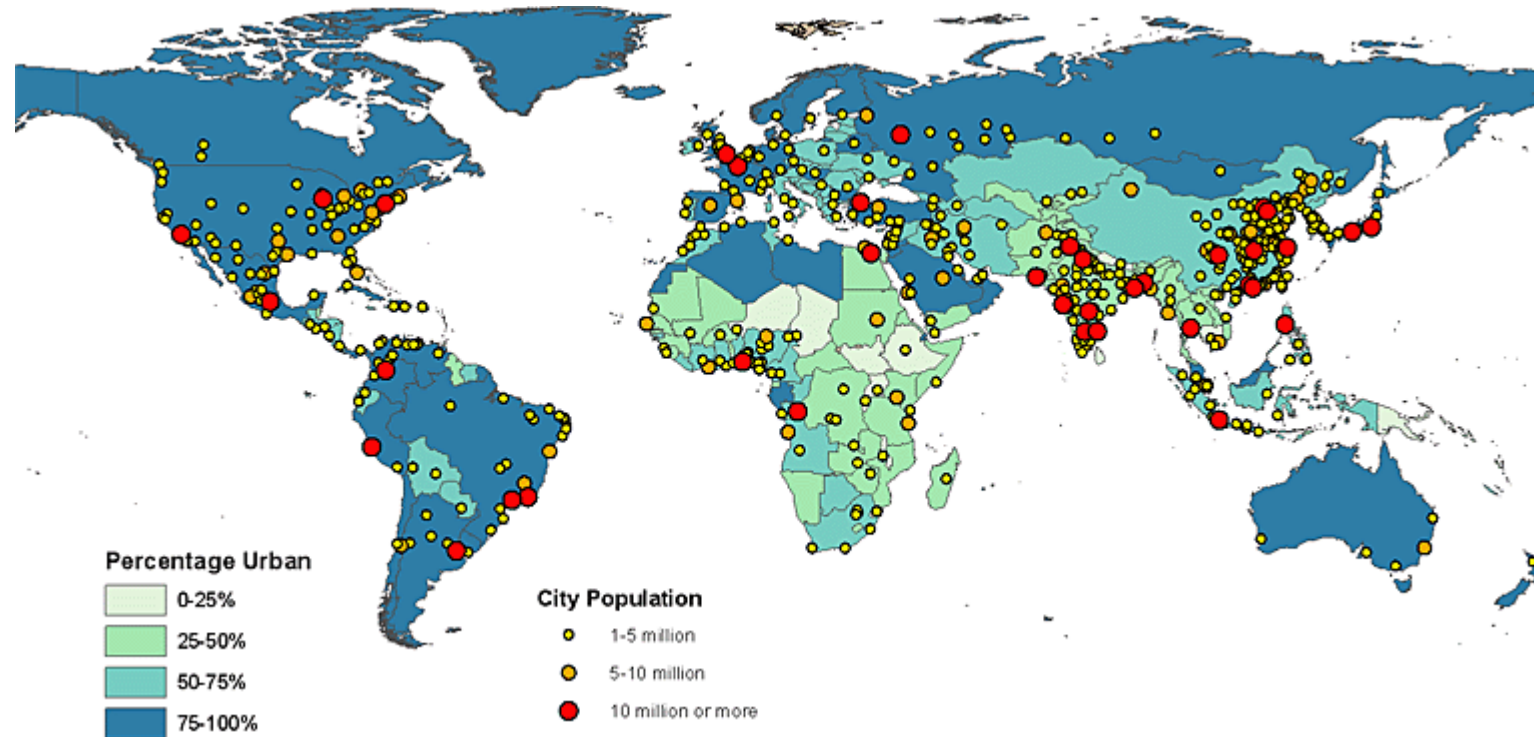


Percentage of urban population and agglomerations by size class, 2011

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

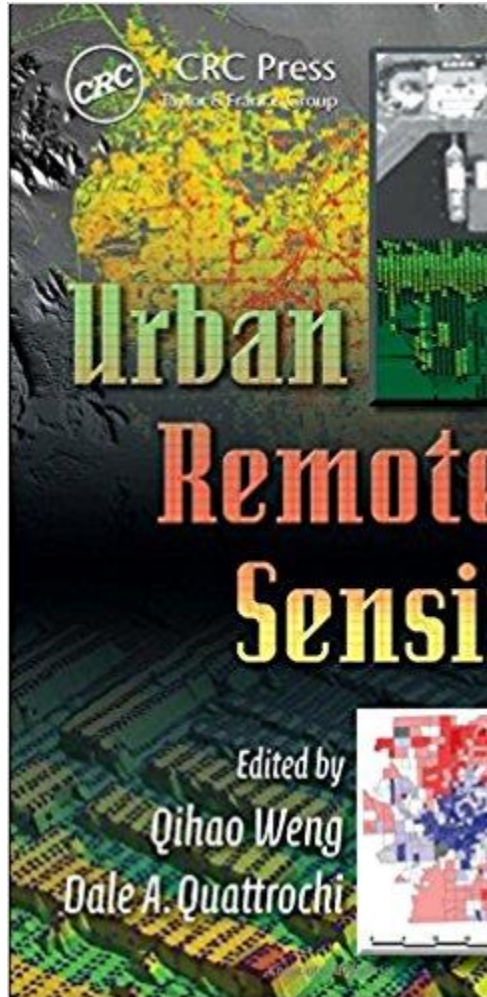
<http://esa.un.org/unpd/wup/index.html>

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



2006

Table of Contents

An Introduction to Urban Remote Sensing

Part I

Urban Feature Extraction

Chapter 1 True Orthoimage Generation for Urban A High Buildings

Guoqing Zhou and John A. Kelmelis

Chapter 2 Urban Terrain and Building Extraction fr LIDAR Data

Jie Shan and Aparajithan Sampath

Chapter 3 Reconstruction of Buildings in SAR Imag Uwe Stilla and Uwe Soergel

Part II

Urban Composition and Structure

Chapter 4 Subpixel Analysis of Urban Landscapes ..

Qihao Weng and Dengsheng Lu

Chapter 5 Bayesian Spectral Mixture Analysis for U Conghe Song

Chapter 6 Urban Mapping with Geospatial Algorith Soe W. Myint

Chapter 7 Applying Imaging Spectrometry in Urban Martin Herold, Sebastian Schiefer, Patrick Hostert, and

Part III

Urban Land Dynamics

Chapter 8 Urban Land Use Prediction Model with S Data Mining and GIS

Weiguo Liu, Karen C. Seto, Zhanli Sun, and Yong Tian

Chapter 9 Assessing Urban Growth with Subpixel Li Surface Coverage

George Xian

Chapter 10 Remote Sensing and Urban Growth Theory 201

Martin Herold, Jeff Hemphill, and Keith C. Clarke

Part IV

Urban Planning and Socioeconomic Applications 221

Chapter 11 Urban Heat Island Identification and Climatologic Analysis in a Coastal, Tropical City: San Juan, Puerto Rico..... 223

Jorge E. González, Jeffrey C. Luvall, Douglas L. Rickman, Daniel Comarazamy, and Ana J. Picón

Chapter 12 Assessing Urban Environmental Quality with Multiple Parameters..... 253

Janet Elizabeth Nichol and Man Sing Wong

Chapter 13 Population Estimation and Interpolation Using Remote Sensing..... 269

Xiaohang Liu and Martin Herold

Chapter 14 Sociodemographic Characterization of Urban Areas Using Nighttime Imagery, Google Earth, Landsat, and "Social" Ground Truthing..... 291

Paul C. Sutton, Matthew J. Taylor, Sharolyn Anderson, and Christopher D. Elvidge

Chapter 15 Integration of Remote Sensing and Census Data for Assessing Urban Quality of Life: Model Development and Validation 311

Guiying M. Li and Qihao Weng

Part V

Progress, Problems, and Prospects..... 337

Chapter 16 Mapping Human Settlements Using the Middle Infrared (3–5 μm): Advantages, Prospects, and Limitations 339

Geoffrey M. Henebry

Chapter 17 New Developments and Trends for Urban Remote Sensing 357

Manfred Ehlers

Chapter 18 Spectral Resolution in the Context of Very High Resolution Urban Remote Sensing 377

Paolo Gamba and Fabio Dell'Acqua



CONTENTS

List of Contributors
Author's Biography
Preface xix

PART 1 INTRODUCTION

1 What is urban monitoring?
XiaoJun Yang

- 1.1 Introduction
 - 1.2 Remote sensing
 - 1.3 Remote sensing
 - 1.4 Algorithms and data extraction 7
 - 1.5 Urban socio-environment
 - 1.6 Urban environment
 - 1.7 Urban growth
- Summary and conclusions 10
References 10

PART 2 REMOTE SENSING SYSTEMS

2 Use of remote sensing in urban monitoring
XiaoJun Yang

- 2.1 Introduction
- 2.2 Landsat products
- 2.3 Mapping urban environment in metropolitan areas
 - 2.3.1 Resolution
 - 2.3.2 Data and processing
 - 2.3.3 Image classification
 - 2.3.4 Change detection
 - 2.3.5 Interferometry
 - 2.3.6 Summary
- 2.4 Discussion
 - 2.4.1 A global perspective
 - 2.4.2 Image classification

5 Very-high-resolution synthetic aperture radar areas: looking in complex environments
Fabio Dell'Aquila, Paolo G. ...

- 5.1 Introduction 64
- 5.2 Before spaceborne high-resolution SAR
- 5.3 High-resolution SAR
 - 5.3.1 Extraction of surface parameters
 - 5.3.2 Damage assessment
 - 5.3.3 Vulnerability mapping

Conclusions 70
Acknowledgments 70
References 70

6 3D building reconstruction from airborne lidar point cloud with aerial imagery
Jonathan Li and Haiyan ...

- 6.1 Lidar-driven building reconstruction
 - 6.1.1 Building detection
 - 6.1.2 Building reconstruction
- 6.2 Our building reconstruction strategy
 - 6.2.1 Building detection
 - 6.2.2 Building reconstruction
- 6.3 Results and discussion
 - 6.3.1 Datasets 85
 - 6.3.2 Results 85

Concluding remarks 89
Acknowledgments 90
References 90

PART 3 ALGORITHMS AND TECHNIQUES FOR ATTRIBUTE EXTRACTION

7 Parameterizing models to improve classification performance
XiaoJun Yang and Libin ...

- 7.1 Introduction 96
- 7.2 Fundamentals of neural networks
 - 7.2.1 Neural network
 - 7.2.2 Network topology
 - 7.2.3 Neural training

- 9.4.1 Rule-based classification
- 9.4.2 Nearest neighbor classification
- 9.5 Results and discussion
 - 9.5.1 Decision tree
 - 9.5.2 Nearest neighbor

Conclusion 139
References 140

10 Spatial enhancement of multispectral images

Bruno Aiazzi, Stefano Garzelli and Massimo ...

- 10.1 Introduction 142
 - 10.1.1 Component selection
 - 10.1.2 Multiresolution
 - 10.1.3 Injection
 - 10.1.4 Quality assessment
- 10.2 Multiresolution fusion
- 10.3 Component selection
- 10.4 Hybrid MRA – component selection
- 10.5 Results 147

Conclusions 152
References 152

11 Exploring the structure of urban areas

Victor Meyer

- 11.1 Introduction 156
 - 11.2 Micro and macro structure
 - 11.3 The temporal landscape
 - 11.4 Structural-functional analysis
 - 11.5 Temporal-structural analysis
 - 11.6 Empirical measurement
- Conclusions 161
References 161

PART 4 URBAN ENVIRONMENTAL ANALYSES

12 A pluralistic and measurable urban environment
Amnon Frentzel and ...

- 12.1 Introduction 166

- 14.2.3 Origin
- 14.2.4 Data
- 14.3 Application in Georgia
 - 14.3.1 Data
 - 14.3.2 Data
 - 14.3.3 Aerial

Conclusions 205
Acknowledgments 206
References 208

15 Who's in the city?

Christopher D.J. Budhendra, Biswajit Ghosh, Daniel ...

- 15.1 Introduction
- 15.2 Methods
 - 15.2.1 Data
 - 15.2.2 Data
- 15.3 Results 213
- 15.4 Discussion

Conclusion 223
Acknowledgments 223
References 223

16 Integrating remote sensing for environmental research

Jeremy Moulin

- 16.1 Introduction
- 16.2 Environmental remote sensing
- 16.3 Remote sensing analysis 227
- 16.4 Integrating remote sensing using GIS 22
- 16.5 Case study: urban environment

Conclusion 234
References 235

PART 5 URBAN ENVIRONMENTAL MONITORING

17 Remote sensing of urban environment
Changshun Wu

- 17.1 Introduction

- 19.3.1 Idea
- 19.3.2 Preliminary
- 19.3.3 Estimation
- 19.4 Results 280
- 19.5 Discussion

19.5.1 Urban environment

19.5.2 Image processing

Conclusions 284
Acknowledgments 285
References 285

20 Characterizing urban areas using remote sensing

Marcus Hall

- 20.1 Introduction
- 20.2 Remote sensing studies
 - 20.2.1 Data
 - 20.2.2 Index
- 20.3 Hierarchical ecosystems
 - 20.3.1 Floor area
 - 20.3.2 Urban environment
- 20.4 Using remote sensing for urbanization
- 20.5 Long-term remote sensing of green areas
- 20.6 Application management

Conclusions 297
Acknowledgments 297
References 300

21 Urban environment quality and remote sensing

Susanne Greis, A. Zelinger

- 21.1 Introduction
- 21.2 Physical and urban areas in regional atmospheric models
 - 21.2.1 Roughness approach 307
 - 21.2.2 Single-layer urban canopy approaches 307

21.1 Introduction

- 23.3 Validating automata models 339
 - 23.3.1 Pixel matching 339
 - 23.3.2 Feature and pattern recognition 340
 - 23.3.3 Running models exhaustively 341

Conclusions 341
Acknowledgments 342
References 342

24 Agent-based urban modeling: simulating urban growth and subsequent landscape change in Suzhou, China

Yichun Xie and Xining Yang

- 24.1 Introduction 348
- 24.2 Design, construction, calibration, and validation of ABM 348
- 24.3 Case study – desakota development in Suzhou, China 350
- 24.4 The Suzhou Urban Growth Agent Model 351
 - 24.4.1 The model design 351
 - 24.4.2 The model construction 352
 - 24.4.3 The model calibration 352
 - 24.4.4 The model validation 353

Summary and conclusion 354
References 355

25 Ecological modeling in urban environments: predicting changes in biodiversity in response to future urban development

Jeffrey Hepinstall-Cymerman

- 25.1 Introduction 360
 - 25.1.1 Using urban remote sensing to develop land cover maps for ecological modeling 360
 - 25.1.2 One example of ecological modeling: modeling species habitat 360
 - 25.1.3 Predicting future land use and land cover 361
 - 25.1.4 Integrating models to predict future biodiversity 362

23.2.5 Coupling automata and exogenous models 338
23.2.6 Automatic calibration 339

- 25.2 Predicting changes in land cover and avian biodiversity for an area north of Seattle, Washington 362
 - 25.2.1 Land cover maps 362
 - 25.2.2 Land use change model 362
 - 25.2.3 Land cover change model 364
 - 25.2.4 Avian biodiversity model 365
 - 25.2.5 Predicted land cover change for study area 365
 - 25.2.6 Predicted changes in avian biodiversity for study area 365

Conclusions 365
Acknowledgments 367
References 368

26 Rethinking progress in urban analysis and modeling: models, metaphors, and meaning

Daniel Z. Sui

- 26.1 Introduction 372
- 26.2 Pepper's world hypotheses: the role of root metaphors in understanding reality 373
- 26.3 Progress in urban analysis and modeling: metaphors urban modelers live by 373
 - 26.3.1 Cities as forms – the spatial morphology tradition 374
 - 26.3.2 Cities as machines – the social physics tradition 375
 - 26.3.3 Cities as organisms – the social biology tradition 375
 - 26.3.4 Cities as arenas – the spatial event tradition 376
- 26.4 Models, metaphors, and the meaning of progress: further discussions 377

Summary and concluding remarks 377
Acknowledgments 378
Notes 378
References 378

Index

Index 383



Contents

Foreword.....
Preface.....
Author.....
1. Introduction.....
2. Characteristics of Urban Heat Island.....
Regional Scales.....
2.1 Introduction.....
2.2 Role of Remote Sensing.....
2.3 Application of Remote Sensing.....
2.4 Mapping Urban Heat Island.....
2.5 Decision Tree.....
2.6 Object-Based Image Classification.....
2.7 Summary.....
3. Characterization of Urban Heat Island.....
3.1 Introduction.....
3.2 Characteristics of Urban Heat Island.....
3.3 Mixing Features.....
3.4 Characterization of Urban Heat Island.....
3.4.1 Spectral Indices.....
3.4.2 Regression.....
3.5 Another Methods.....
3.5.1 Artificial Neural Network.....
3.5.2 Support Vector Machine.....
3.6 Summary.....
4. Regional and Global Urban Heat Island.....
4.1 Introduction.....
4.2 Characterization of Urban Heat Island.....
4.2.1 Development of Urban Heat Island in the World.....
4.2.2 Update of Urban Heat Island.....
4.2.3 Urban Heat Island between Land and Water.....

4.5 Map Global Urban Heat Island.....
4.5.1 Urban Heat Island.....
4.5.2 Classification.....
4.5.3 MODIS.....
4.5.4 Training.....
4.5.5 Urban Heat Island.....
4.5.6 Classification.....
4.5.7 Accuracy.....
4.6 New Progress.....
4.6.1 Remote Sensing.....
4.6.2 Image.....
4.6.2.1.....
4.6.2.2.....
4.6.3 Multi-Temporal.....
4.6.4 Urban Heat Island.....
4.7 Summary.....
5. Assessment of Water Quality.....
5.1 Introduction.....
5.2 Parameters of Water Quality.....
5.3 Satellites Measurement of Different Water Quality.....
5.3.1 Chl-a.....
5.3.2 Color.....
5.3.3 TSSC.....
5.4 Characterization of Water Quality.....
5.5 Satellite-Derived Water Quality.....
5.5.1 Suspended Solids.....
5.5.2 Water Temperature.....
5.5.2.1.....
5.5.2.2.....
5.5.3 Water Quality in Taihu Lake.....
5.6 Summary.....
6. Natural Hazard Assessment.....
6.1 Introduction.....
6.2 Urban Development of Mexico Region.....
6.3 Flood Risks in Urban Resolution Remote Sensing.....
6.4 Landslide Assessment.....
6.4.1 Detection.....

6.4.2 Assessment of Urban Heat Island Area.....
6.4.2.1.....
6.4.2.2.....
6.4.2.3.....
6.5 Summary.....
7. Air Quality in Urban Area.....
7.1 Overview.....
7.2 Satellite Remote Sensing.....
7.3 Medium-Resolution Remote Sensing.....
7.3.1 Terra.....
7.3.2 Terra.....
7.3.3 Envisat.....
7.3.4 Aqua.....
7.3.5 Meteosat.....
7.3.6 Other.....
7.4 Species Observation.....
7.4.1 Trace Gases.....
7.4.2 Aerosols.....
7.5 Assessments.....
7.5.1 Assessment.....
7.5.2 Nitrogen Dioxide.....
7.5.3 Ozone.....
7.6 Urban Land Use.....
7.7 Summary.....
8. Air Quality in Urban Area.....
8.1 Introduction.....
8.2 Satellite System.....
8.3 Methods of Urban Air Quality Component.....
8.4 Applications.....
8.4.1 Characterization.....
8.4.2 Interactions.....
8.5 Summary.....
9. Urban Heat Island.....
9.1 Introduction.....
9.2 Calculation of LST from Remote Sensing.....
9.2.1 AVHRR Instrument.....
9.2.2 Landsat Imagery.....

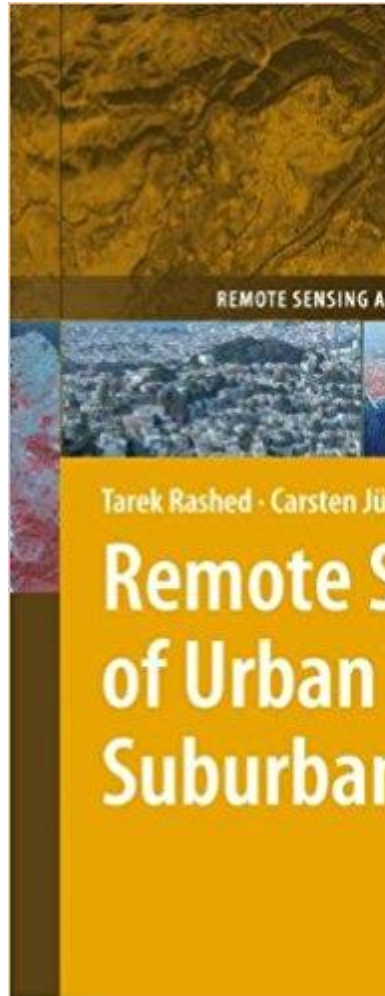
viii
9.3 Quantification of UHI Using Remotely Sensed LST Products... 174
9.3.1 UHI Effects in a Local Scale 175
9.3.2 Analysis of UHI Using Gridded Temperature and Land Cover Datasets 178
9.3.3 UHI Effect across the Continental United States 182
9.3.4 Regional UHI Effects in Europe 185
9.4 Global Aspect of UHI Effect 187
9.5 Climate Impacts of UHI 188
9.6 Summary 190
References..... 191
Index..... 213

Contents

2016

18–23 November





2010

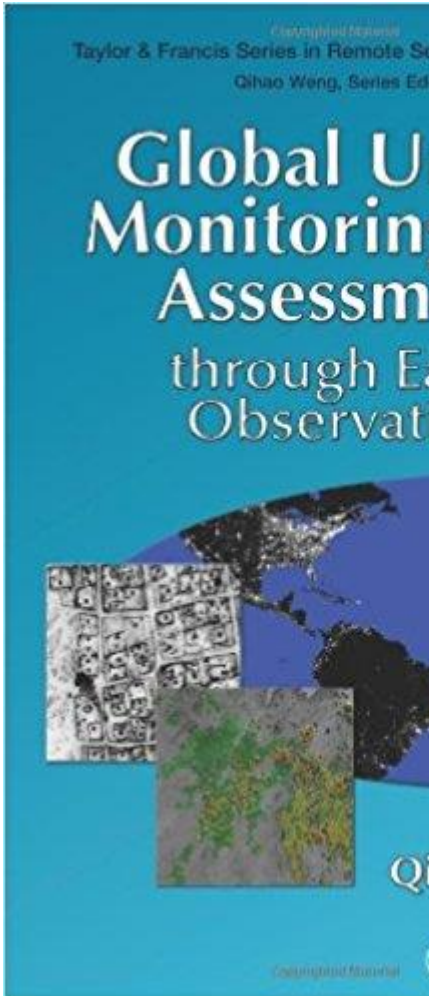
18–23 November 2019

Contents

1 Urban and Suburban Areas as a Research Topic for Remote Sensing	Maik Netzband and Carsten Jürgens
Part I Theoretical Aspects	
2 The Structure and Form of Urban Settlements	Elena Besussi, Nancy Chin, Michael Batty, and Paul
3 Defining Urban Areas	John R. Weeks
4 The Spectral Dimension in Urban Remote Sensing	Martin Herold and Dar A. Roberts
5 The Spatial and Temporal Nature of Urban Objects	Richard Sliuzas, Monika Kuffer, and Ian Masser
6 The V-I-S Model: Quantifying the Urban Environment	Renee M. Gluch and Merrill K. Ridd
Part II Techniques and Applications	
7 A Survey of the Evolution of Remote Sensing Image Systems and Urban Remote Sensing Applications	Debbie Fugate, Elena Tarnavsky, and Douglas Stow
8 Classification of Urban Areas: Inferring Land Use from the Interpretation of Land Cover	Victor Mesev

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viii	Contents
9 Processing Techniques for Hyperspectral Data	165
Patrick Hostert	
10 Segmentation and Object-Based Image Analysis	181
Elisabeth Schöpfer, Stefan Lang, and Josef Strobl	
11 Data Fusion in Remote Sensing of Urban and Suburban Areas	193
Thierry Ranchin and Lucien Wald	
12 Characterization and Monitoring of Urban/Peri-urban Ecological Function and Landscape Structure Using Satellite Data	219
William L. Stefanov and Maik Netzband	
13 Remote Sensing of Desert Cities in Developing Countries	245
Mohamed Ait Belaid	
14 Remote Sensing of Urban Environmental Conditions	267
Andy Kwarteng and Christopher Small	
15 Remote Sensing of Urban Land Use Change in Developing Countries: An Example from Büyükçekmece, Istanbul, Turkey	289
Derya Maktav and Filiz Sunar Erbek	
16 Using Satellite Images in Policing Urban Environments	313
Meshgan Mohammad Al-Awar and Farouk El-Baz	
17 Using DMSP OLS Imagery to Characterize Urban Populations in Developed and Developing Countries	329
Paul C. Sutton, Matthew J. Taylor, and Christopher D. Elvidge	
Index	349



2014

18–23 November 2019 | C

Contents

Foreword
 Editor
 Contributors
 MATLAB® Statement.....

Chapter 1 What Is Spec
Qihao Weng

SECTION I Glob and

Chapter 2 Global Urban
 Address the I
*Qihao Weng,
 and George X*

Chapter 3 EO Data Proc
 Characterizat
*Paolo Gamba
 Inmaculada I*

Chapter 4 Urban Observ
*Qihao Weng, I
 Linlin Lu, Tho
 Huiran Jin, Hi
 Iphigenia Ker
 and Christoph*

SECTION II Glo and

Chapter 5 Mapping Glo
 Data Acquire

Chapter 6 National Trends in
*Christopher D. El
 and Tilottama Gh*

Chapter 7 Development of a
 Satellite Images a
*Hiroyuki Miyazak
 and Ryosuke Shil*

Chapter 8 Building of a Glo
 Remotely Sensed
*Martino Pesaresi,
 Matina Halkia, T*

SECTION III Urban Forec

Chapter 9 Spatial Dynamics
 of Chinese Megac
*Hannes Taubenbe
 Andreas Felbier, A*

Chapter 10 Mapping and Mon
 People Using EO
Thomas Kemper

Chapter 11 Assessment of Fir
*Linlin Lu, Huado
 and Stefano Ferri*

Chapter 12 Climatological an
 Pandemic of Infl
*Bing Xu, Zhenyu
 Michael Timberla*

Chapter 13 Investigations of t
 Greece, by Statist
 Temperature Images and Pattern Analysis.....
Iphigenia Keramitsoglou

Contents

vii

SECTION IV Innovative Concepts and Techniques in Urban Remote Sensing

Chapter 14 Integrated Urban Sensing in the Twenty-First Century
Günther Sagl and Thomas Blaschke 269

Chapter 15 Object-Based Image Analysis for Urban Studies.....
Vivek Dey, Bahram Salehi, Yun Zhang, and Ming Zhong 287

Chapter 16 Defining Robustness Measures for OBIA Framework: A Case
 Study for Detecting Informal Settlements
Peter Hofmann 303

Chapter 17 Automated Techniques for Change Detection Using Combined
 Edge Segment Texture Analysis, GIS, and 3D Information
*Manfred Ehlers, Natalia Sofina, Yevgeniya Filippovska,
 and Martin Kada* 325

Chapter 18 Fusion of SAR and Optical Data for Urban Land Cover
 Mapping and Change Detection.....
Yifang Ban, Osama Yousif, and Hongtao Hu 353

Index..... 387

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

- 1 Urban remote sensing
- 2 **Technical flow of urban mapping**
- 3 Urban extent mapping
- 4 Urban land cover/land use mapping
- 5 Urban thematic mapping
- 6 ISA estimation and mapping
- 7 Change detection
- 8 Conclusions and Advances

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

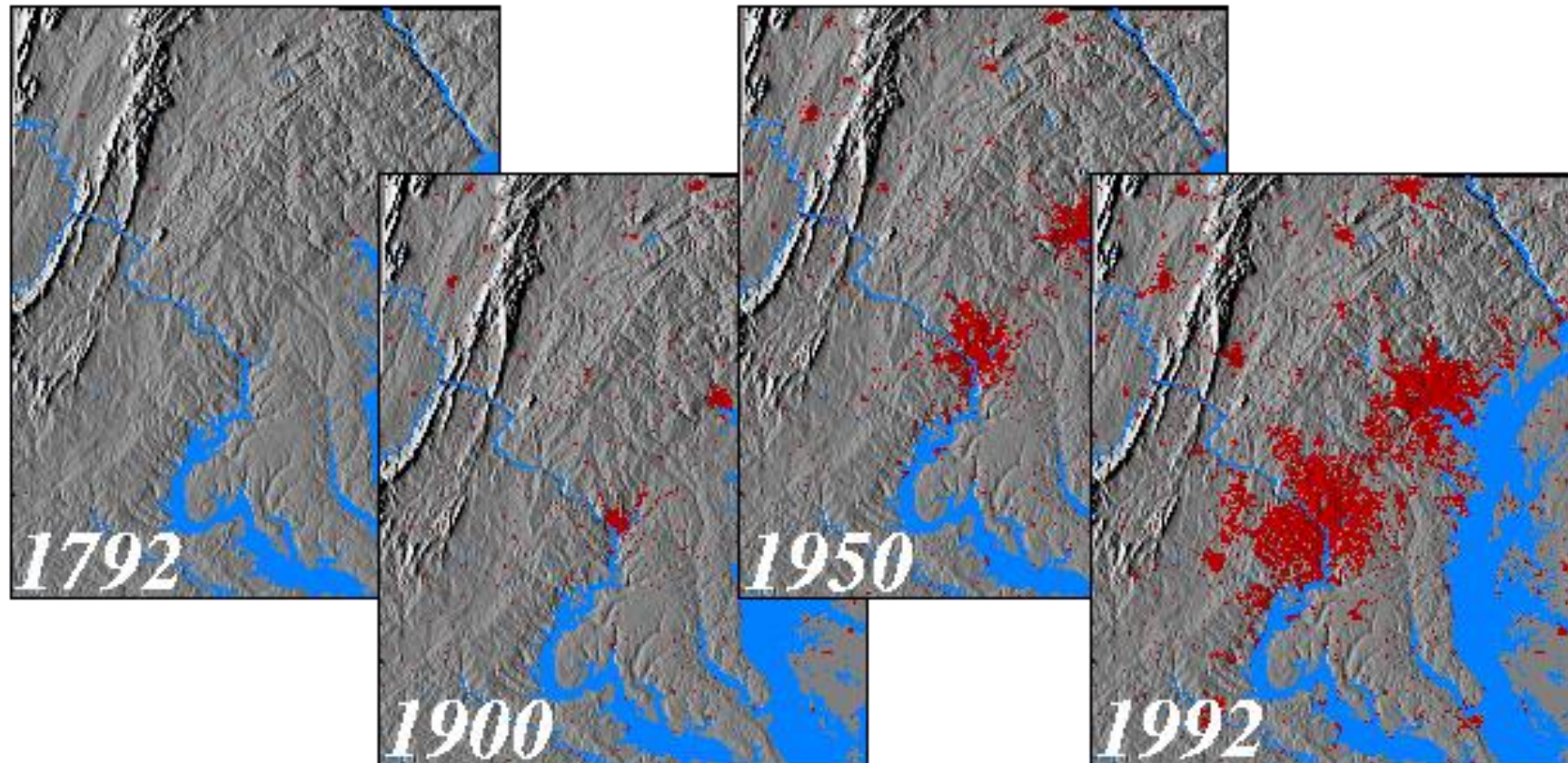
Temporal urban mapping develops a historical perspective of urban development by combining a variety of data sources into an integrated, multi-scale, and multi-resolution database.

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/>

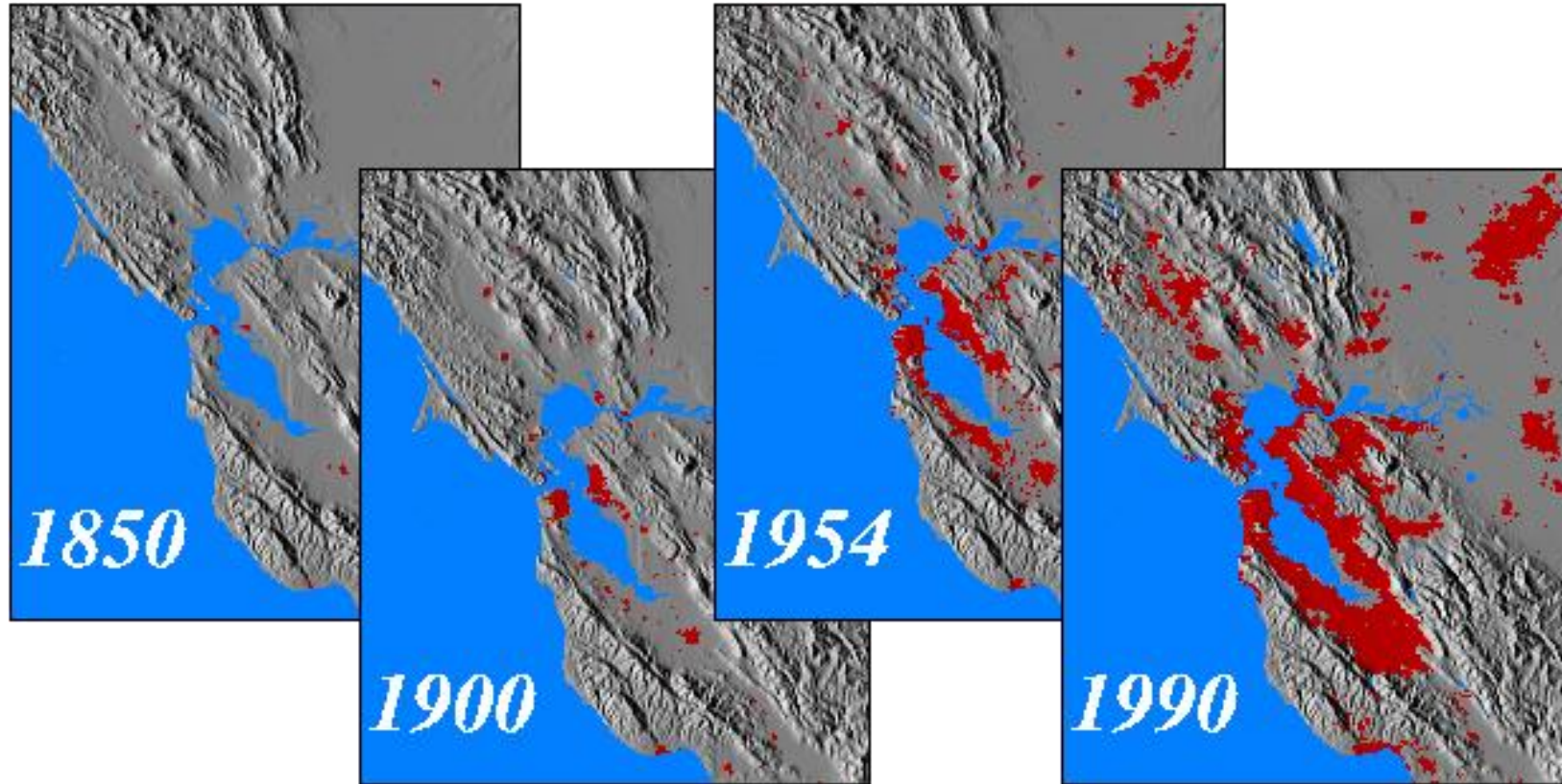
Urban Dynamics: Temporal Urban Mapping



[Baltimore-Washington area](http://landcover.usgs.gov/urban/umap/)

<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.

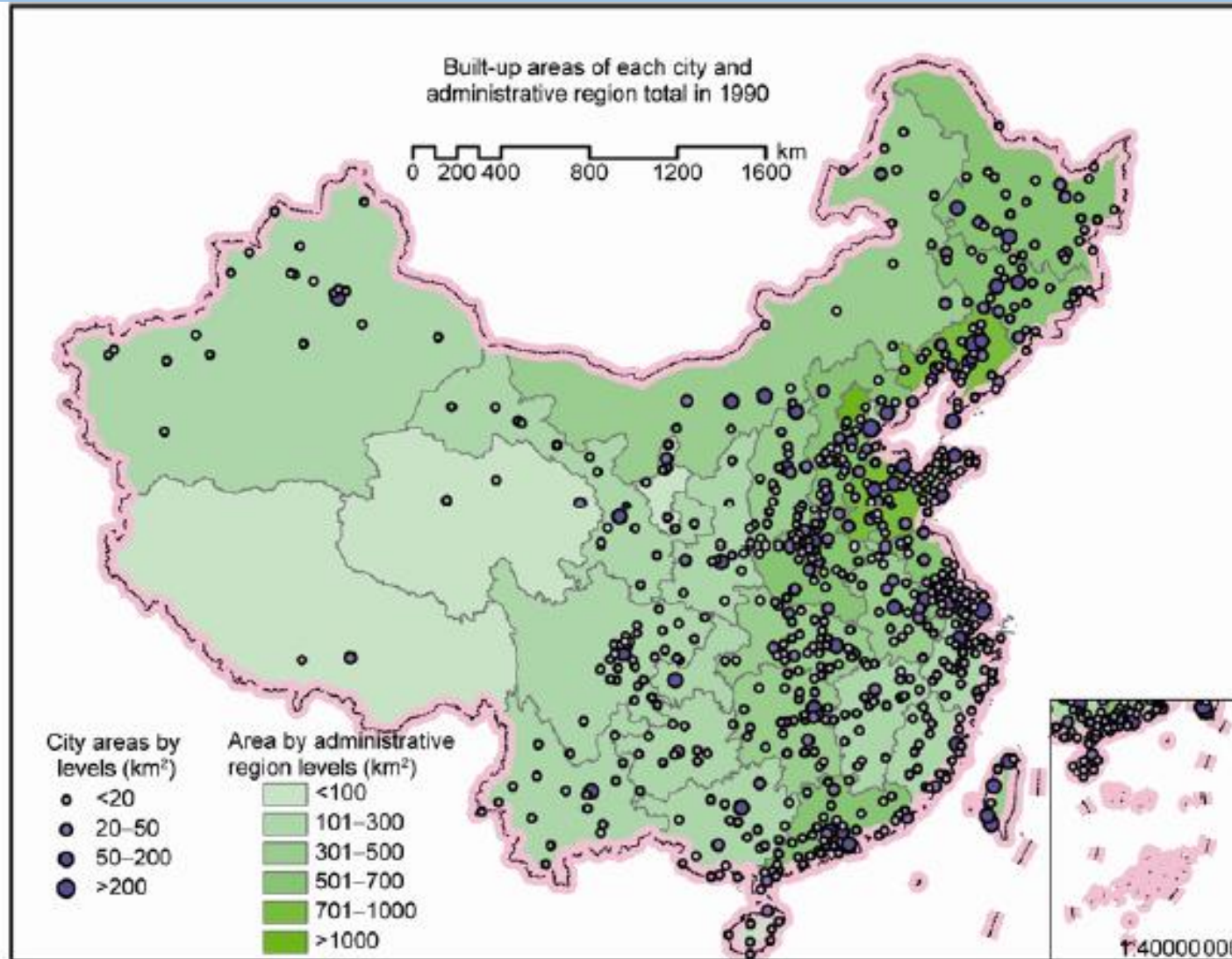
GRUMP incorporates urban and rural information derived from satellite data and other sources, encouraging new insights into urban population distribution and the global extents of human settlements.

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

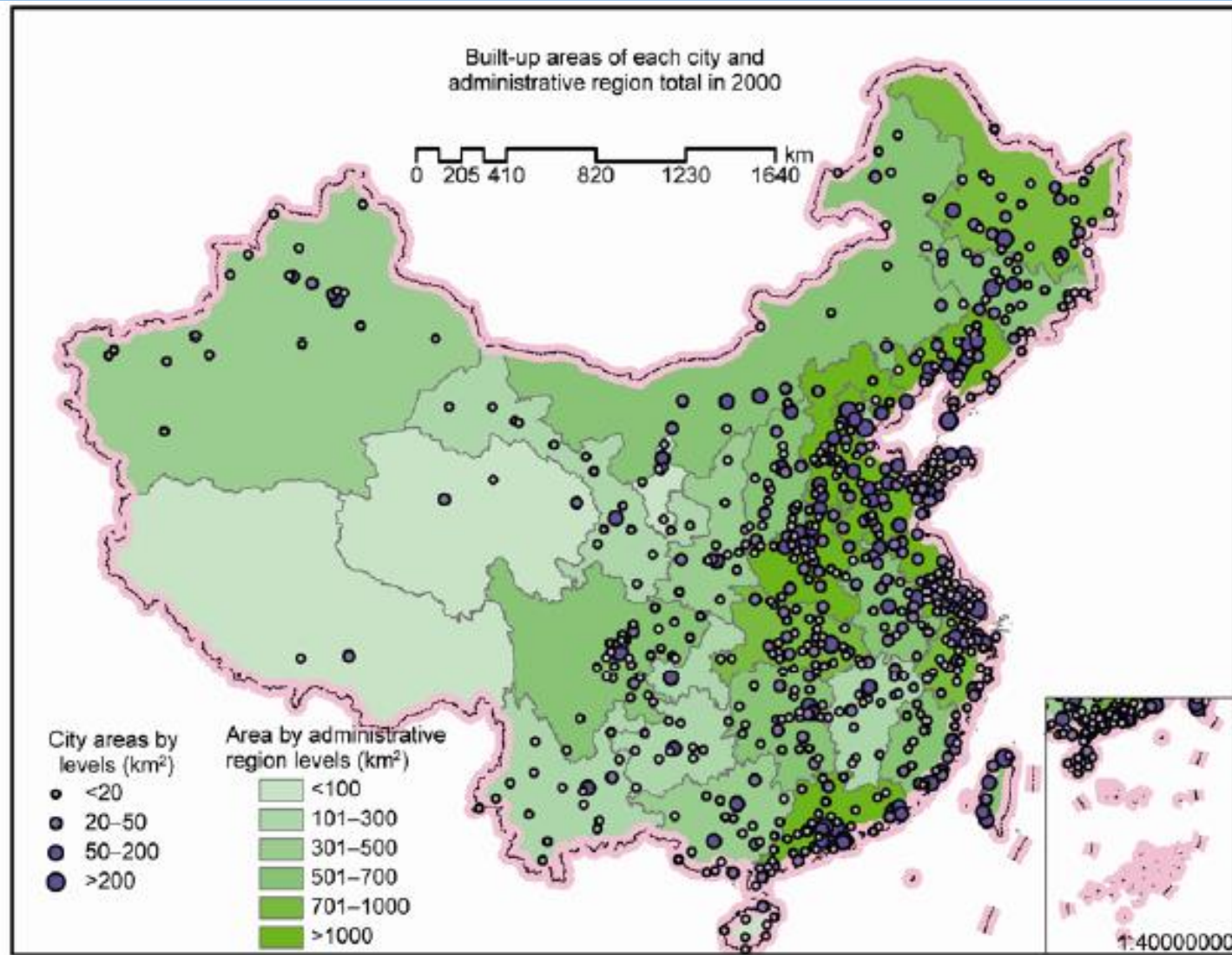
<http://sedac.ciesin.columbia.edu/gpw>

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

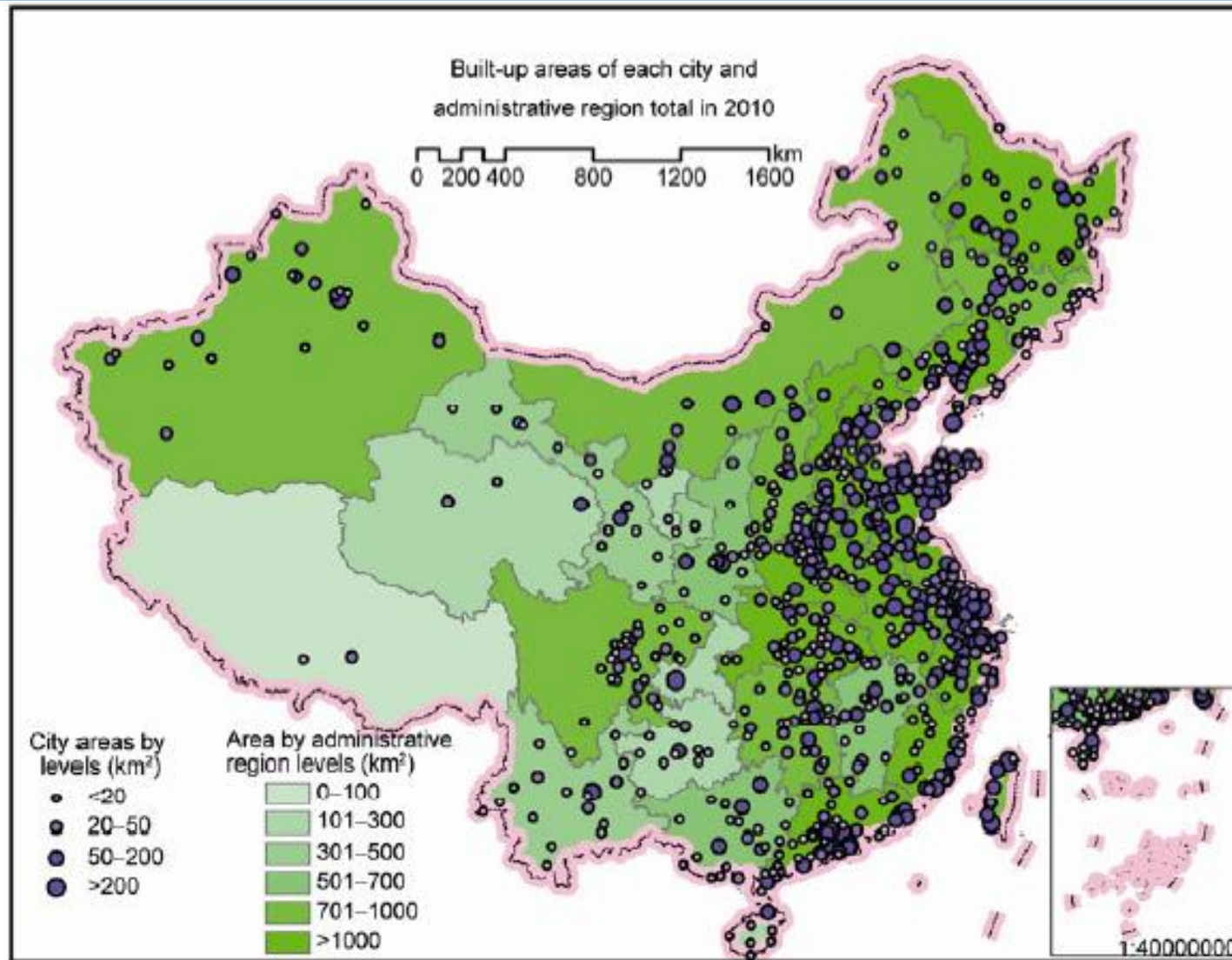
WANG Lei, LI CongCong, YING Qing, et al. **China's urban expansion from 1990 to 2010 determined with satellite remote sensing**. Chinese Science Bulletin 2012 Vol. 57 (22): 2802-2812



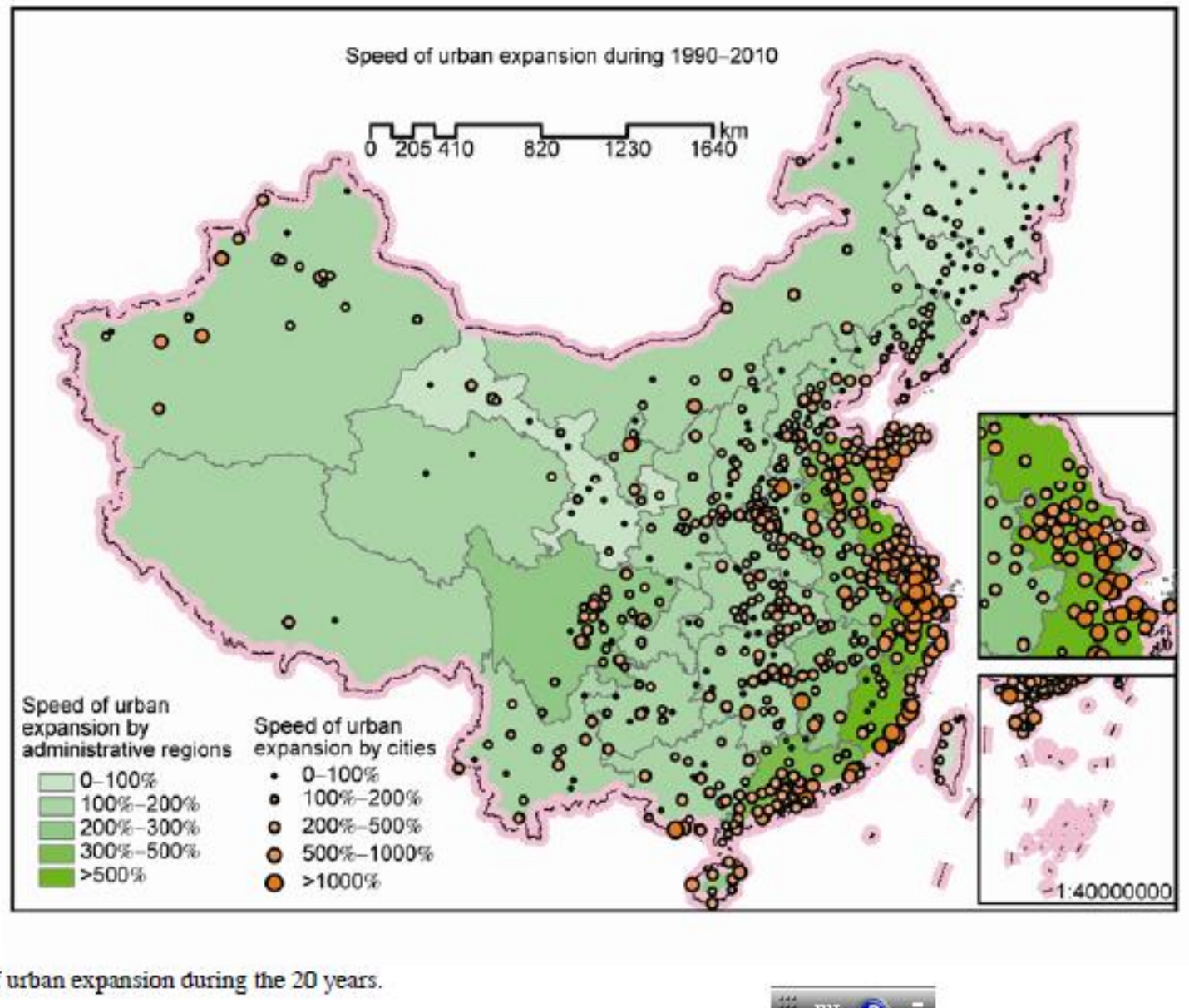
Built-up areas of each city in different size classes and administrative region total of different classes in the background for 1990 period.



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.

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.

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 Built-up Land	
	17 Other Urban or Built-up Land	

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.

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.

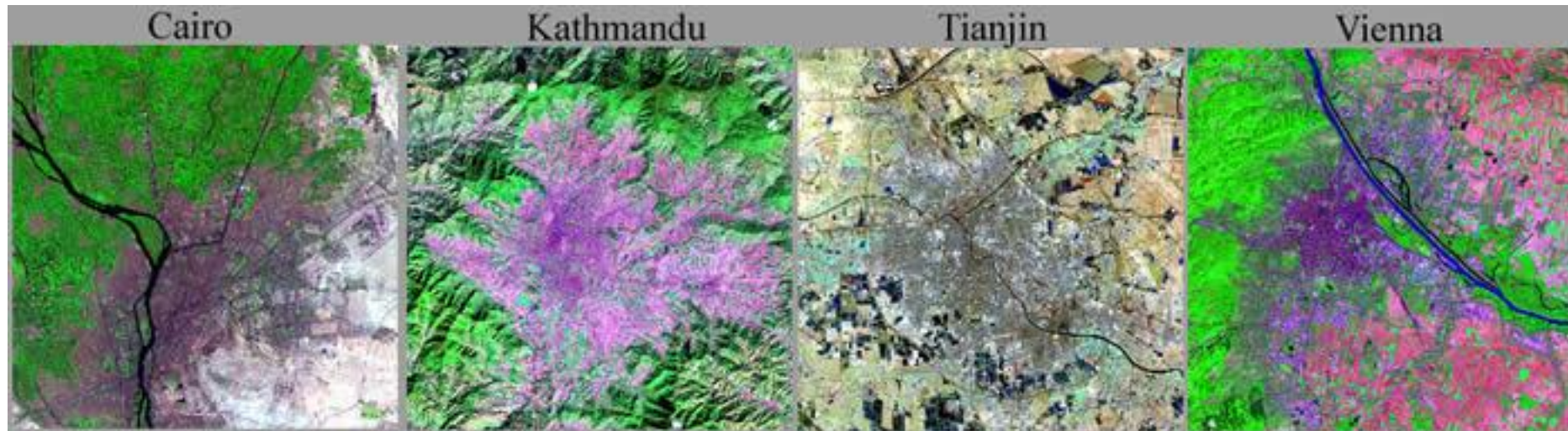
Major roads were instead captured as a separate principle transportation data layer.

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.

Data for urban mapping: medium multispectral images



Landsat 7 ETM+

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

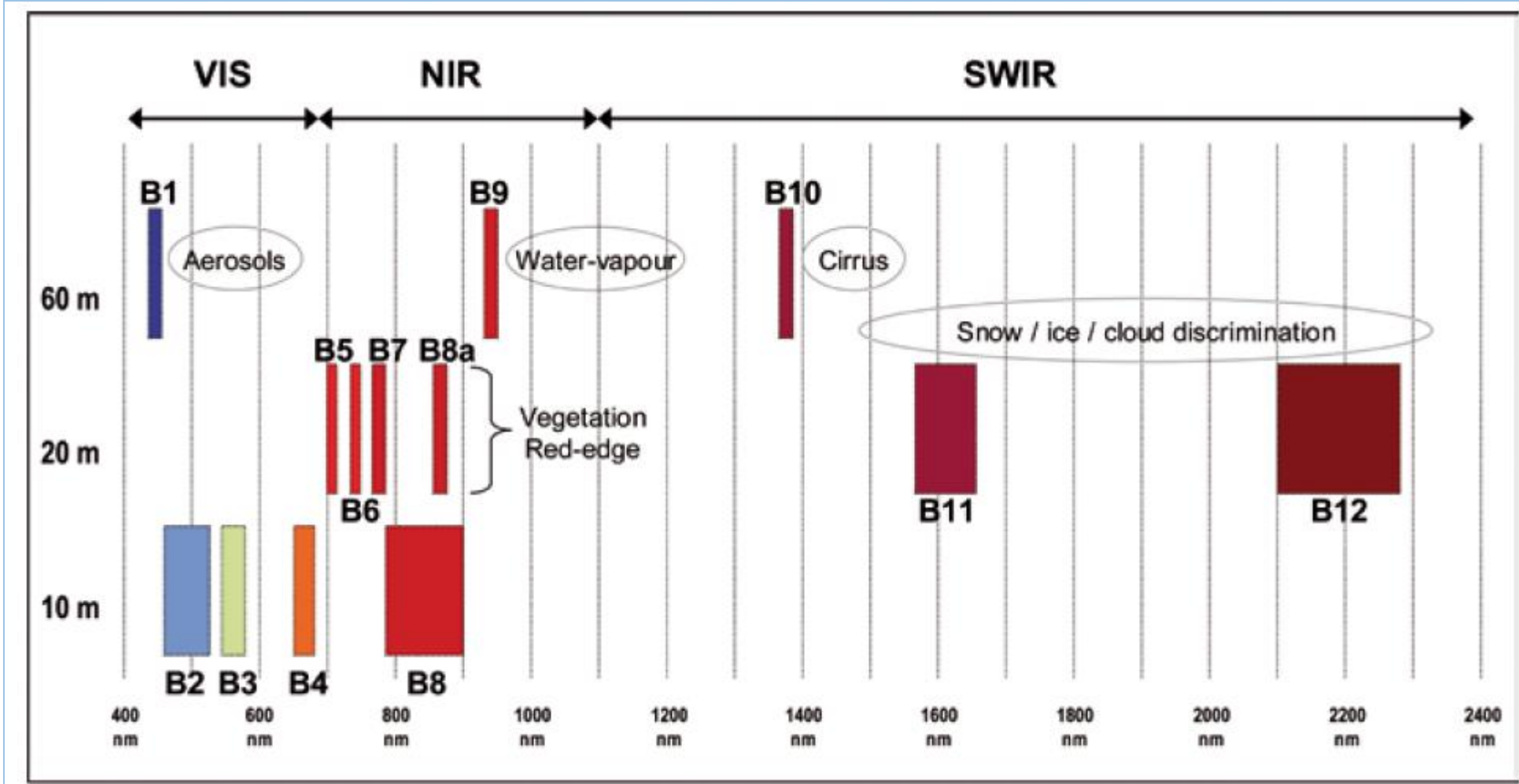
Data for urban mapping: medium multispectral images

Sentinel 2 MS images

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

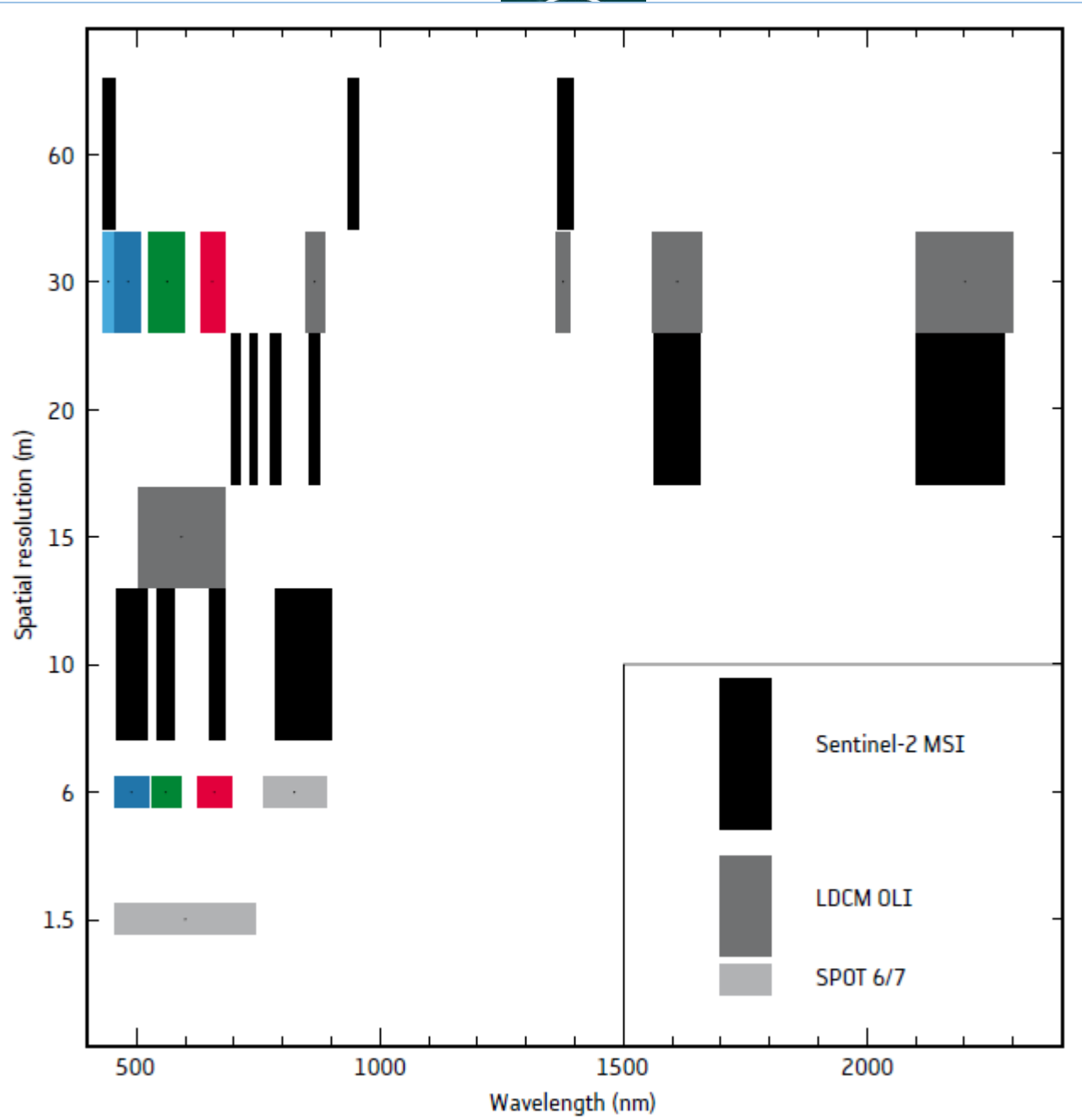
Band number	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)	L_{ref} ($W m^{-2} sr^{-1} \mu m^{-1}$)	SNR @ L_{ref}
1	443	20	60	129	129
2	490	65	10	128	154
3	560	35	10	128	168
4	665	30	10	108	142
5	705	15	20	74.5	117
6	740	15	20	68	89
7	783	20	20	67	105
8	842	115	10	103	174
8b	865	20	20	52.5	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
	* LCOM mission targeted early 2013	** SPOT-6 targeted end 2012		

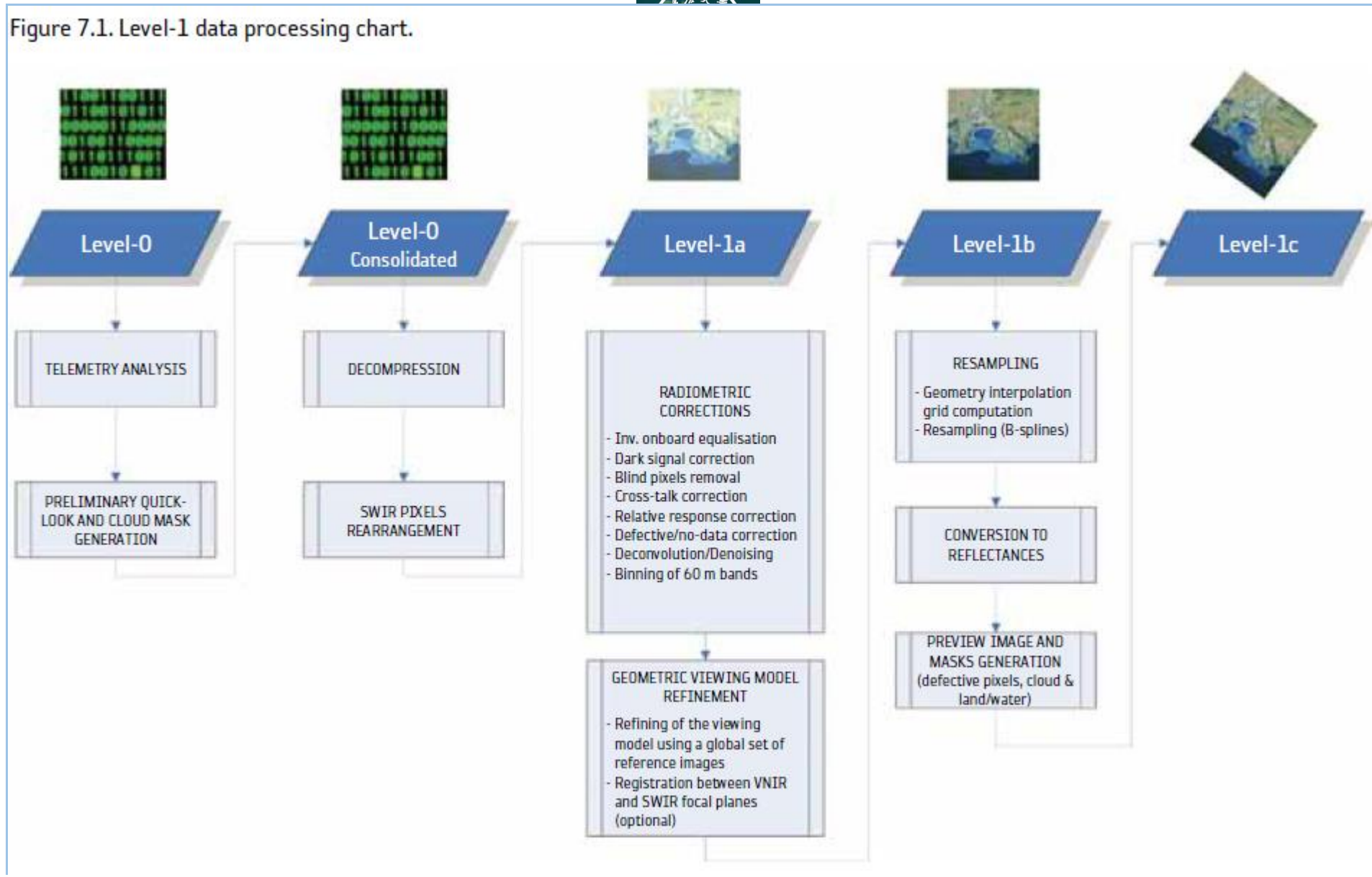


Sentinel 2 MS images

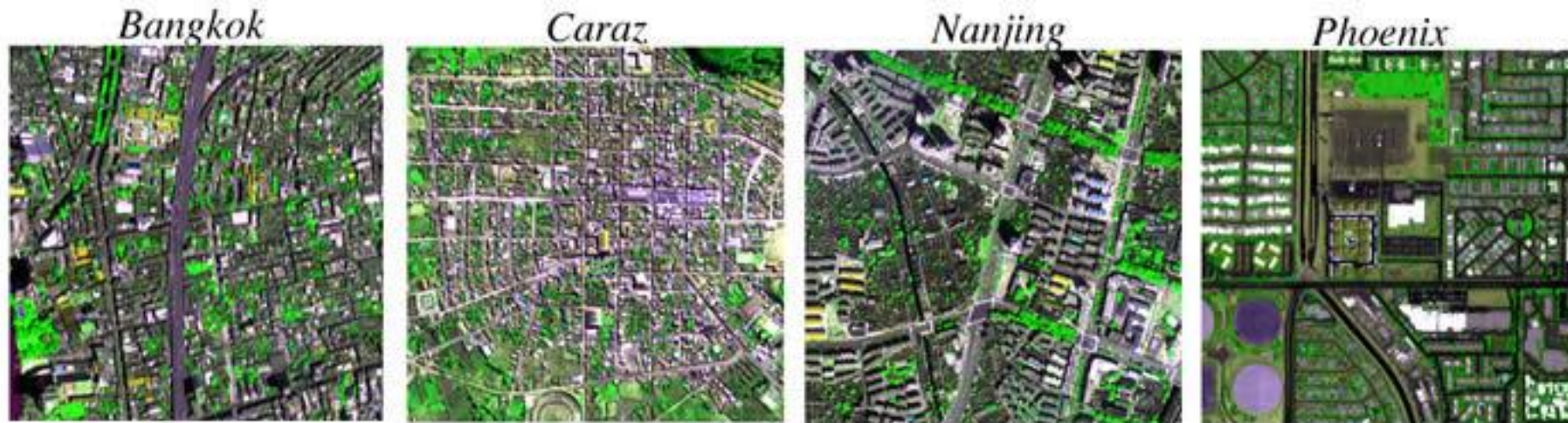
Table 4.2. Sentinel-2 data product dissemination strategies.

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.

Data for urban mapping: high-resolution images

GF -1(China)

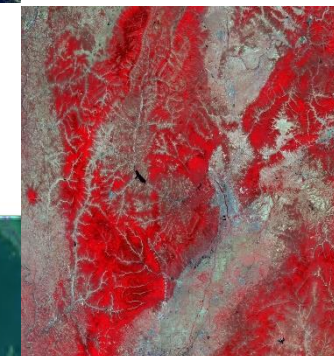
	Band number	Wavelength (μm)	Resolution (m)
Panchromatic & multispectral camera	1	0.45–0.90	2
	2	0.45–0.52	8
	3	0.52–0.59	
	4	0.63–0.69	
	5	0.77–0.89	
Multispectral camera	6	0.45–0.90	16
	7	0.45–0.52	
	8	0.52–0.59	
	9	0.63–0.69	

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



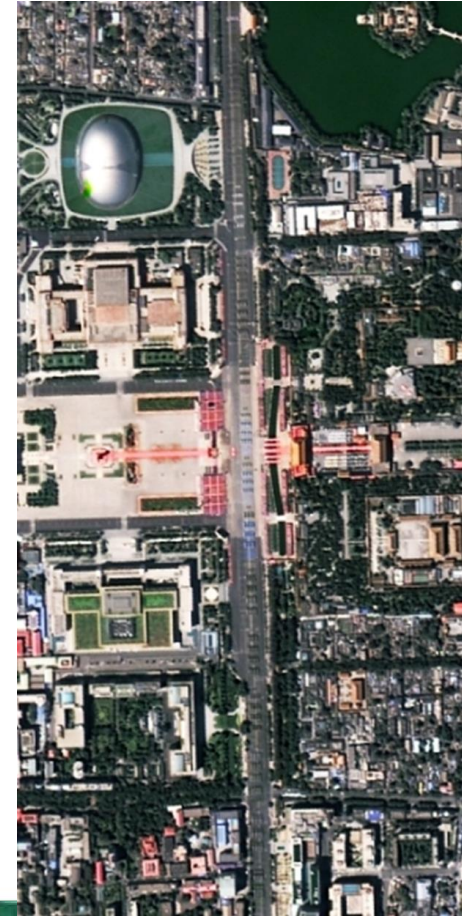
Multispectral image



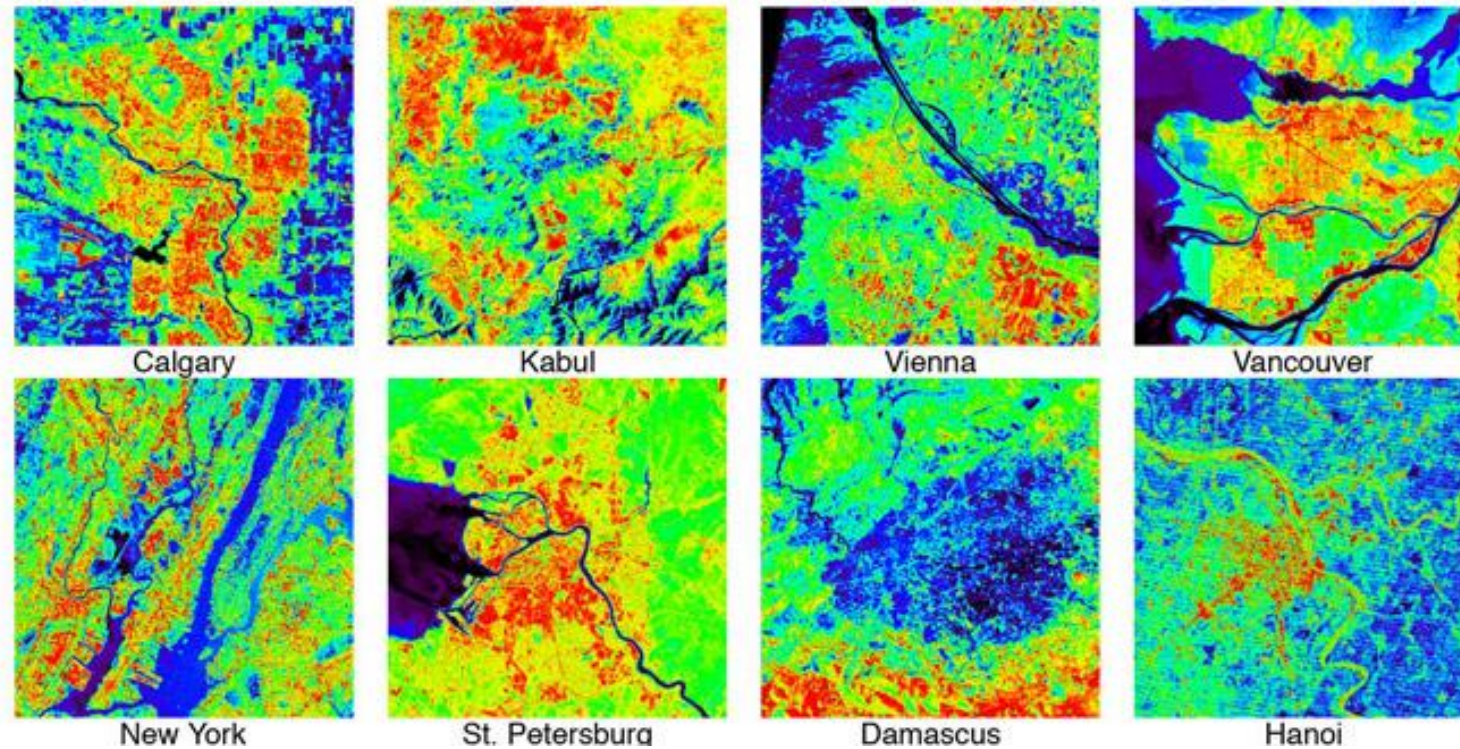
Data for urban mapping: high-resolution images

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	



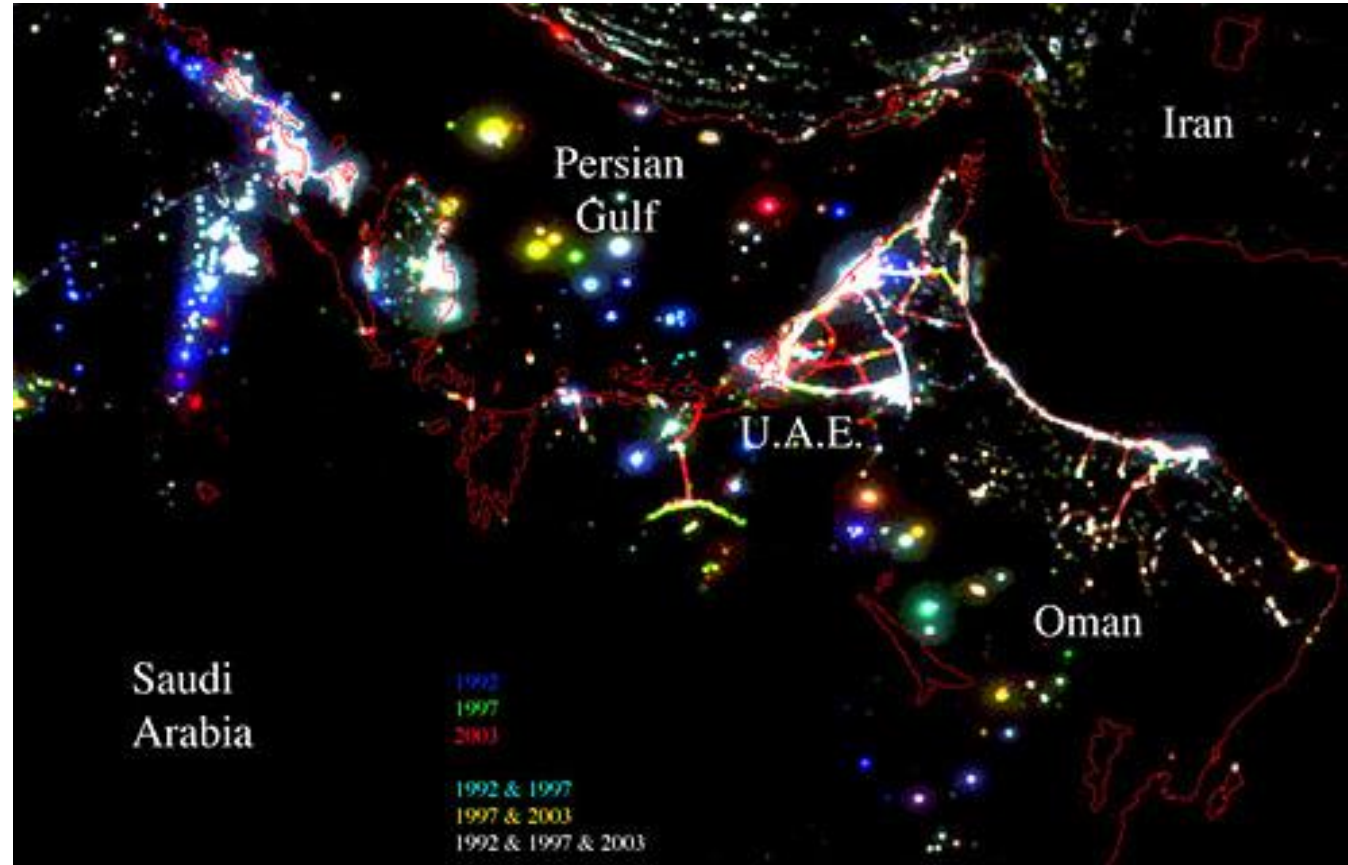
Data for urban mapping: thermal images



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

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

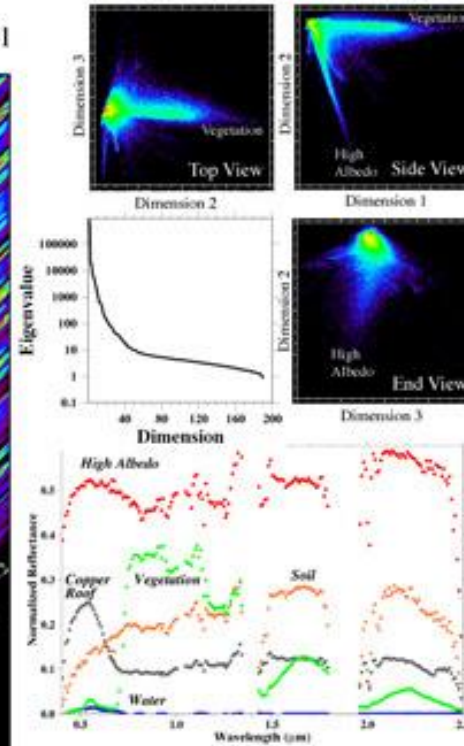
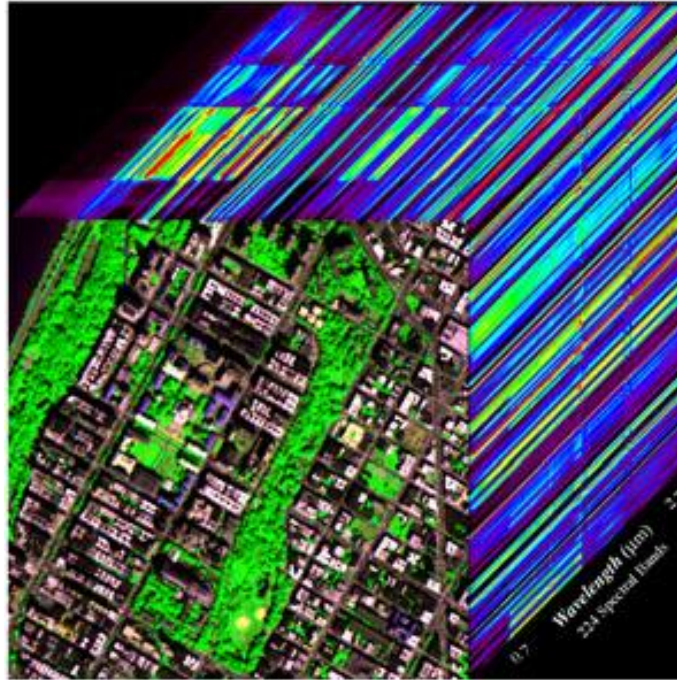
Data for urban mapping: Nighttime data



[Night Lights](#) - *Global spatial analysis and comparison of DMSP night lights with Landsat 7*

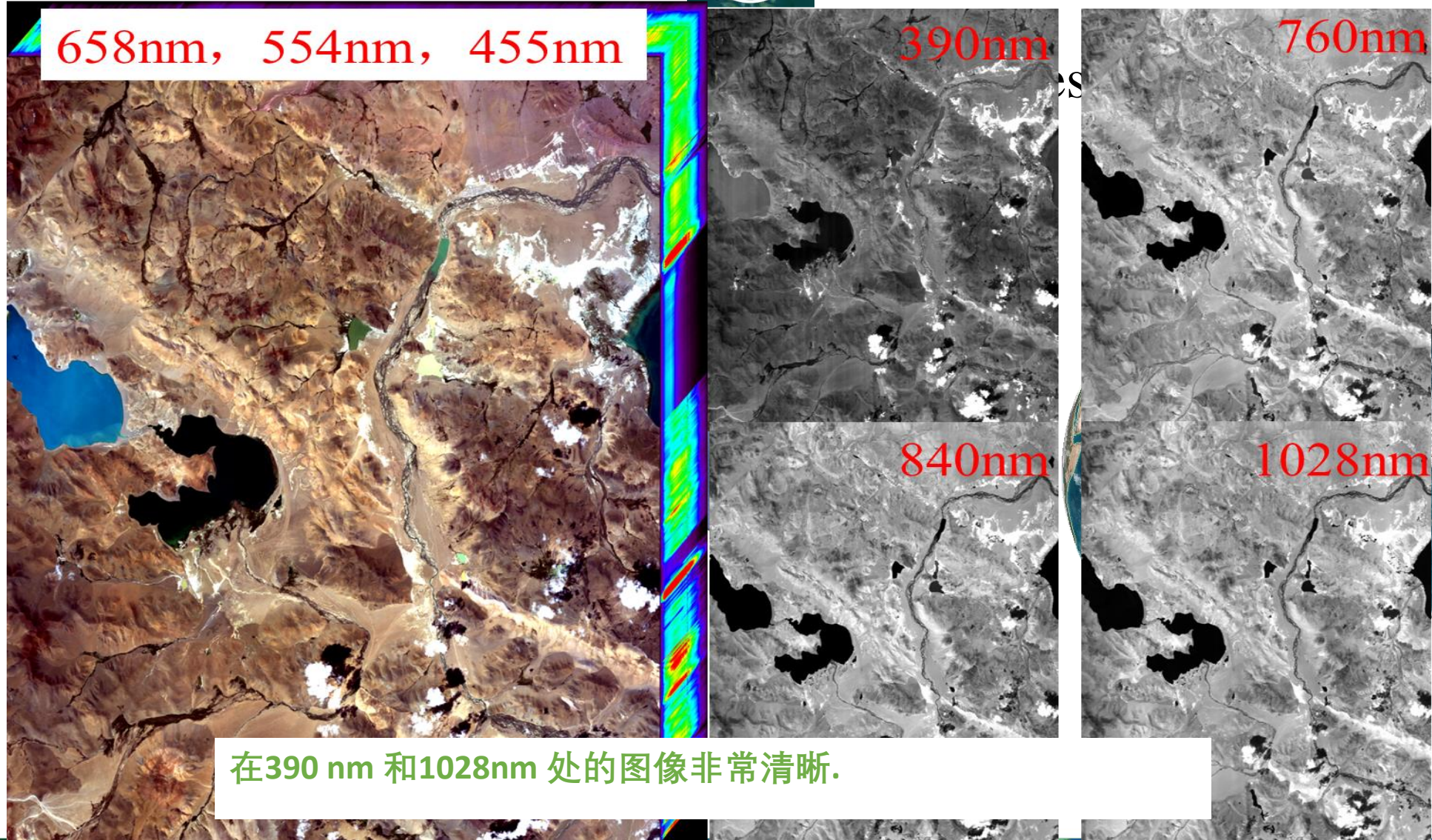
Data for urban mapping: Hyperspectral images

AVIRIS 4 meter Manhattan 16 September, 2001

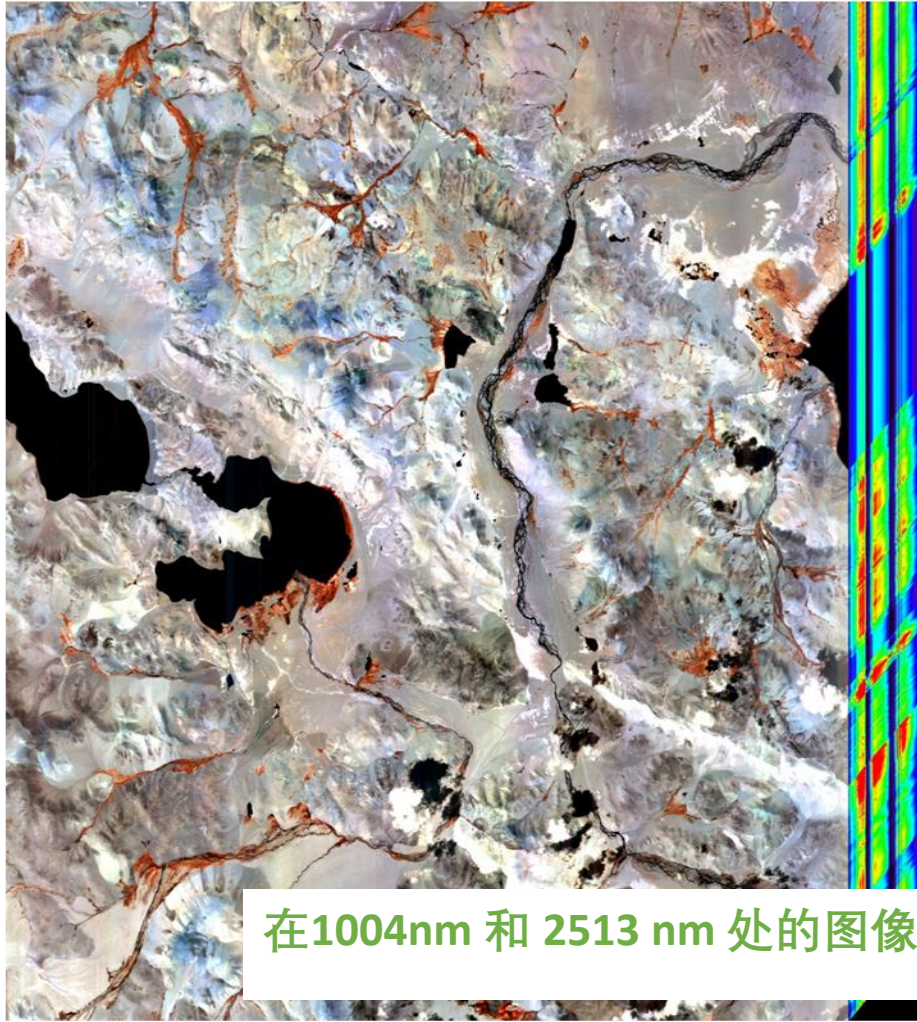


Hyperspectral - Comparison of pervious and impervious surface reflectance properties

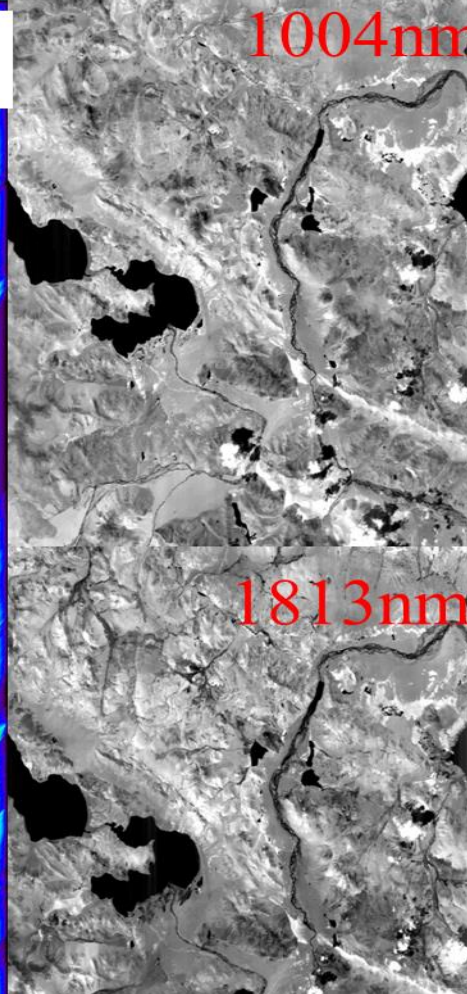
<http://www.ideo.columbia.edu/~small/Urban/>



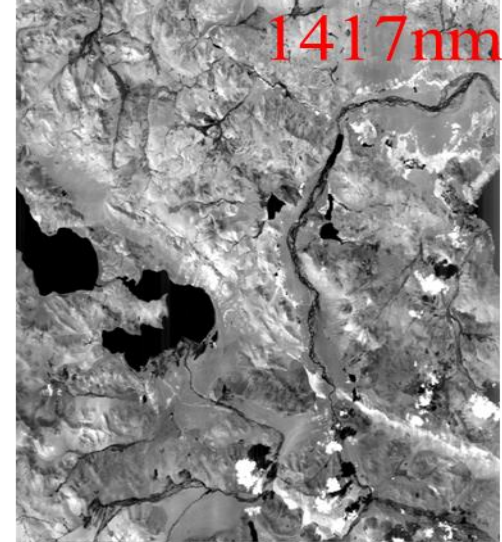
1233nm, 1566nm, 2116nm



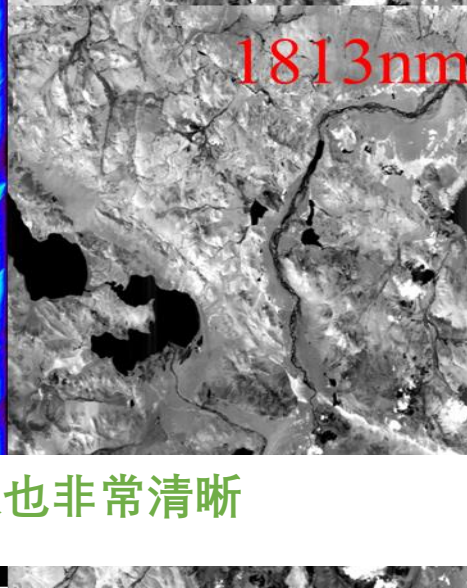
1004nm



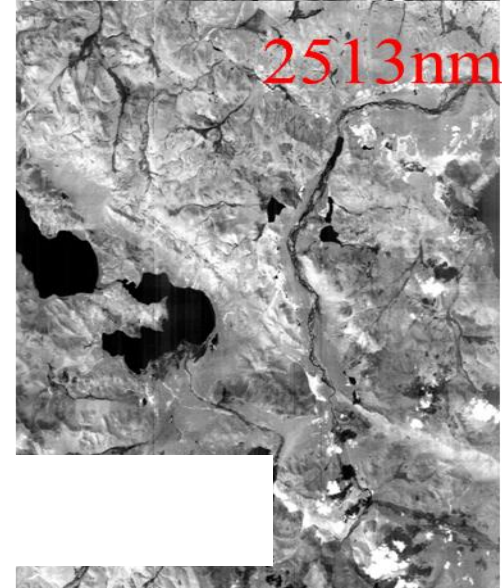
1417nm



1813nm



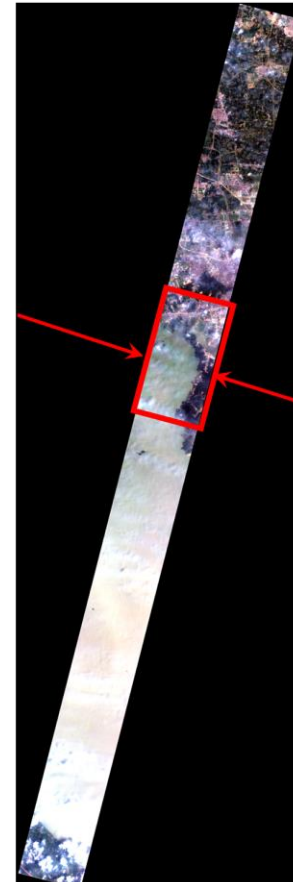
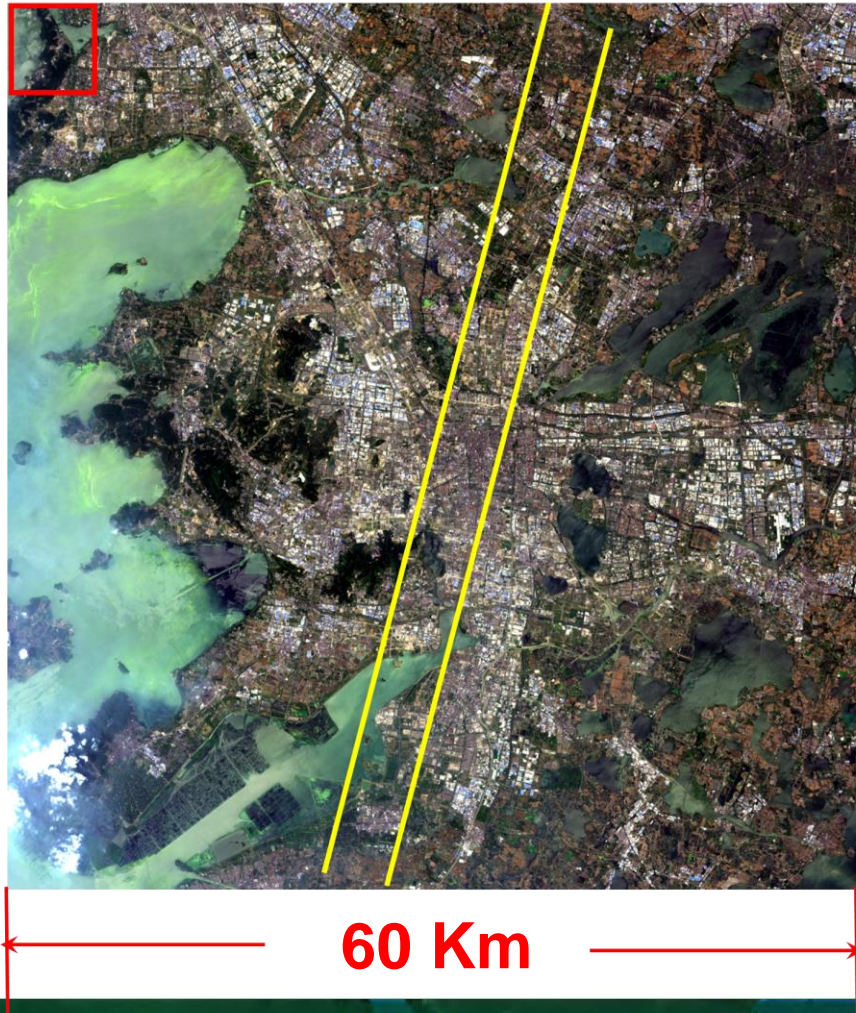
2513nm

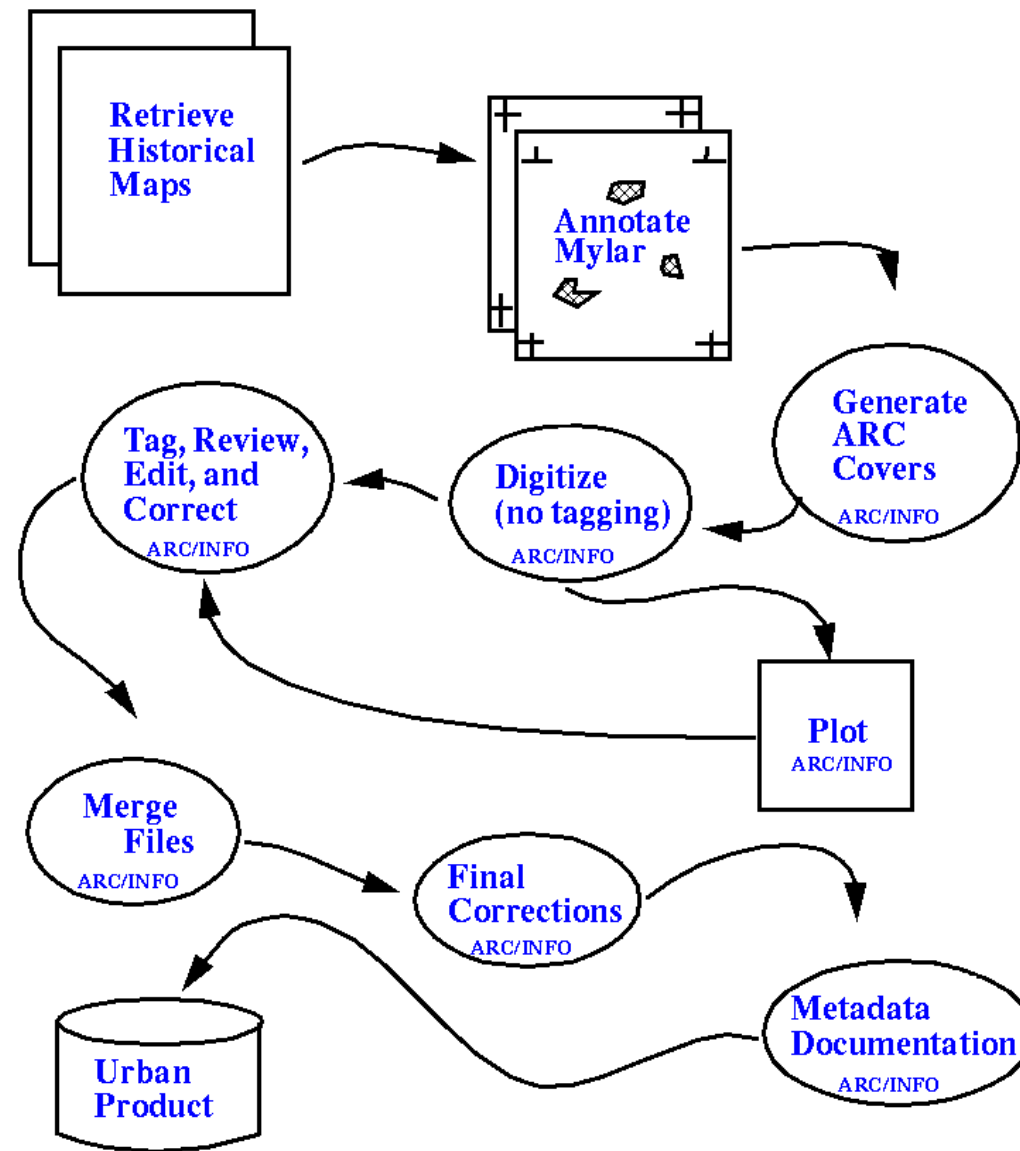


在1004nm 和 2513 nm 处的图像也非常清晰

GF-5 AHSI 苏州太湖

Hyperion 苏州太湖





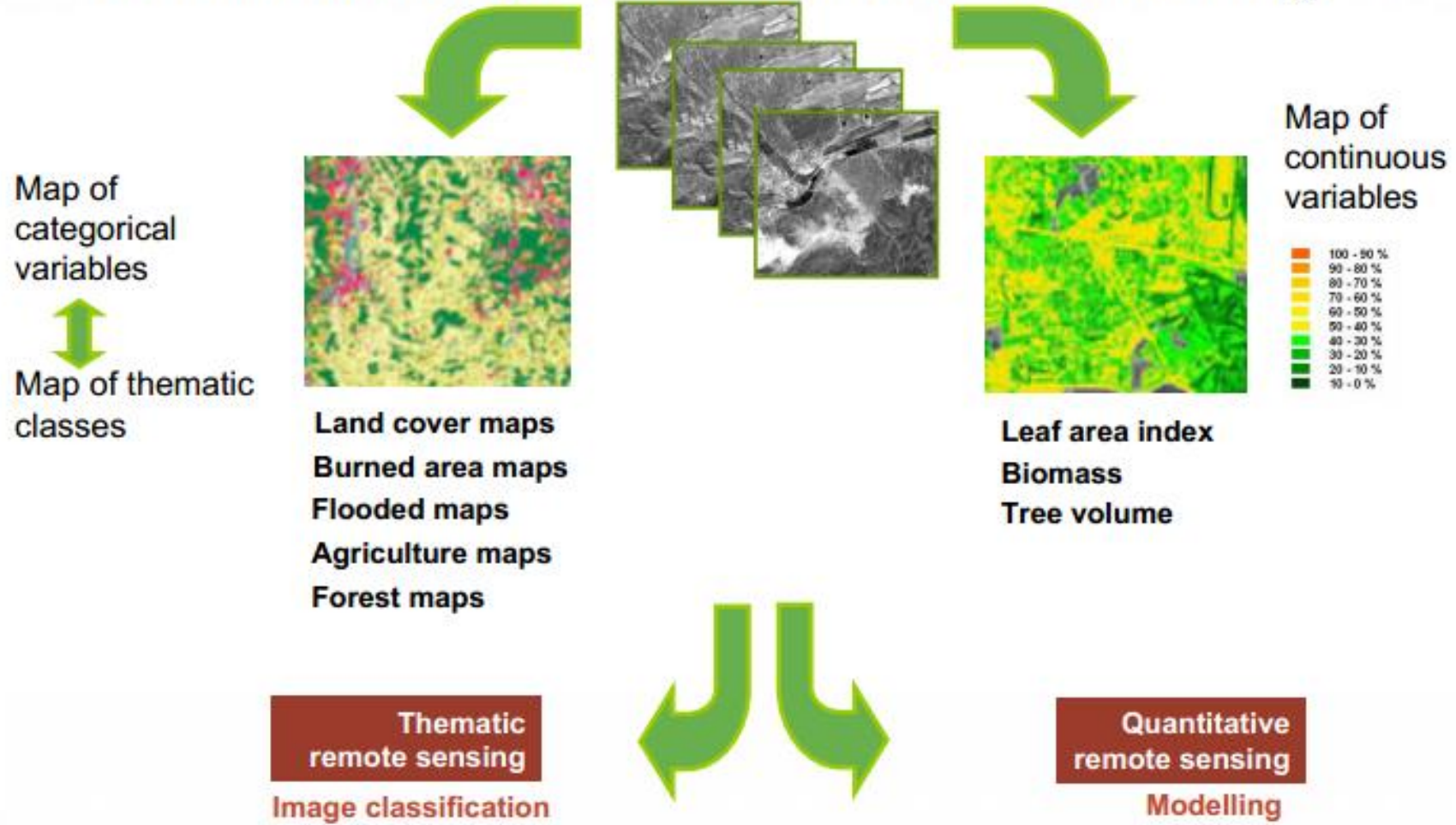
Flow chart depicting the steps involved in delineating urban extent from topographic maps.

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/absolute),
 - 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.

 Map Info

- Proj: UTM, Zone 50S
- Pixel: 20 Meters
- Datum: WGS-84
- UL Geo: 112°7' 20.41"E, 0°2' 46.19"S
- UL Map: 30999.250, 9976411.750

Band Names...

Default Bands to Load...

Spectral Library Names...

Wavelengths...

Bad Bands List...

FWHM...

Gains...

Offsets...

Map Info...

RPC or RSM Projection Emulation...

Associate DEM File...

Geographic Corners...

Pixel Sizes...

Classification Info...

Z-Plot Information...

Reflectance Scale Factor...

Data Ignore Value...

Sensor Type...

Default Stretch...

Complex Lookup Function...

Major / Minor Frame Offsets...

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

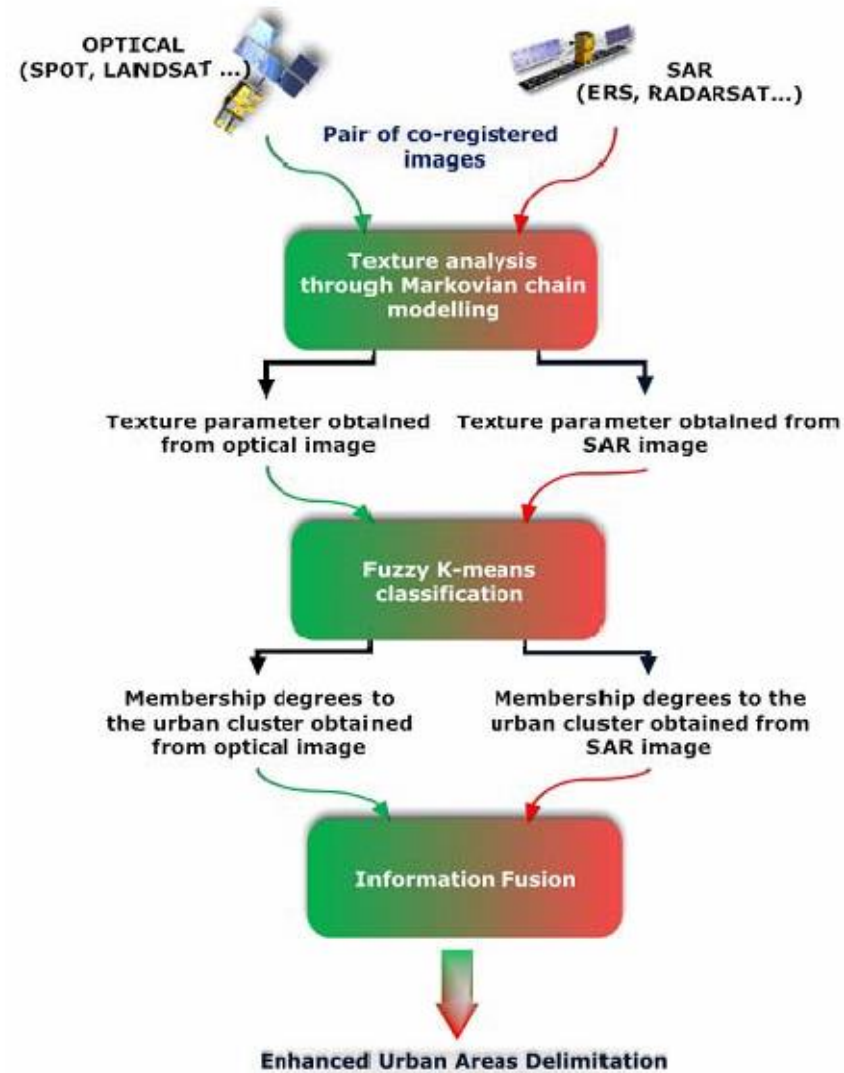
➤ Post-processing

- 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?

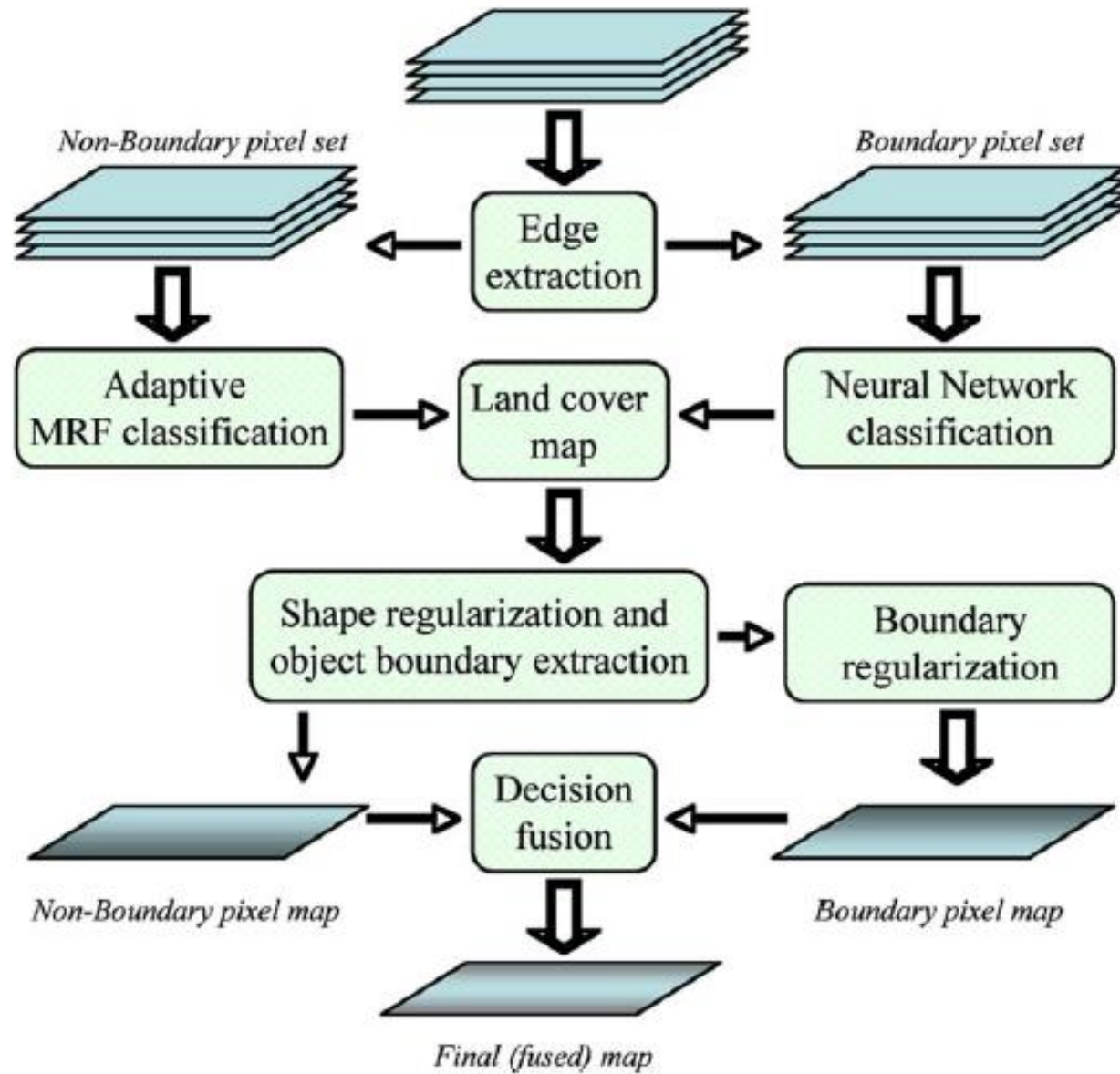
Figure 1. Flow chart of the three-step procedure for rapid urban mapping based on the synergy between SAR and optical sensors.



**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

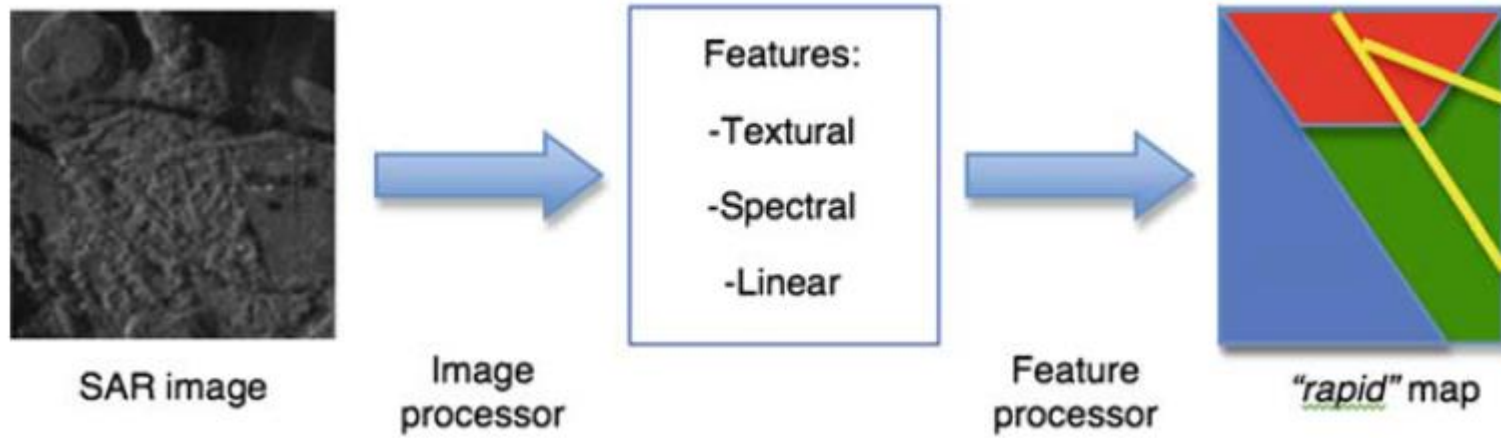


Fig. 2.4 The urban area extraction procedure

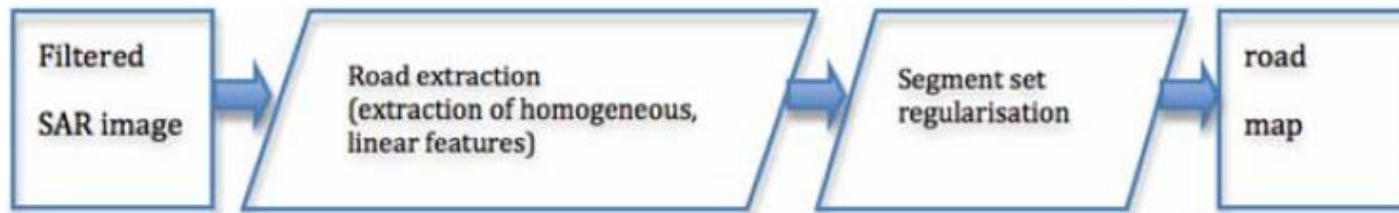


Fig. 2.6 The road extraction procedure

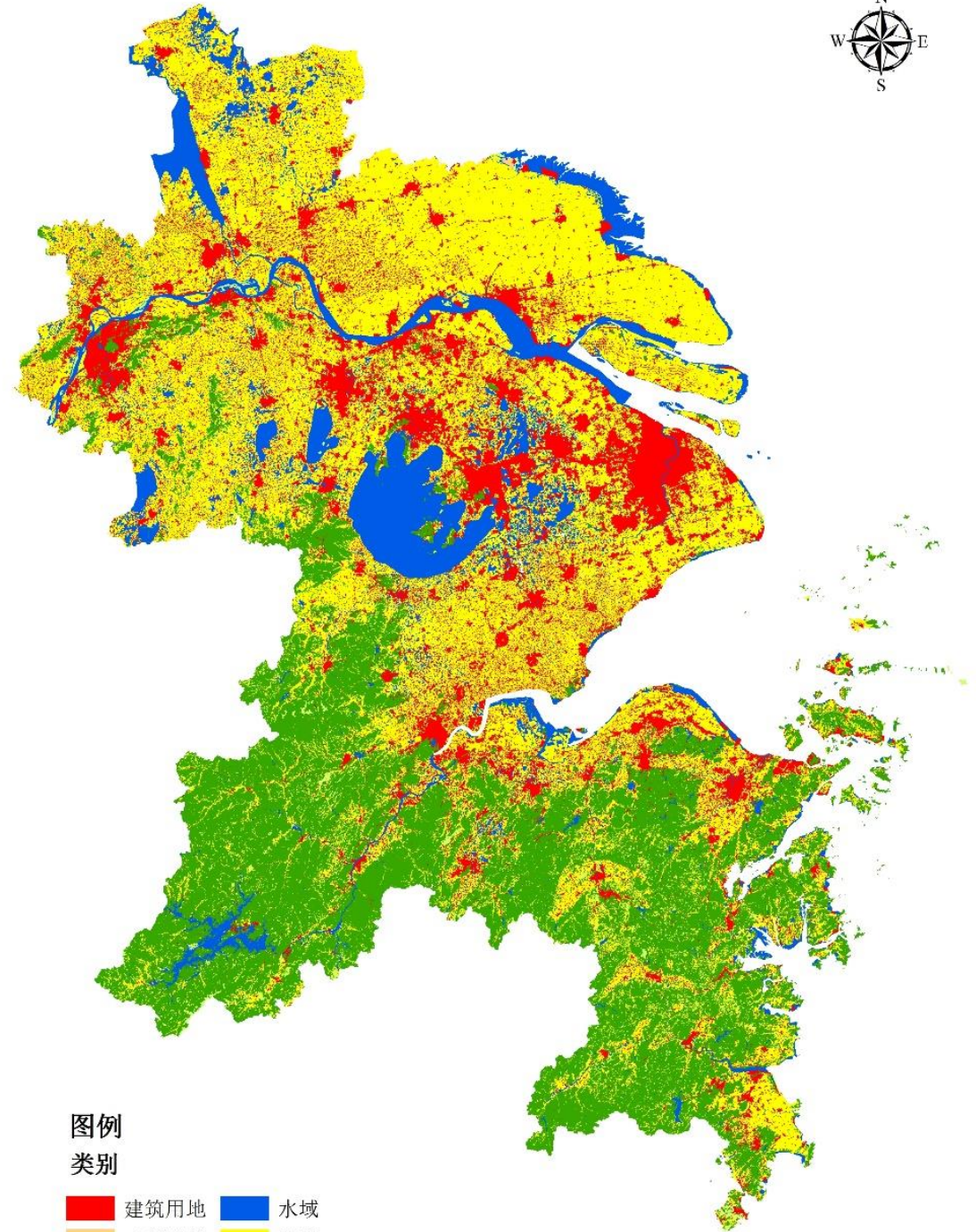
Fabio Dell'Acqua and Paolo Gamba. **Rapid Mapping Using Airborne and Satellite SAR Images**. In: **Global mapping of human settlement: Experiments, datasets and prospects** (Edited by Paolo Gamba and Martin Herold)

Content

- 1 Urban remote sensing
- 2 Technical flow of urban mapping
- 3 Urban extent mapping**
- 4 Urban land cover/land use mapping
- 5 Urban thematic mapping
- 6 ISA estimation and mapping
- 7 Change detection
- 8 Conclusions and Advances

- 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 mosaic 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.

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 focus on robust physical characterization of urban reflectance properties and on comparative analyses of diverse urban environments.

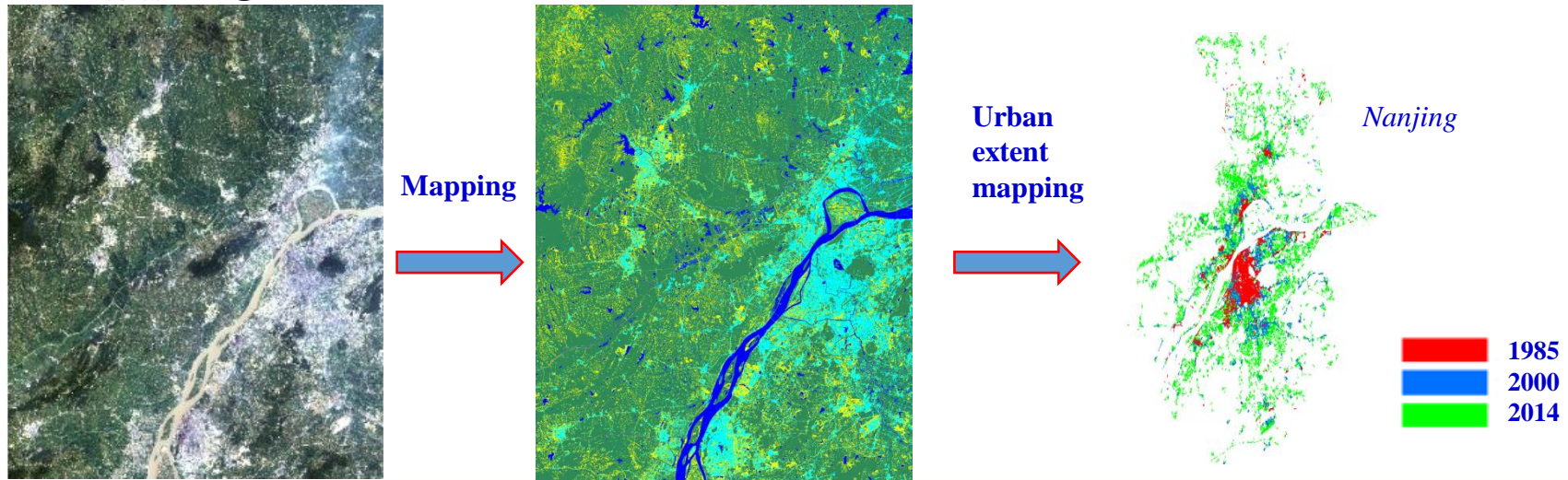
Spectral Mixture Analysis is investigated as a means to accommodate the variable spatial scale and spectral heterogeneity of the urban mosaic.

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



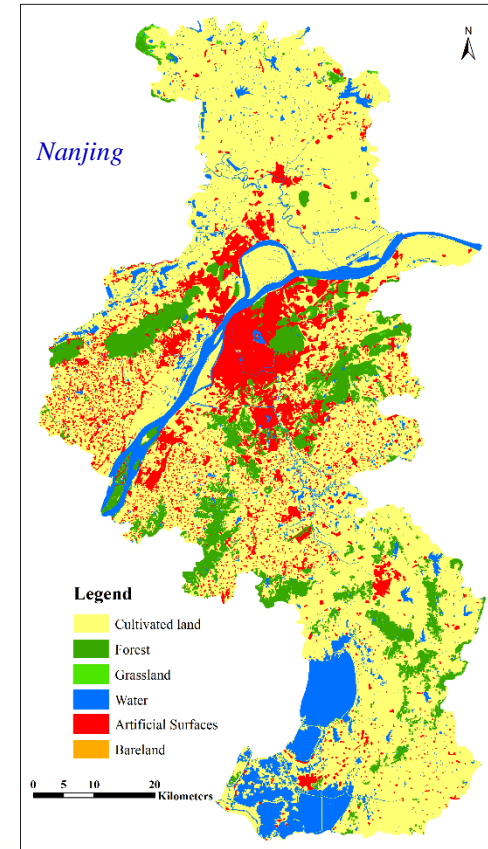
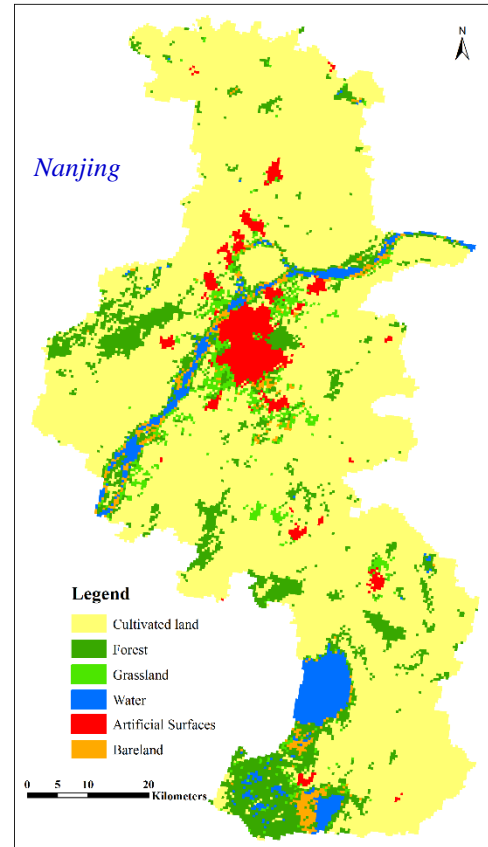
Solution 3: **multi-scale images based solution**

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



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):

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

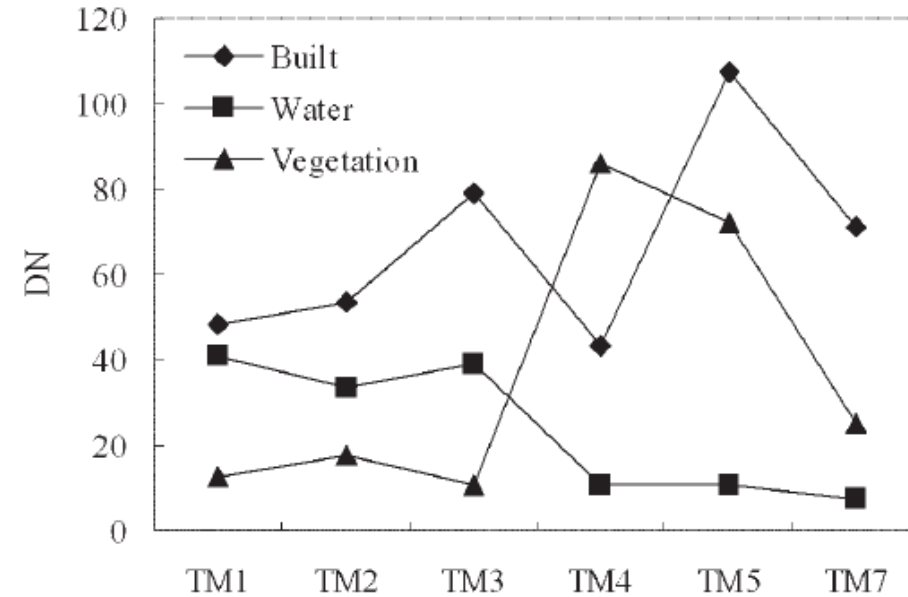
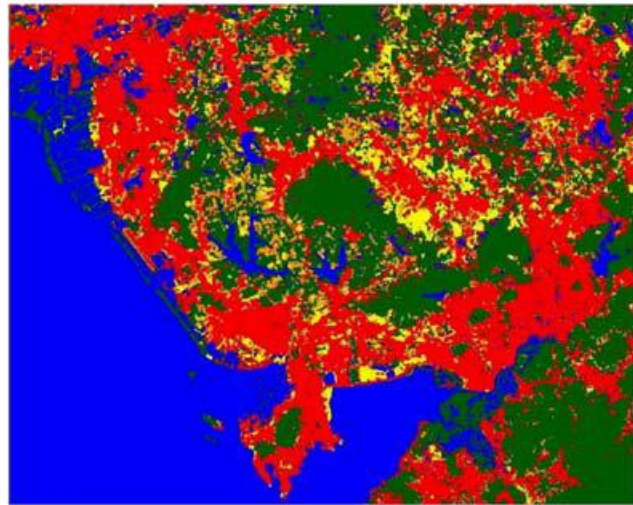


Figure 3. Spectral signatures represented by the mean of three urban land-use classes taking the Quanzhou image as an example.

For Landsat TM/ETM+ images

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

Land-use

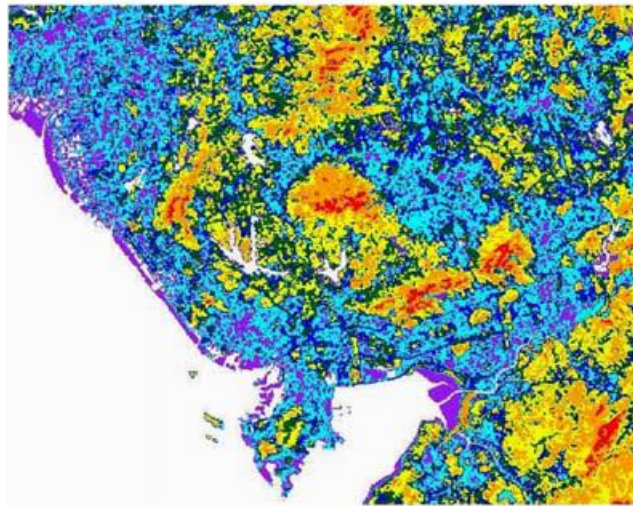


Legend



(a)

NDVI

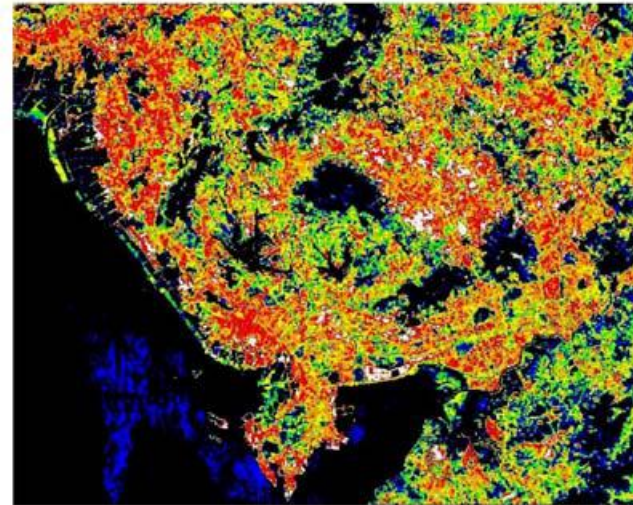


Legend

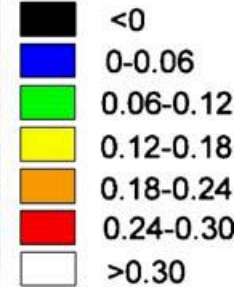


(c)

NDBI

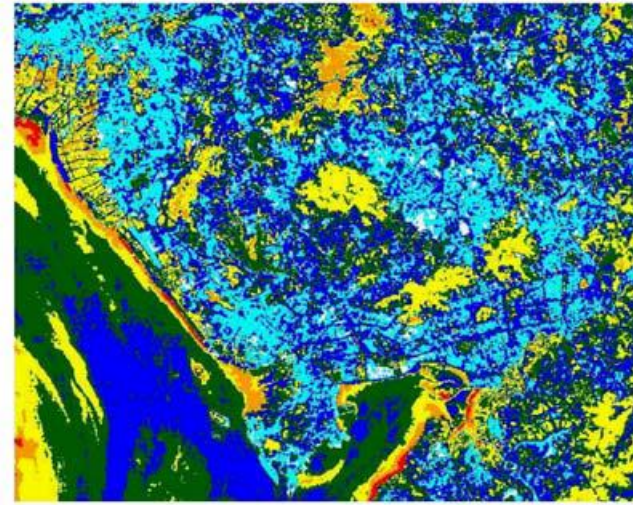


Legend

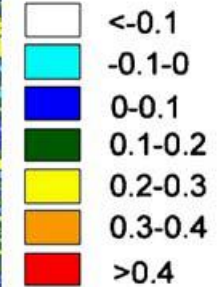


(b)

NDWI



Legend



(d)

Extraction of Built-up area by **IBI** (Index-Based Built-up index, Xu

Hanqiu, IJRS, 2008):

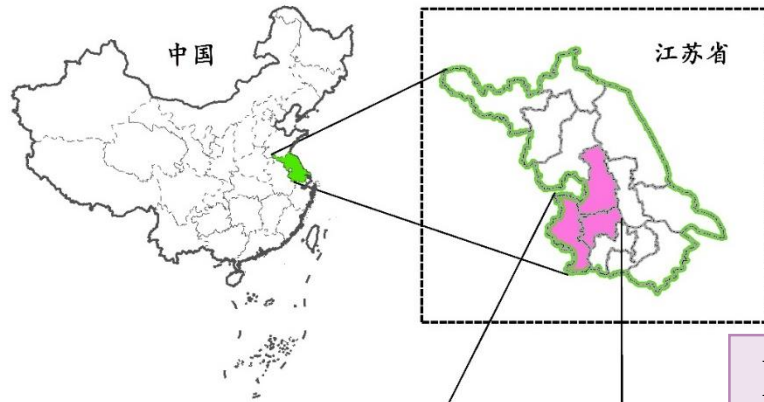
$$IBI = \frac{[NDBI - (SAVI + MNDWI)/2]}{[NDBI + (SAVI + MNDWI)/2]}$$

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

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

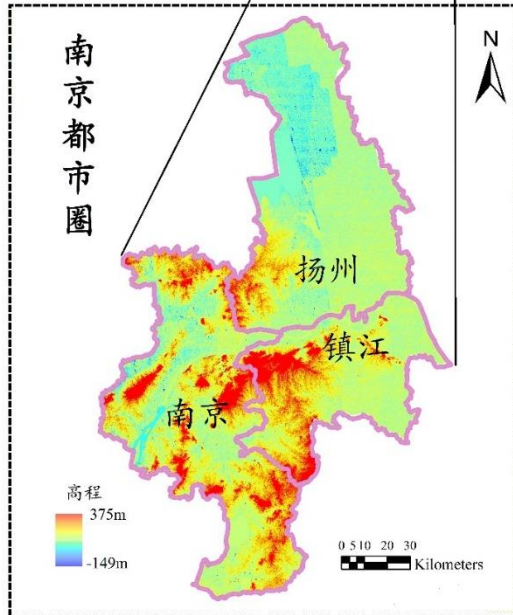
$$MNDWI = \frac{(Green - MIR)}{(Green + MIR)}$$

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

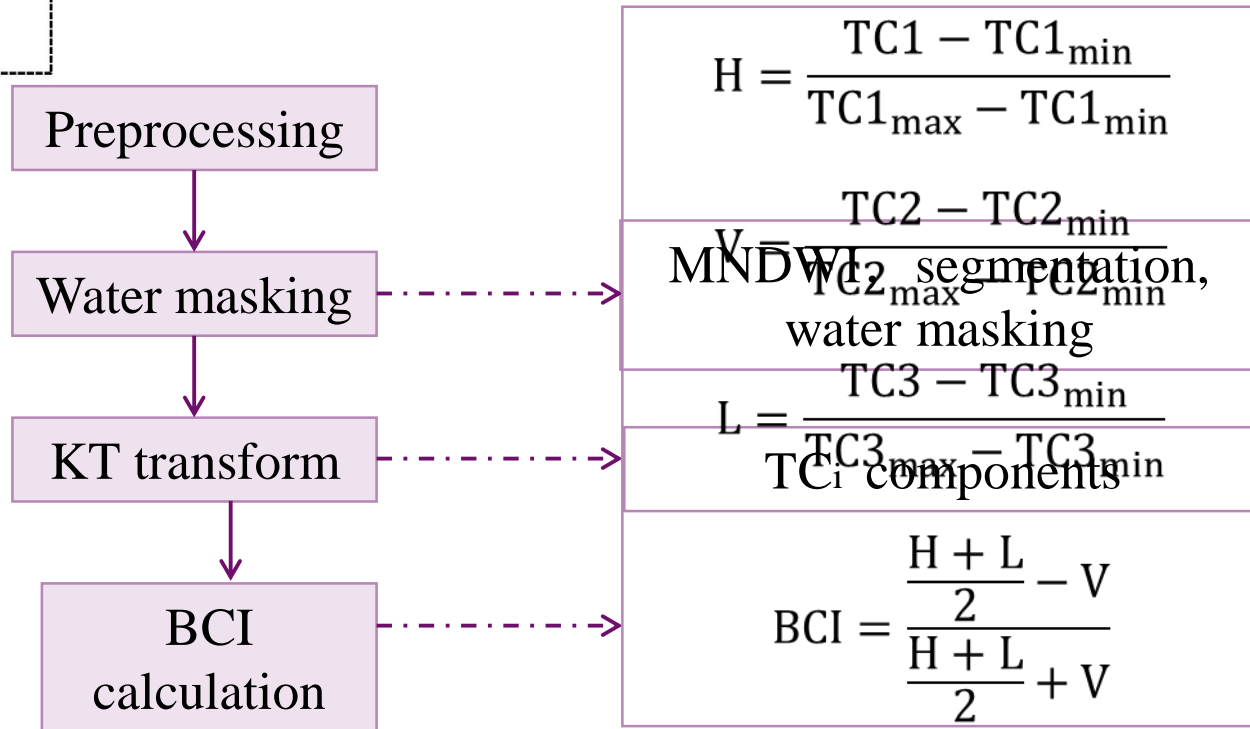


➤ BCI (Biophysical Composition Index, Deng *et al.* 2012)

(118°15' E, 33°35' N)

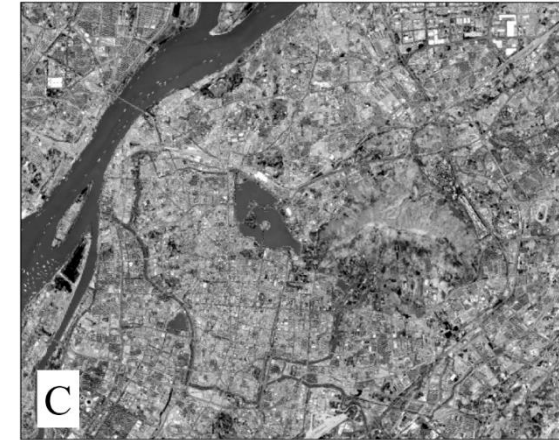


(120° E, 31° N)





-0.35 | 0.35



-0.90 | 0.40



-0.35 | 0.90



-1 | 0.55

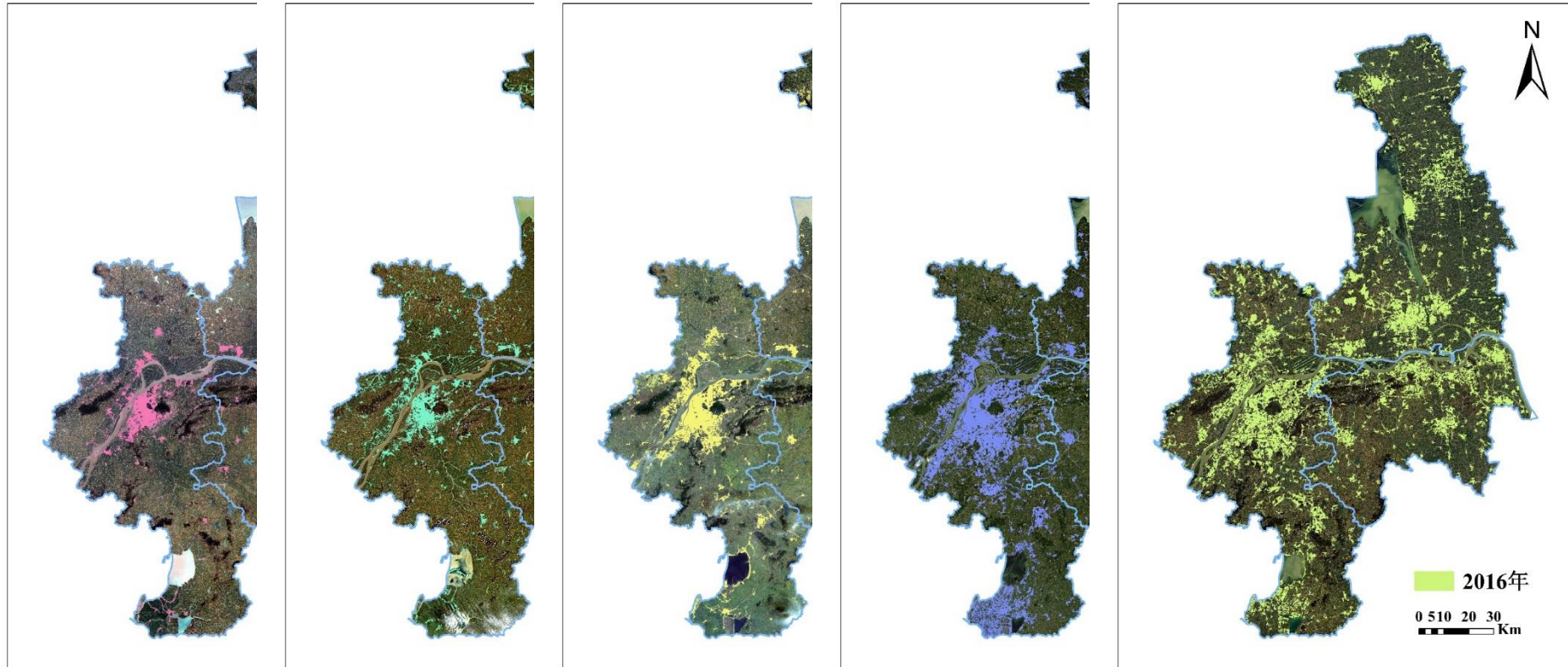
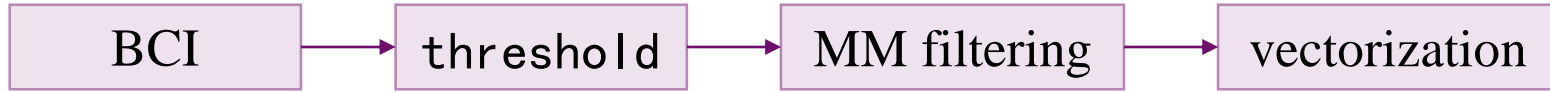
A. True color image

B. NDBI

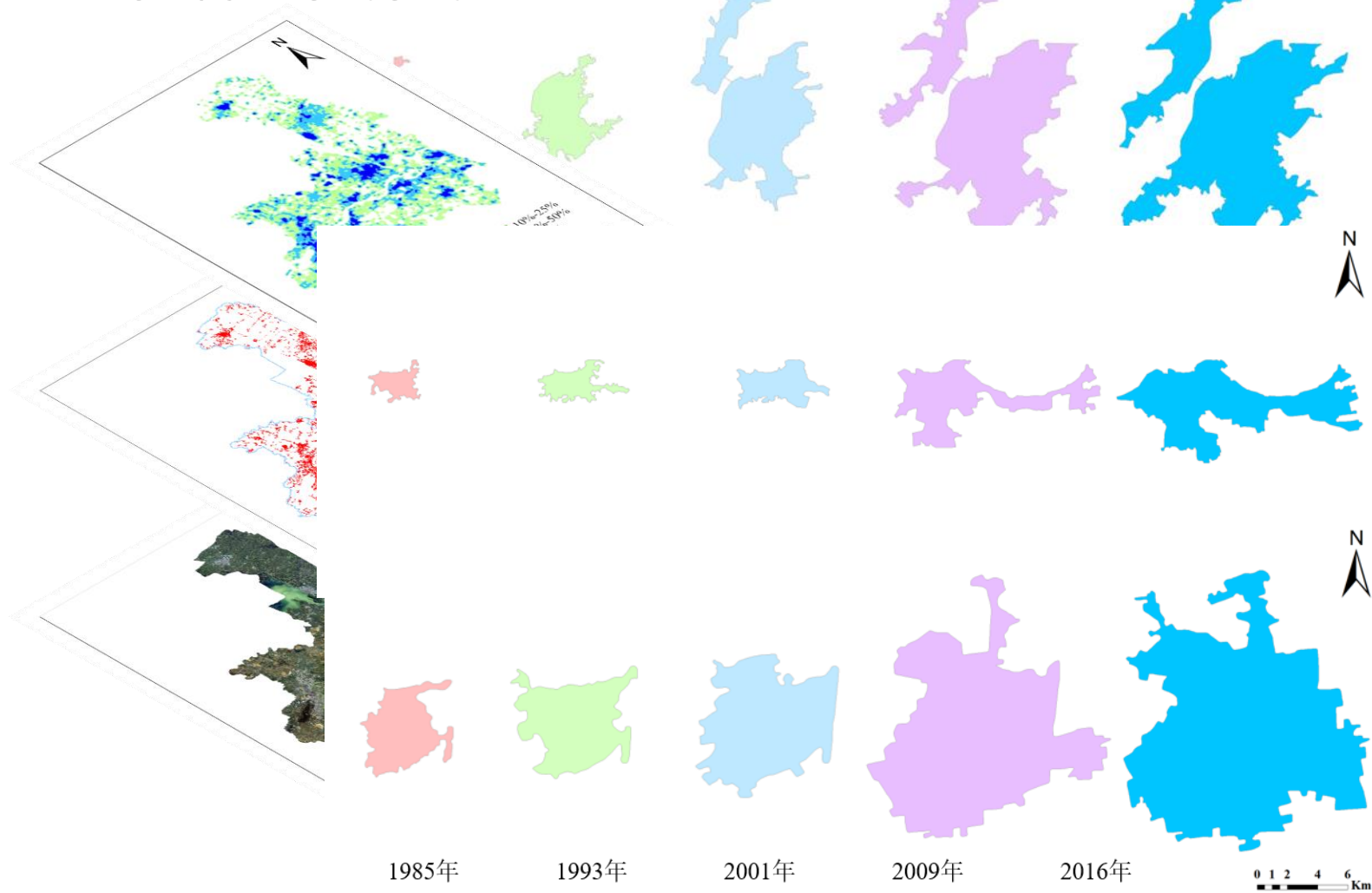
C. IBI

D. BCI

E. CBI



- Urban extent



Content

- 1 Urban remote sensing
- 2 Technical flow of urban mapping
- 3 Urban extent mapping
- 4 Urban land cover/land use mapping**
- 5 Urban thematic mapping
- 6 ISA estimation and mapping
- 7 Change detection
- 8 Conclusions and Advances

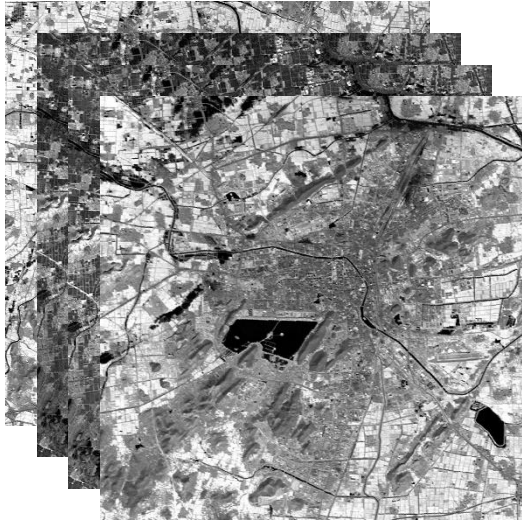
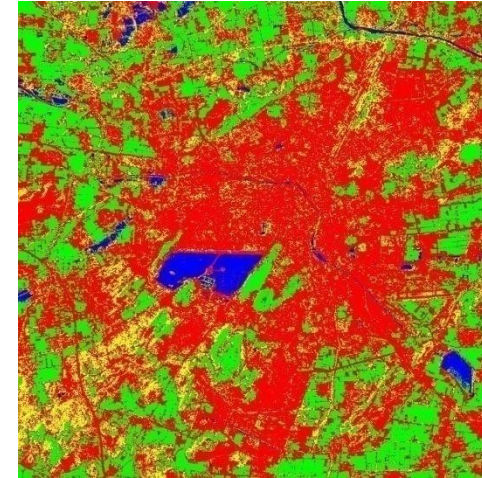


Image spatial space



Allocation of a class
to each pixel



Classification map

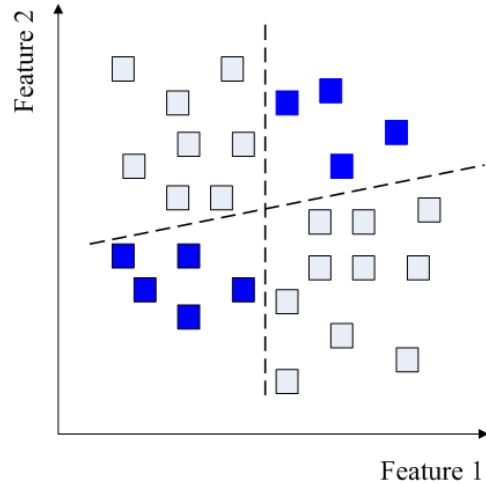


Image feature space

- 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

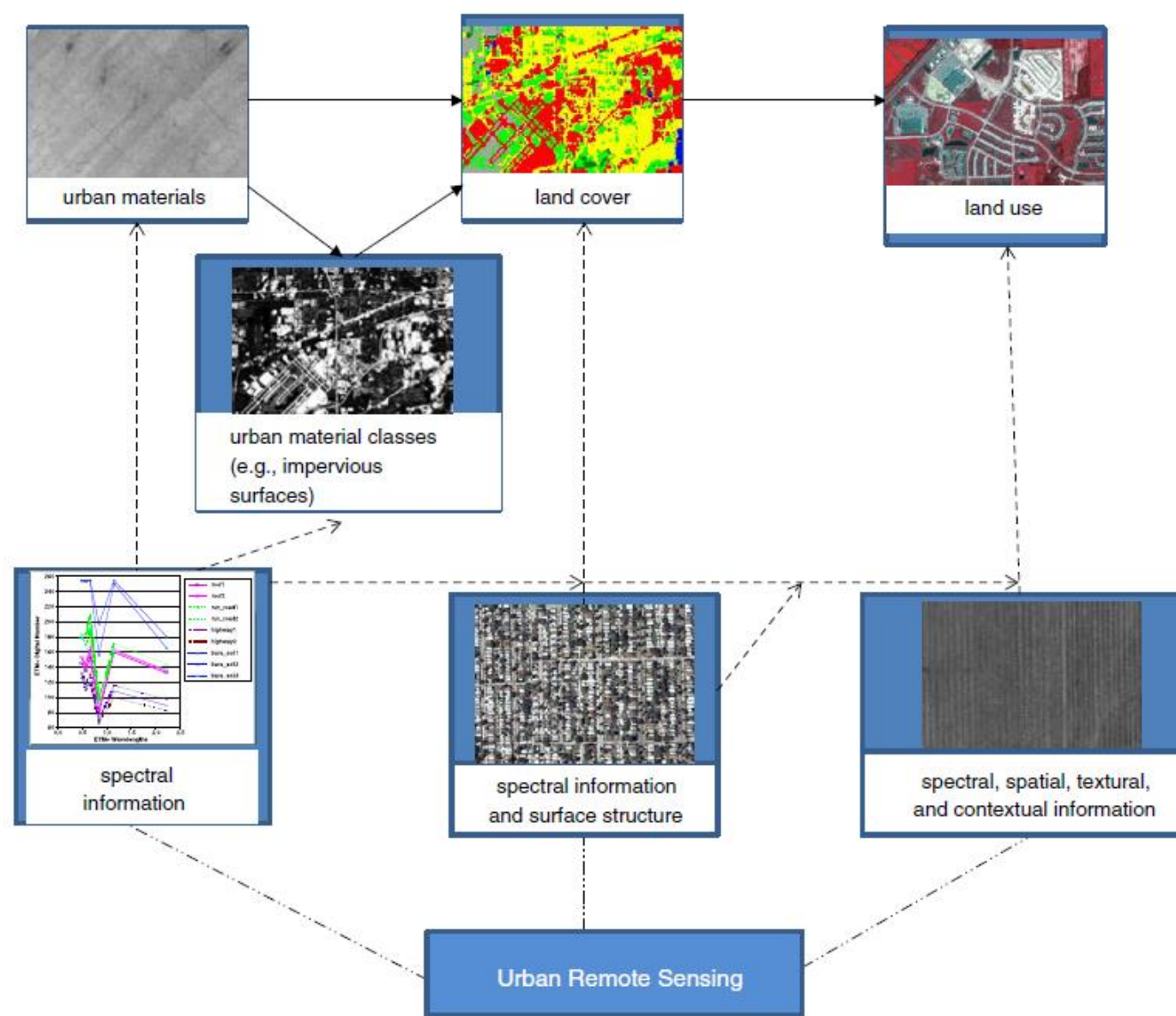
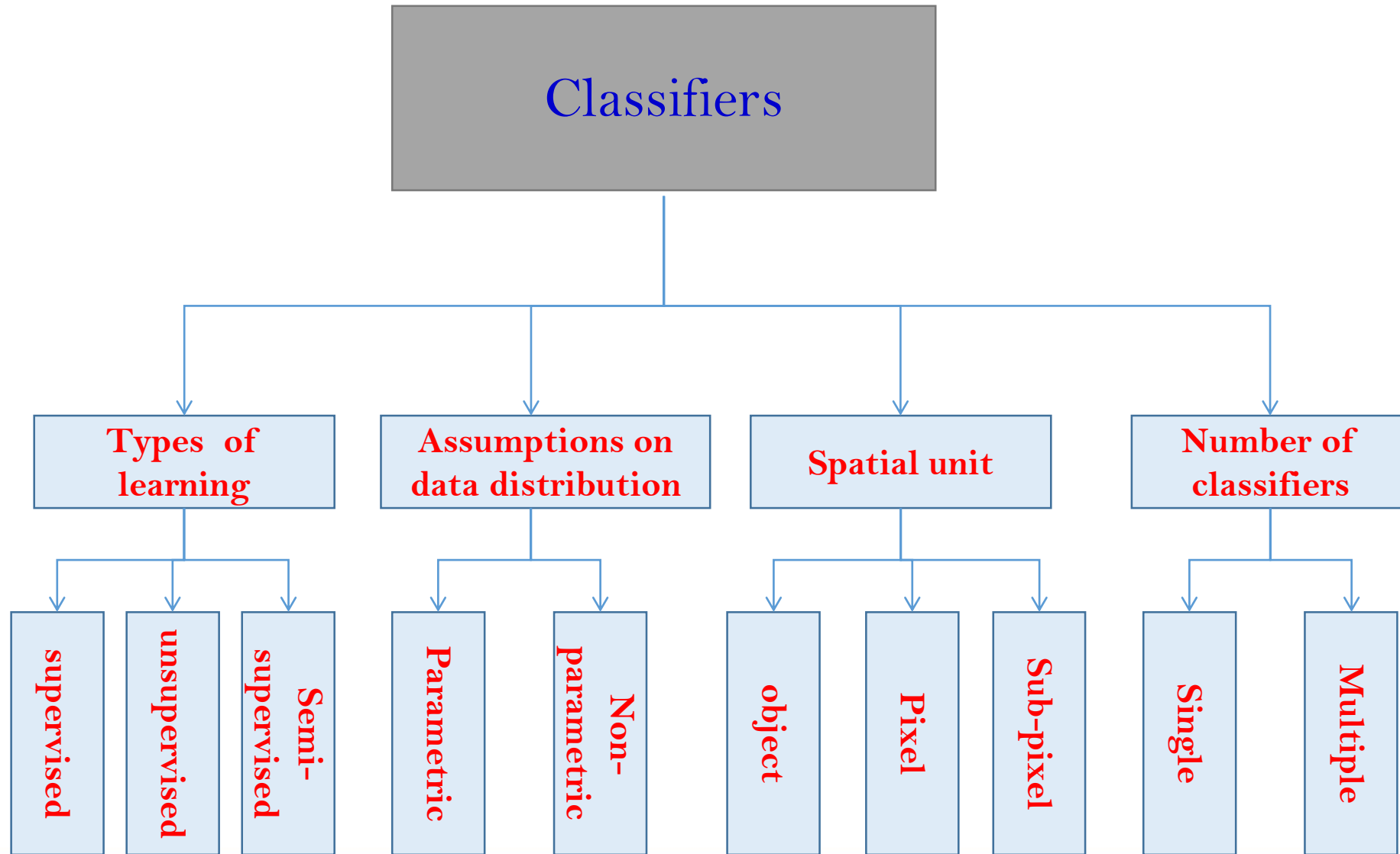
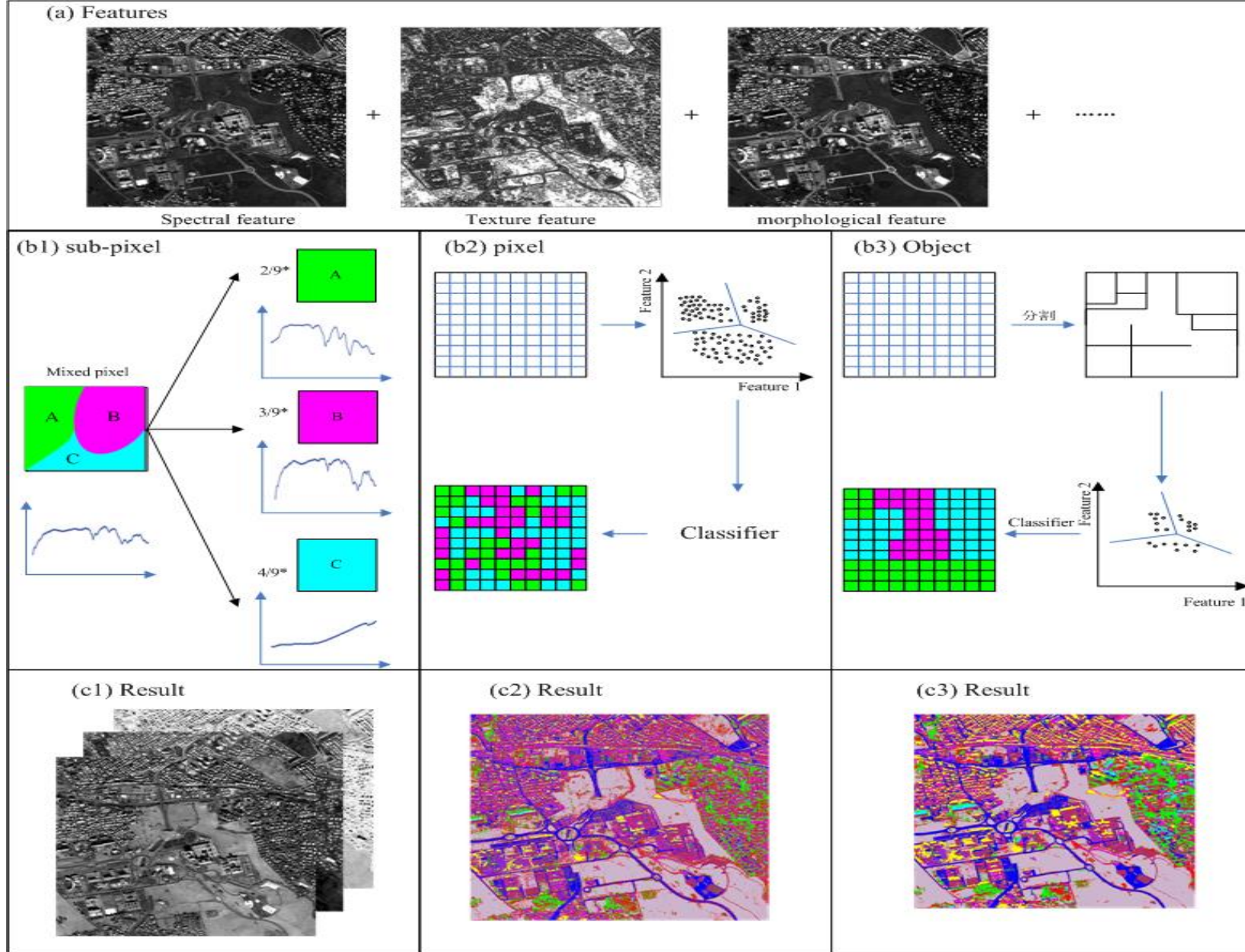


Illustration of the relationship among remote sensing of urban materials, land cover, and land use (after Weng & Lu, 2009).

Major steps of image classification

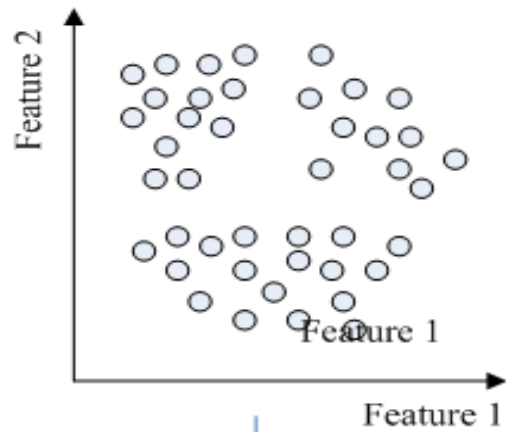
- determination of a suitable classification system
- selection of training samples
- Image preprocessing
- feature extraction
- selection of suitable classification approaches
- post-classification processing
- accuracy assessment



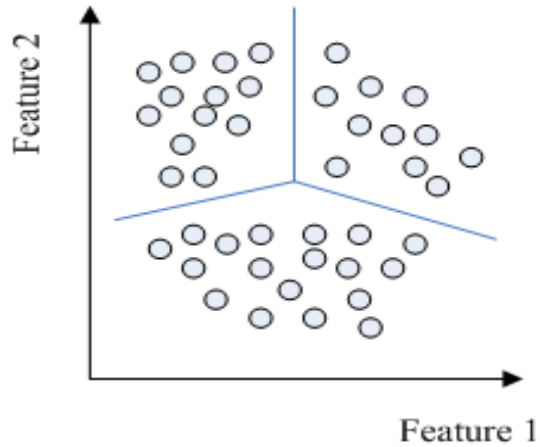


(1) Unsupervised classification

Including only unlabeled pixels $\{x\}$

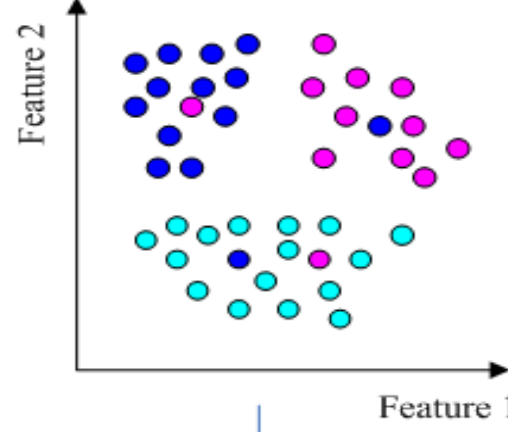


Classifier

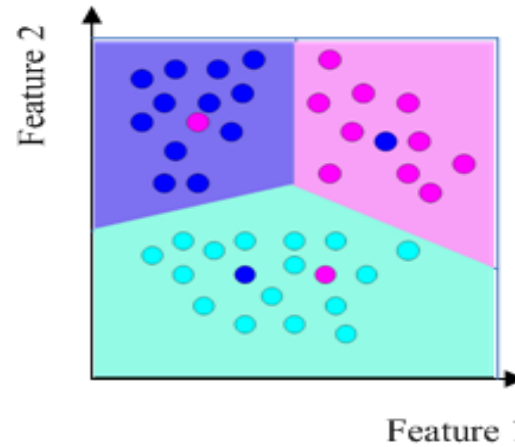


(2) Supervised classification

Including labeled pixels $\{x, y\}$

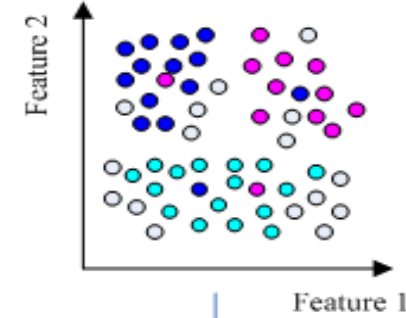


Classifier

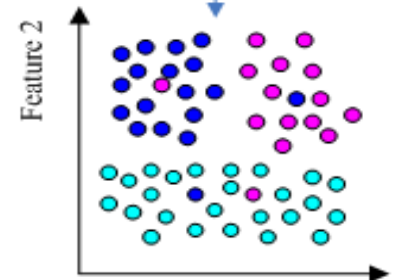


(3) Semi-supervised classification

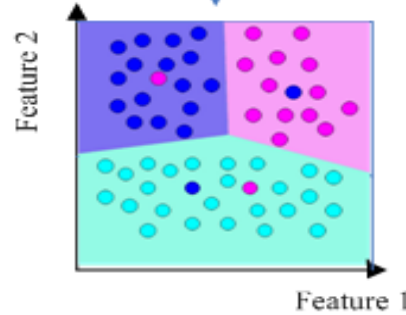
Including both labeled and unlabeled pixels



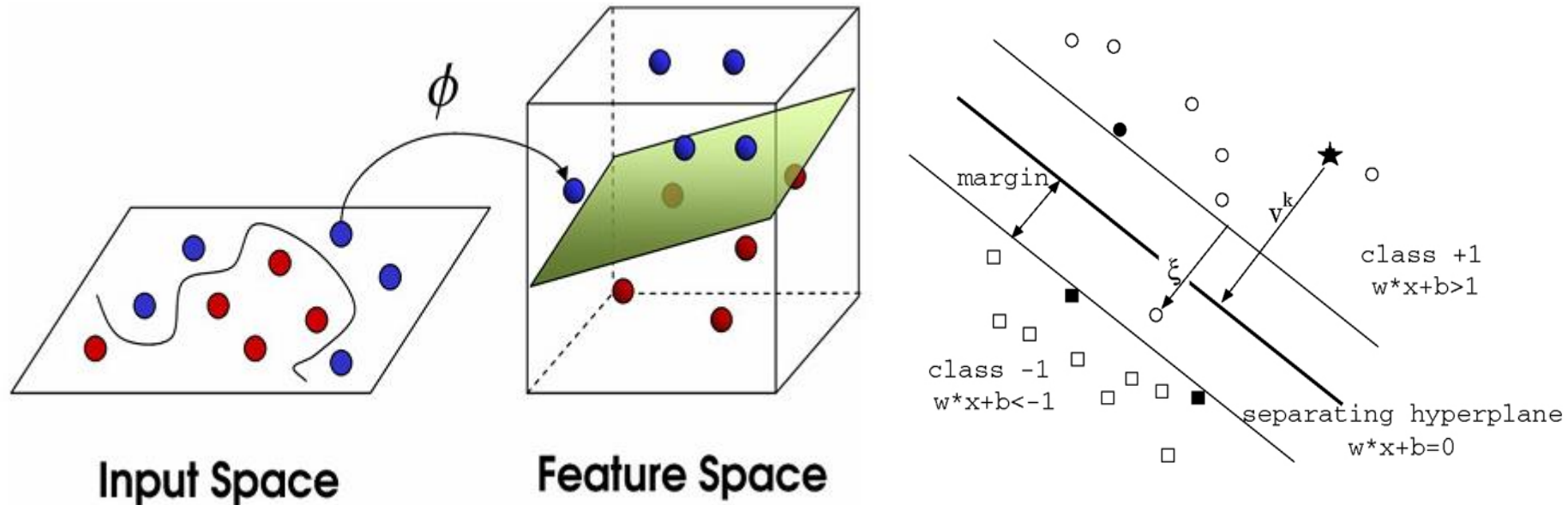
Labeled



Classifier



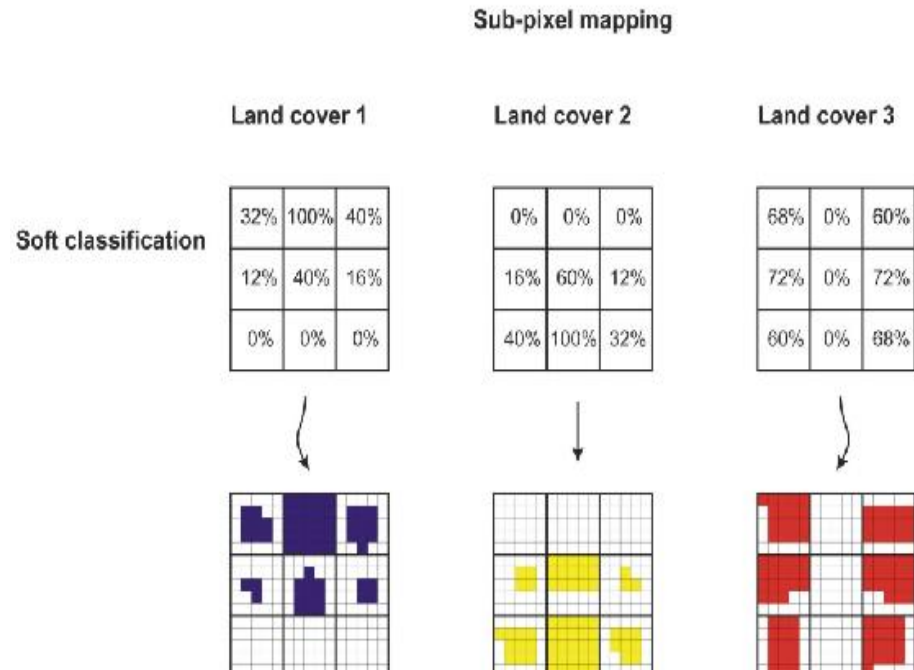
Support Vector Machines (SVM)



- 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**.



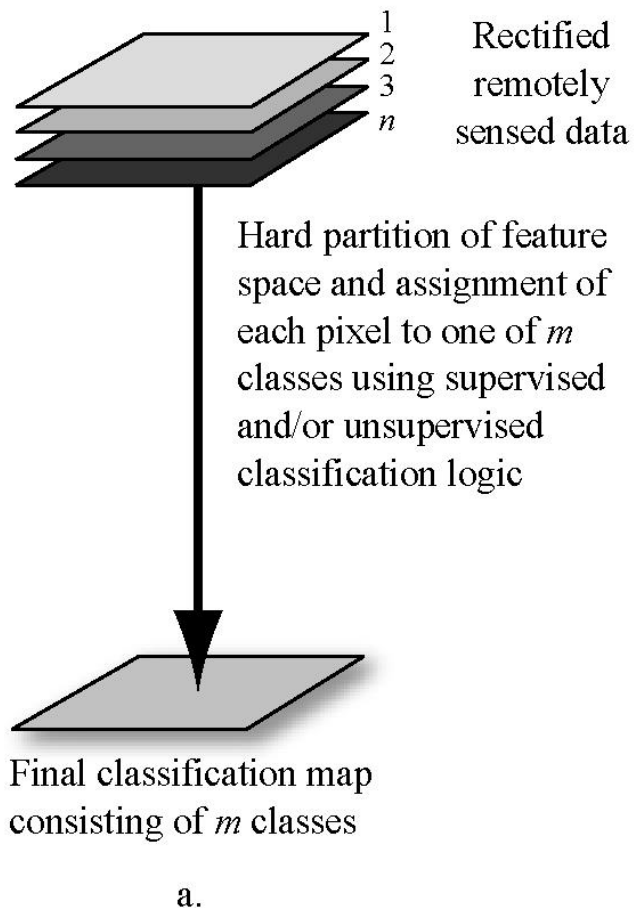
➤ Mixed pixels in an image varies mainly with

- Landscape fragmentation
- Sensor's spatial resolution

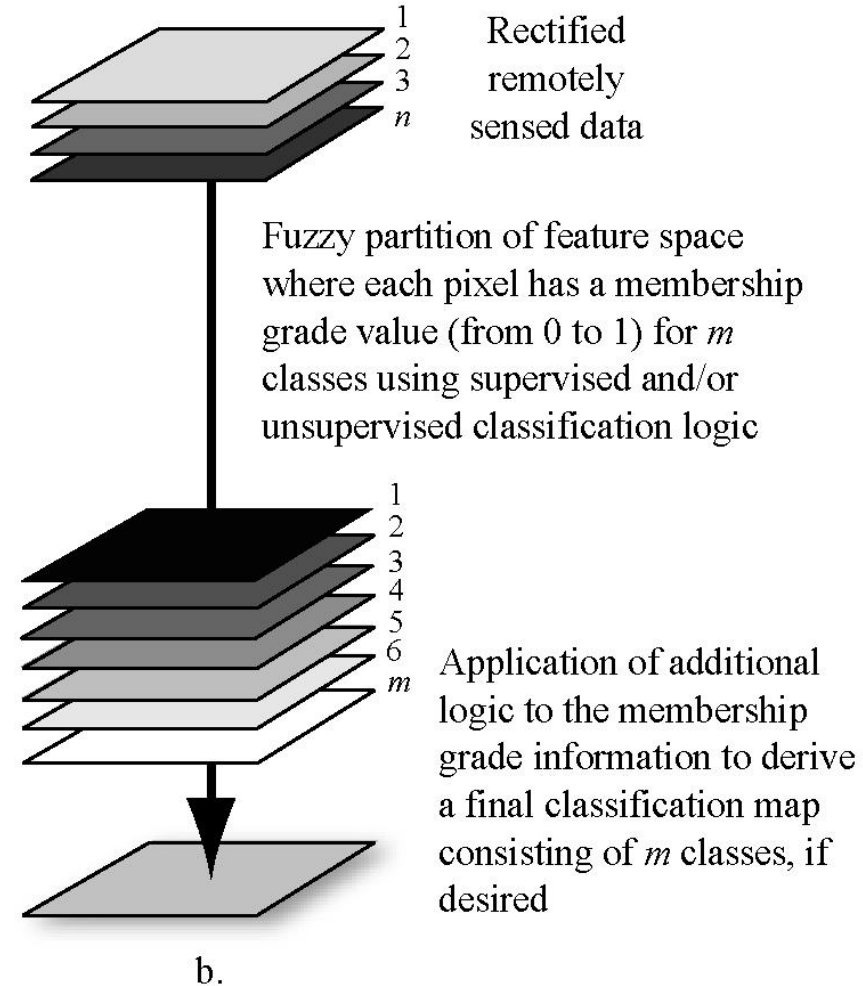
➤ Mixed pixel exists

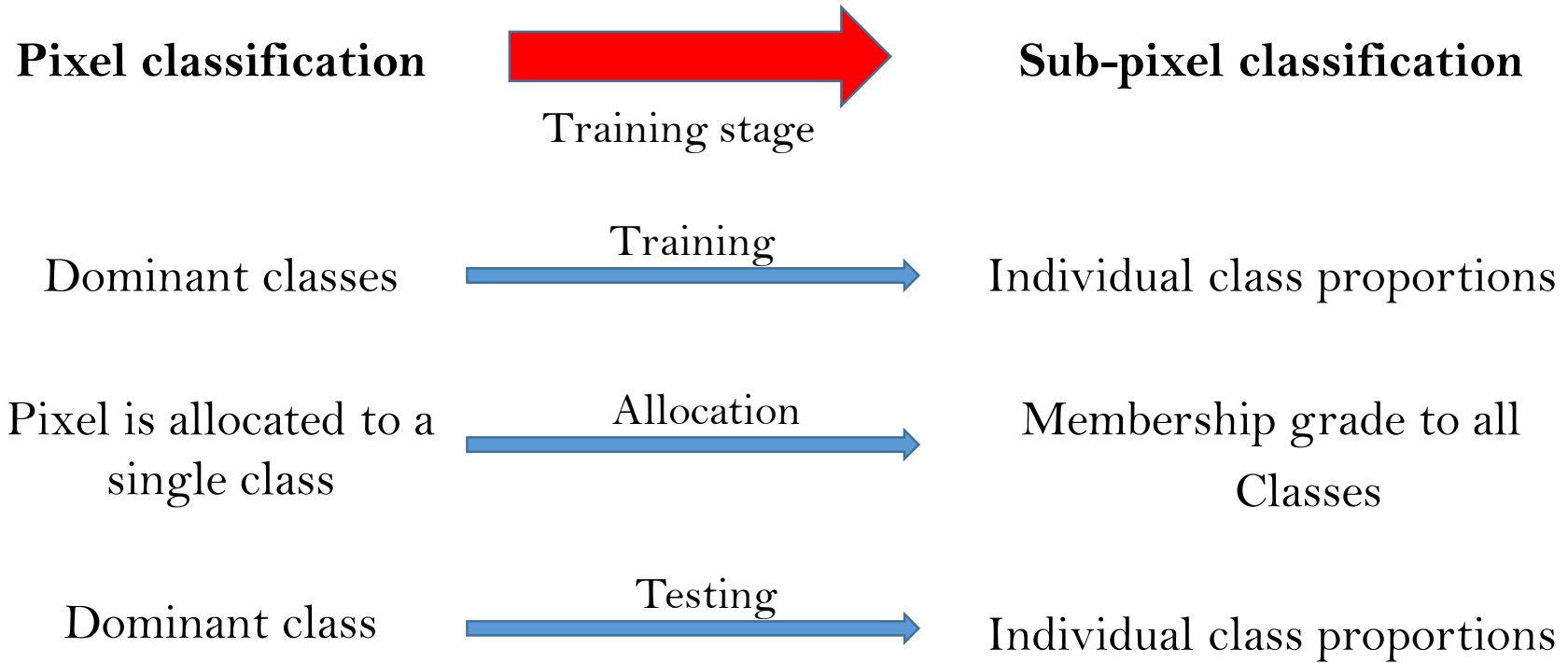
- Presence of small, sub-pixel targets
- Presence of boundaries of discrete land cover classes
- Gradual transition between land cover classes
- Contribution of areas outside the area represented by a pixel

Single-stage Hard Classification of One Pixel to One Class



Computation of Fuzzy Membership Grades and Final Classification

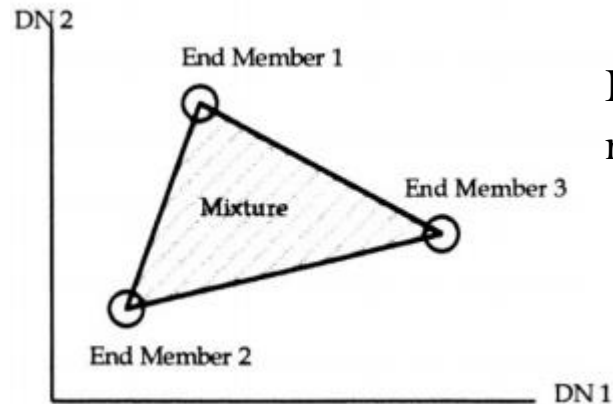




Common sub-pixel classifiers: fuzzy c-means, possibility c-means, fuzzy rule based classifications, fuzzy set theory, ANN

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

OPEN ACCESS

sensors

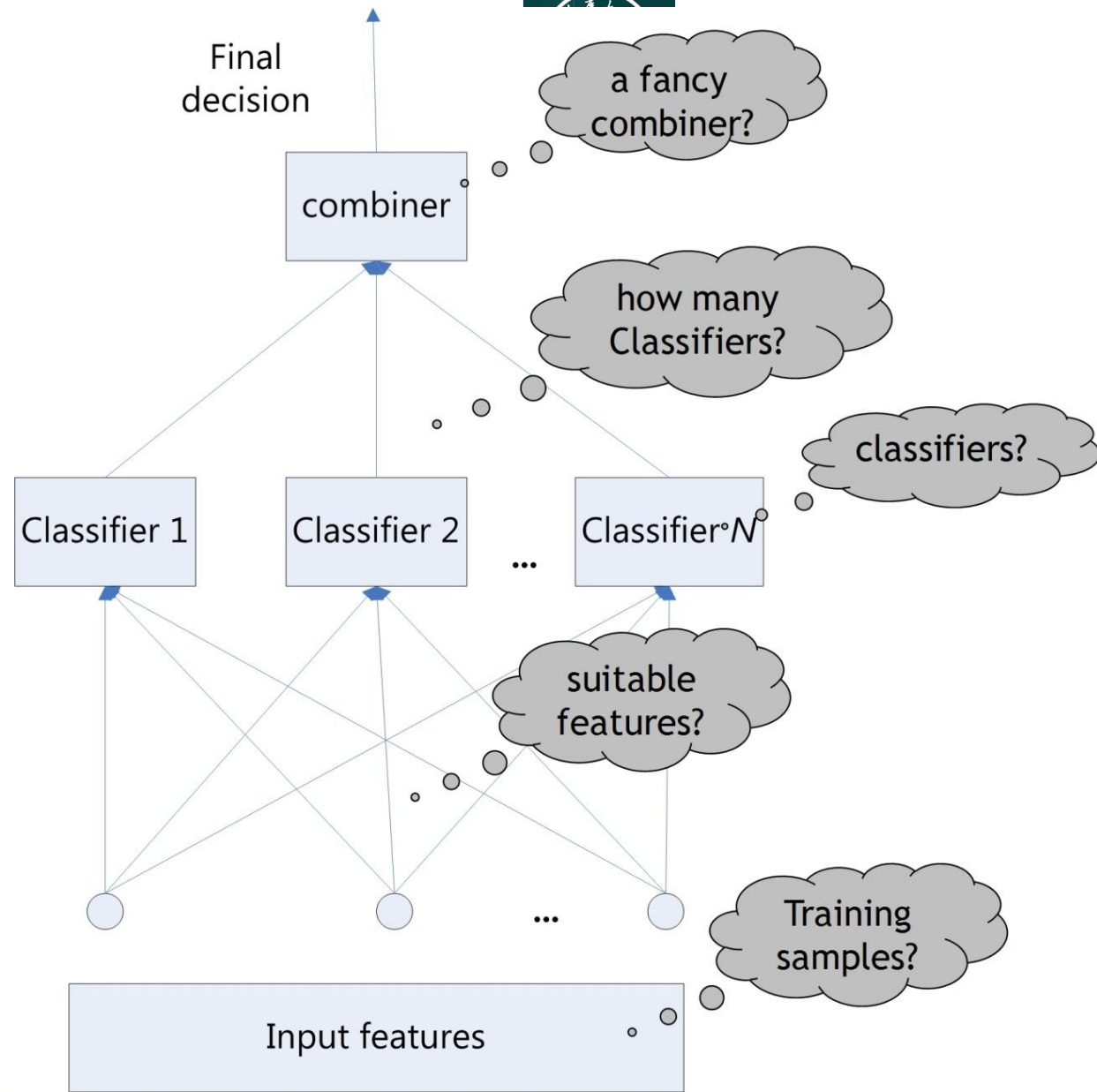
ISSN 1424-8220

www.mdpi.com/journal/sensors

Review

Multiple Classifier System for Remote Sensing Image Classification: A Review

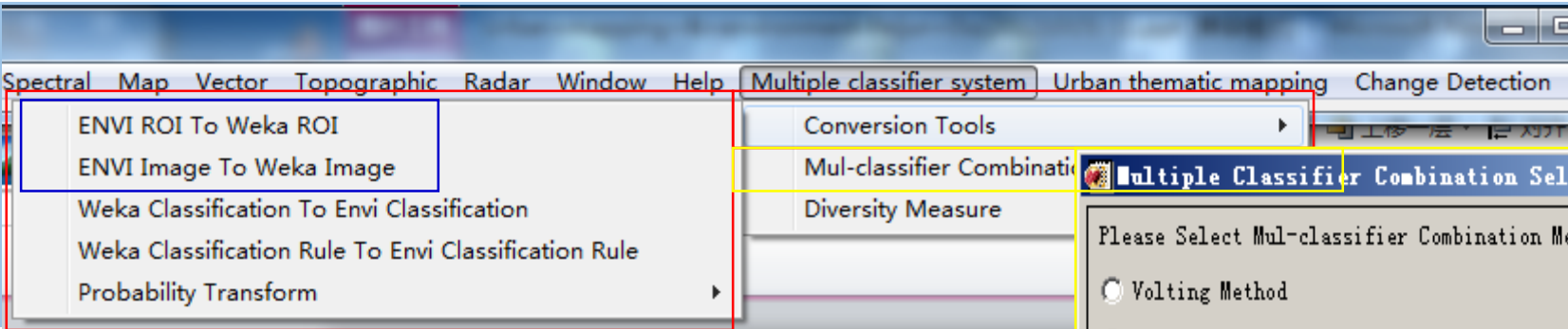
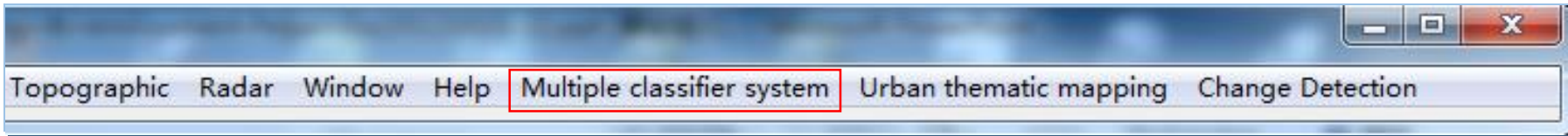
Peijun Du ^{1,2,*}, Junshi Xia ², Wei Zhang ³, Kun Tan ², Yi Liu ² and Sicong Liu ²

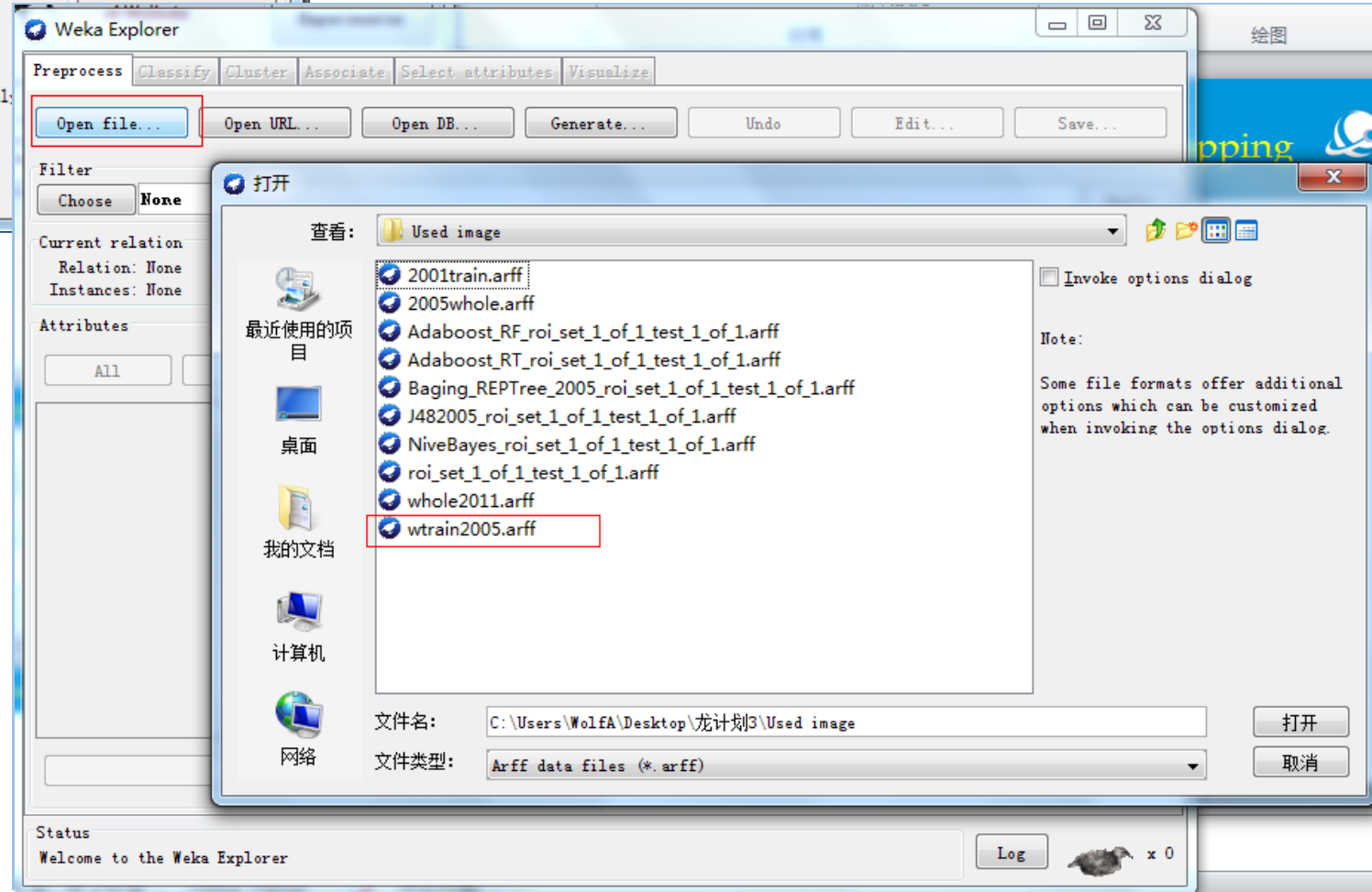
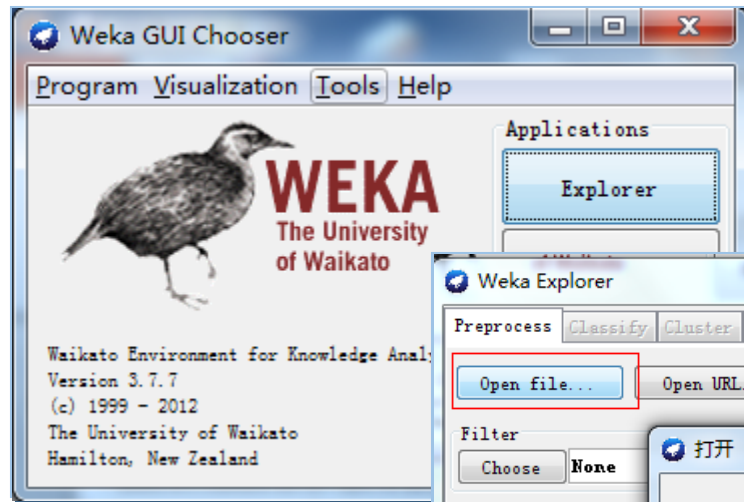


Ensemble in different processing sites

- 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 computation	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





Weka KnowledgeFlow Environment

Design

- DataSources
 - ArffLoader
 - C45Loader
 - CSVLoader
 - DatabaseLoader
 - JSONLoader
 - LibSVMLoader
 - MatlabLoader
 - SerializedInstanceLoader
 - SVMLightLoader
 - TextDirectoryLoader
 - XRFFLoader
- DataSinks
 - ArffSaver
 - C45Saver
 - CSVsaver
 - DatabaseSaver
 - JSONSaver
 - LibSVMsaver
 - MatlabSaver
 - SerializedInstanceSaver
 - SVMLightSaver
 - XRFFSaver
- Filters
 - Classifiers
 - bayes
 - functions
 - lazy
 - meta
 - AdaBoostM1
 - AdditiveRegression
 - AttributeSelection
 - Bagging
 - Classification
 - CostSensitiveClassifier
 - CVPParameterSelector
 - FilteredClassifier
 - LogitBoost
 - MultiClassClassifier
 - MultiClassClassifier

Untitled1 x

```

    graph LR
      ArffLoader[ArffLoader] -- data Set --> TrainSetMaker[Training Set Maker]
      TrainSetMaker -- training Set --> ClassAssigner[Class Assigner]
      ClassAssigner -- training Set --> Bagging[Bagging]
      ArffLoader2[ArffLoader2] -- data Set --> TestSetMaker[Test Set Maker]
      TestSetMaker -- test Set --> ClassAssigner2[Class Assigner2]
      ClassAssigner2 -- test Set --> ArffSaver[Arff Saver]
      Bagging -- batch Classifier --> PredictionAppender[Prediction Appender]
      ArffSaver -- test Set --> PredictionAppender
  
```

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
- Dynamic Cluster Selection

OK Cancel

#1 Band 1: Majority Voting Fusion CD Result

File Overlay Enhance Tools Window

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

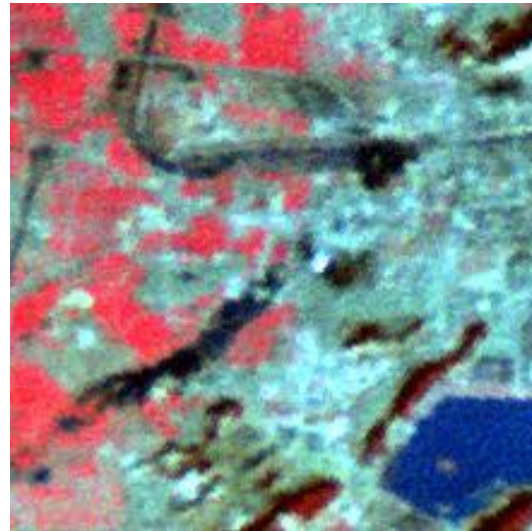
Dims 1000 x 1000 (Byte) [BSQ]

Band Display #1

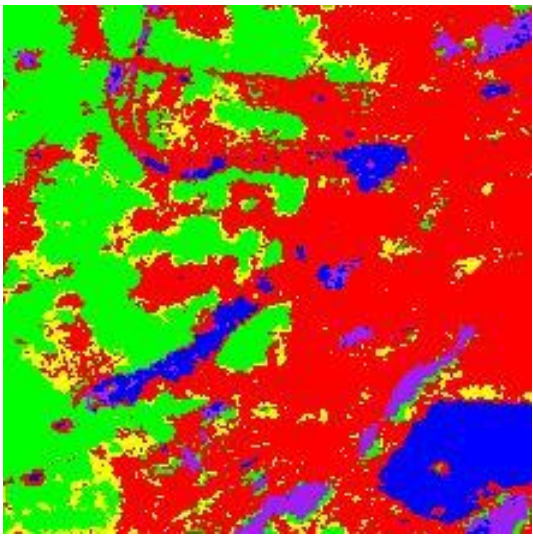
#1 Scroll (0.25600)

#1 Zoom [4...]

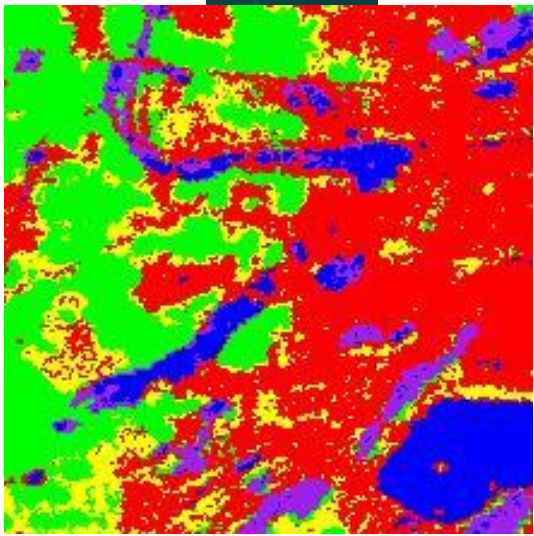
BJ-1 PAN and MS images



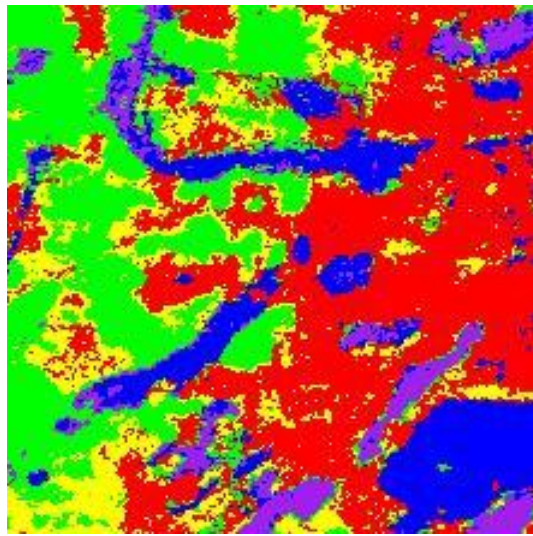
(a) Multispectral image (b) Panchromatic image



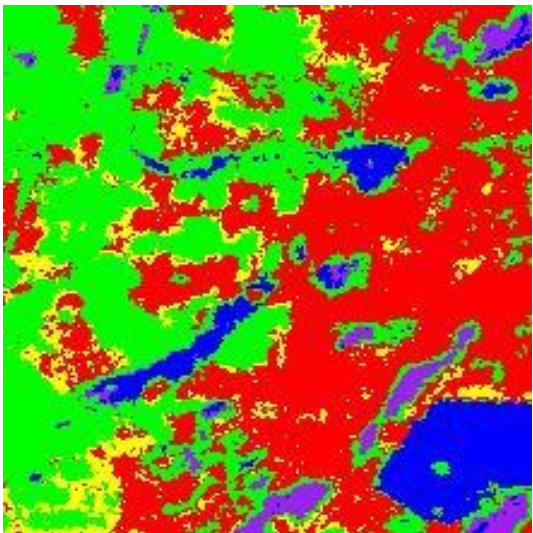
MLC



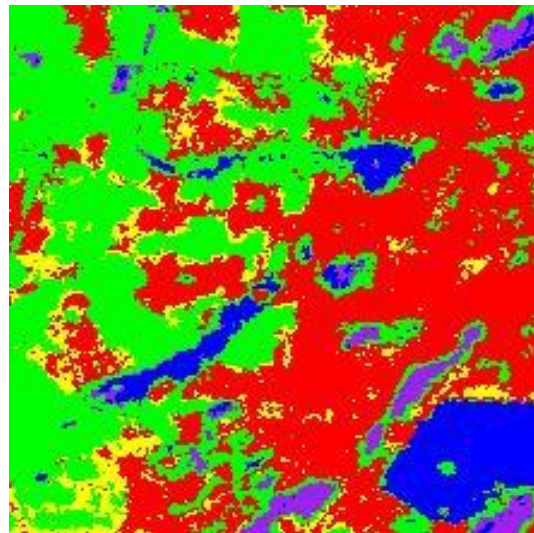
SVM



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

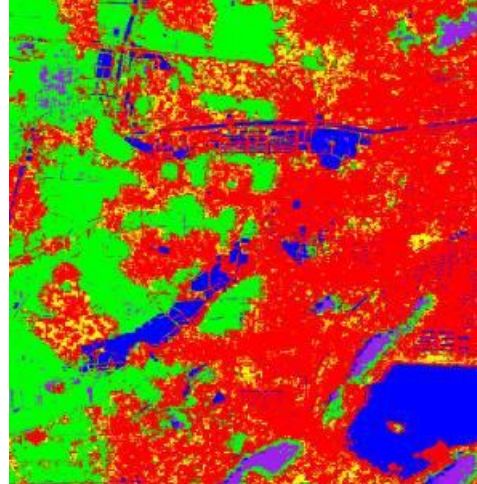
(d) Gram-Schmidt

	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

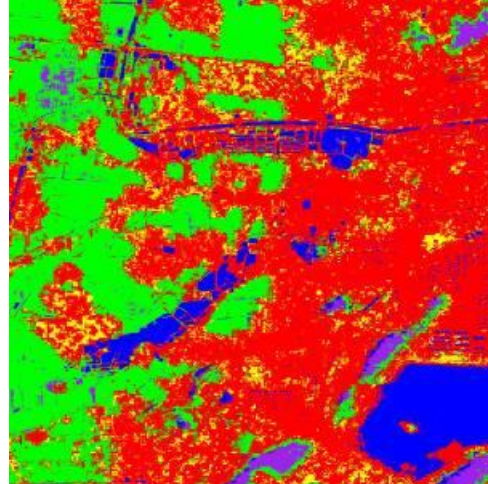
	BPNN	RBFNN	DTC
Base classifier	88.0635	85.5429	92.2685
25% Bagging	90.6689	84.7067	91.6142
50% Bagging	90.0267	83.4828	91.4687
75% Bagging	89.5540	83.4707	91.8686
100% Bagging	88.8997	84.4644	91.9292
Boosting	89.2874	86.1003	92.0625

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

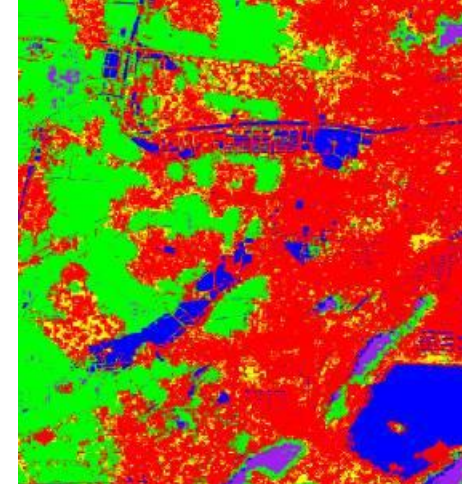
MLC+SVM+DTC



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

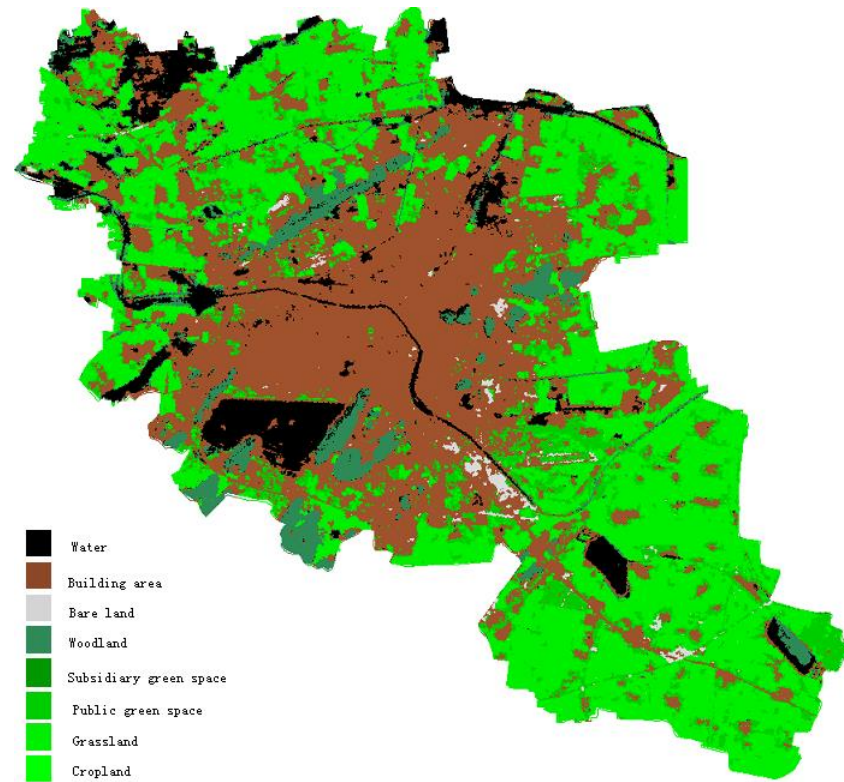
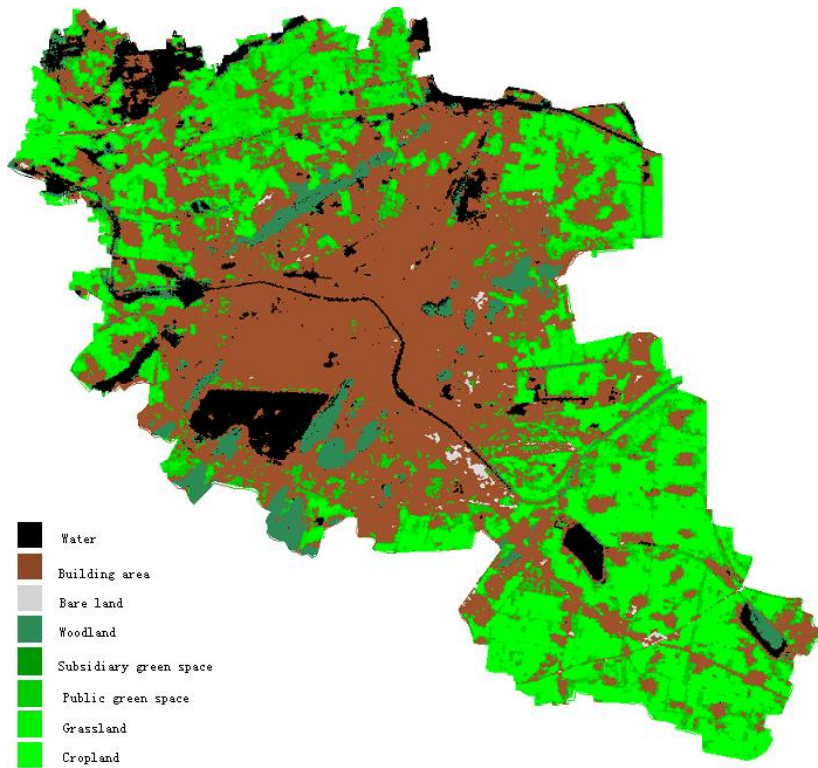
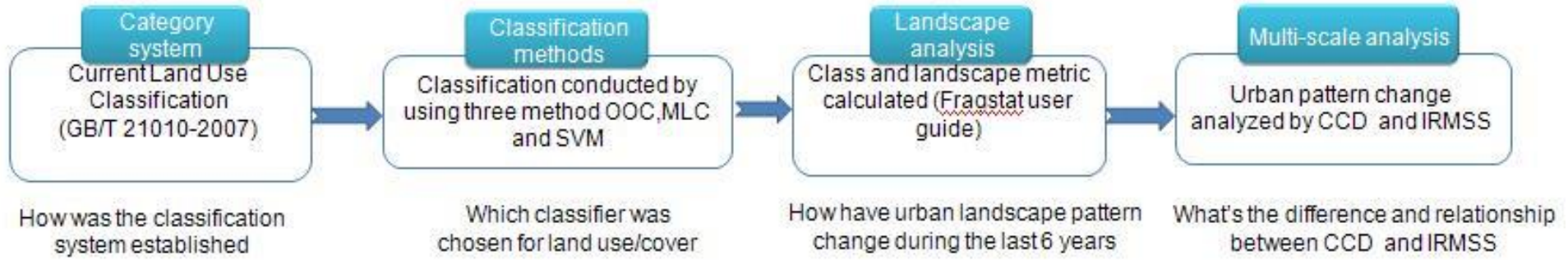
urban land cover classification based on multi-temporal CBERS imagery

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

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

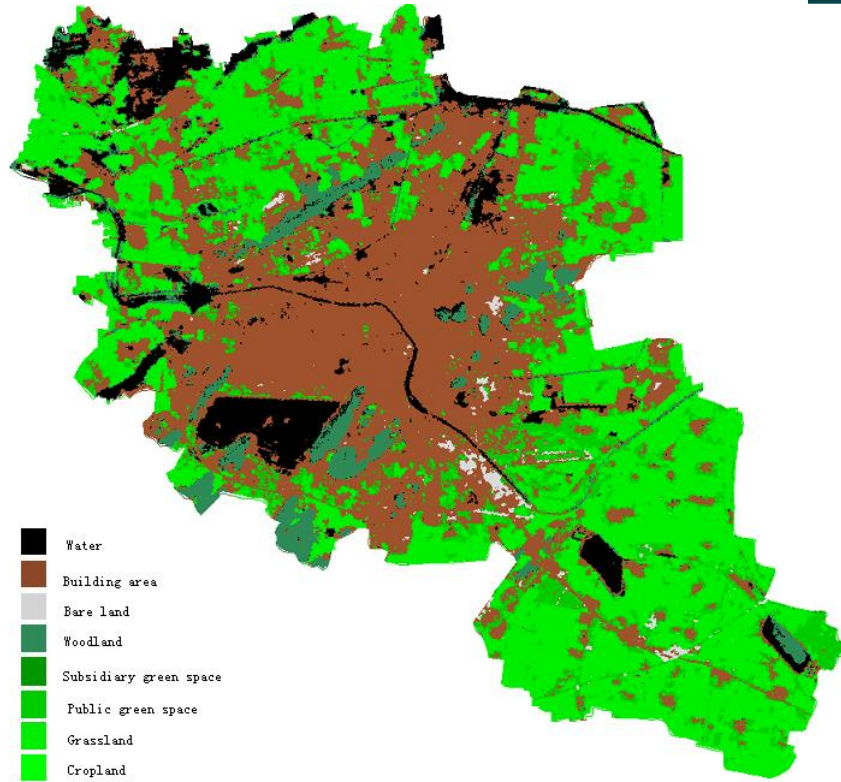
CBERS-02 CCD images (patch=371, row=62) on **March 18, 2005, April 11, 2007**
and

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.

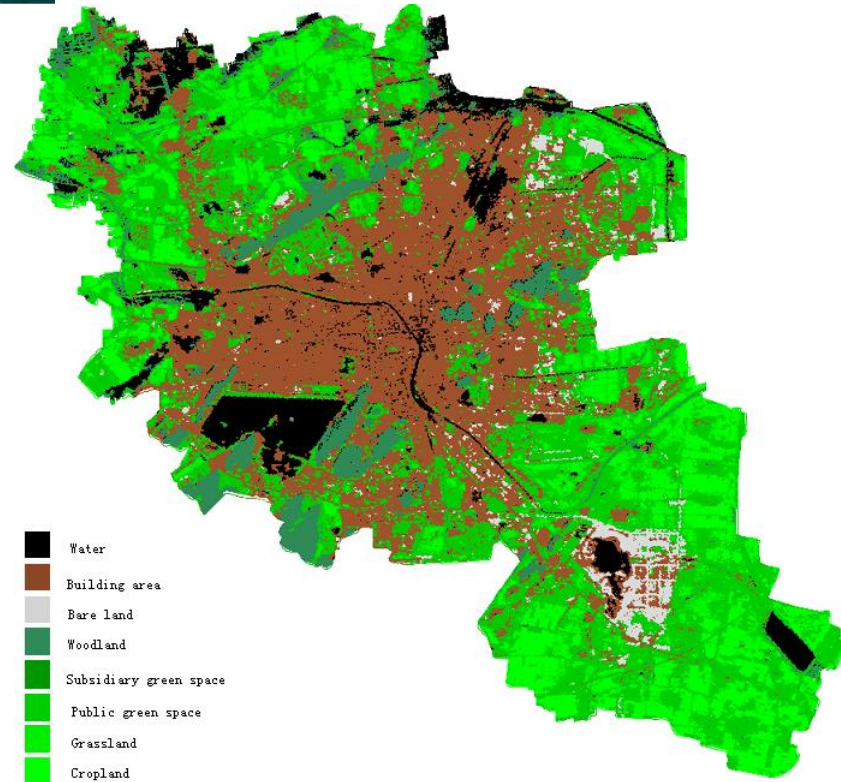


Land cover map in 2001 (CCD) Land cover map in 2005 (CCD)

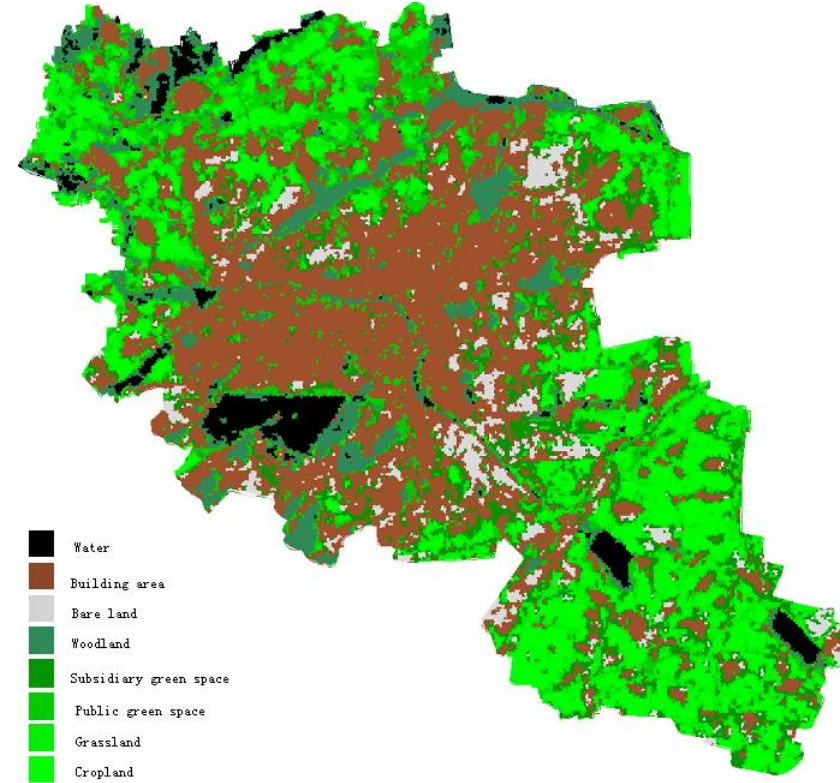
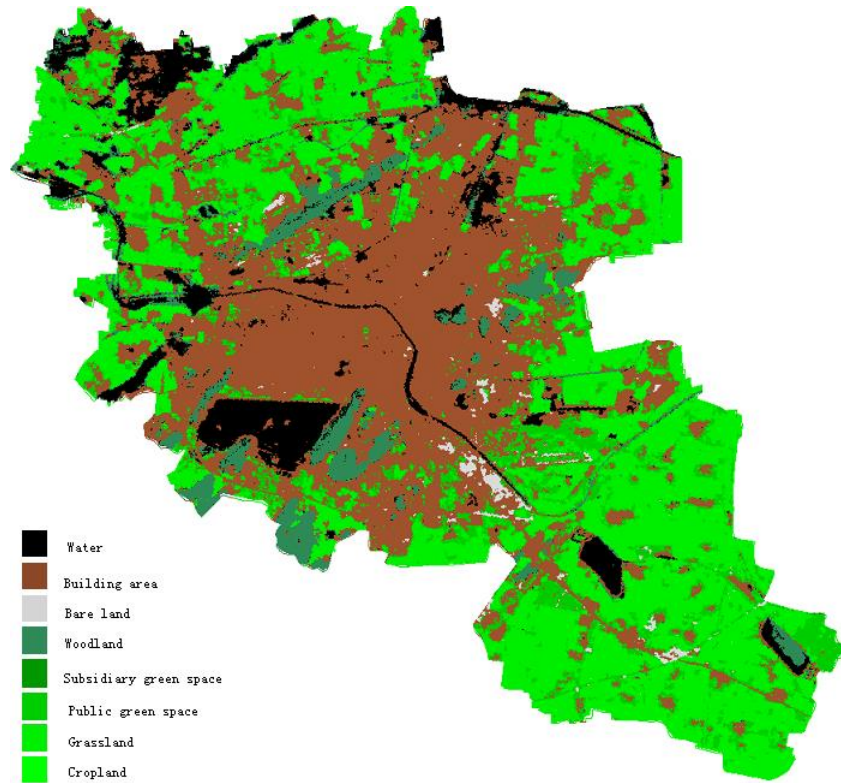
18–23 November 2019 | Chongqing University | Chongqing, P.R. China



Land cover map in 2005 (CCD)



Land cover map in 2007 (CCD)



Land cover map in 2005 (CCD)

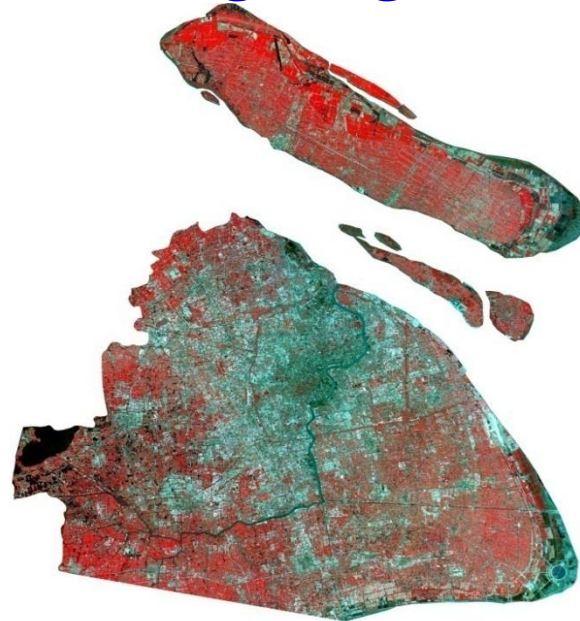
Land cover map in 2005 (IRMSS)

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)

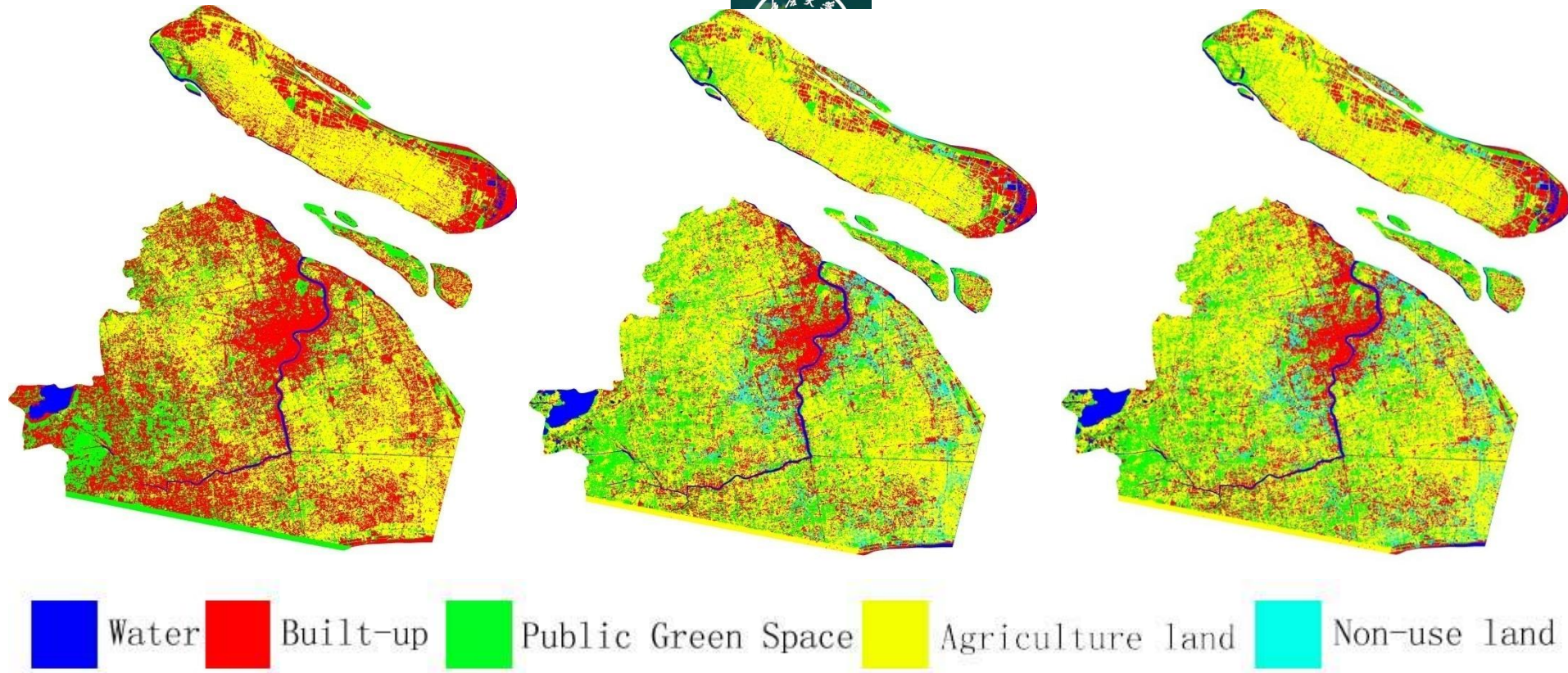


May 11th,2009
BJ-1

(R:NIR, G:Red, B: Green)

Land cover classification:Maximum likelihood classifier

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

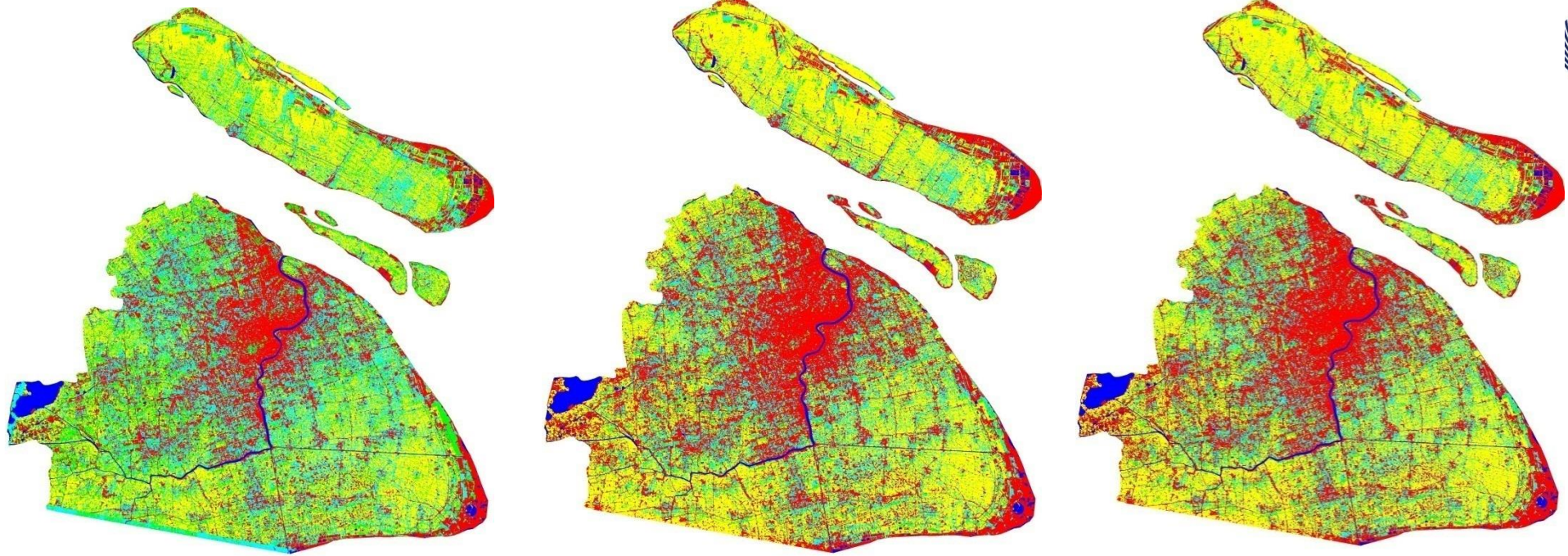


(a) MLC

(b) SVM-RBF

(c) SVM-Polynomial

Classifications Results of 2002

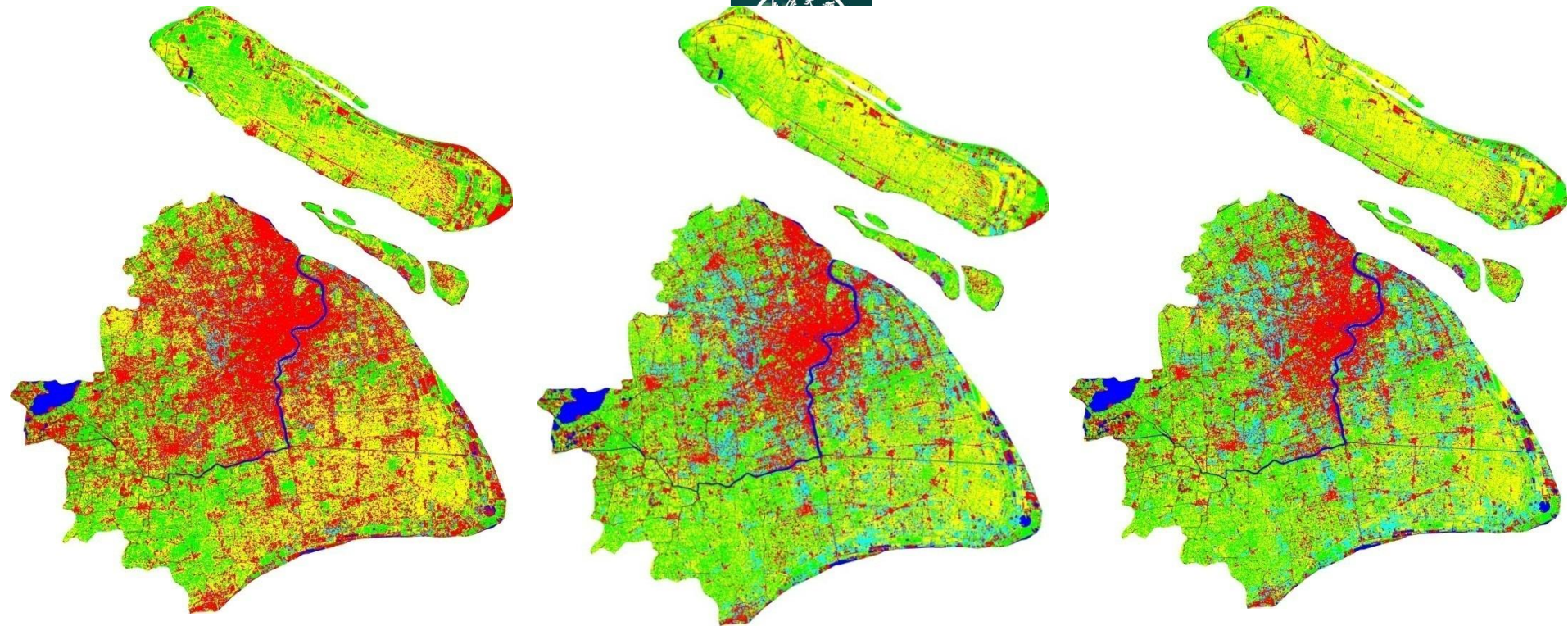


(a) MLC

(b) SVM-RBF

(c) SVM-Polynomial

Classifications Results of 2005



(a) MLC

(b) SVM-RBF

(c) SVM-Polynomial

Classifications Results of 2009

Accuracy assessment

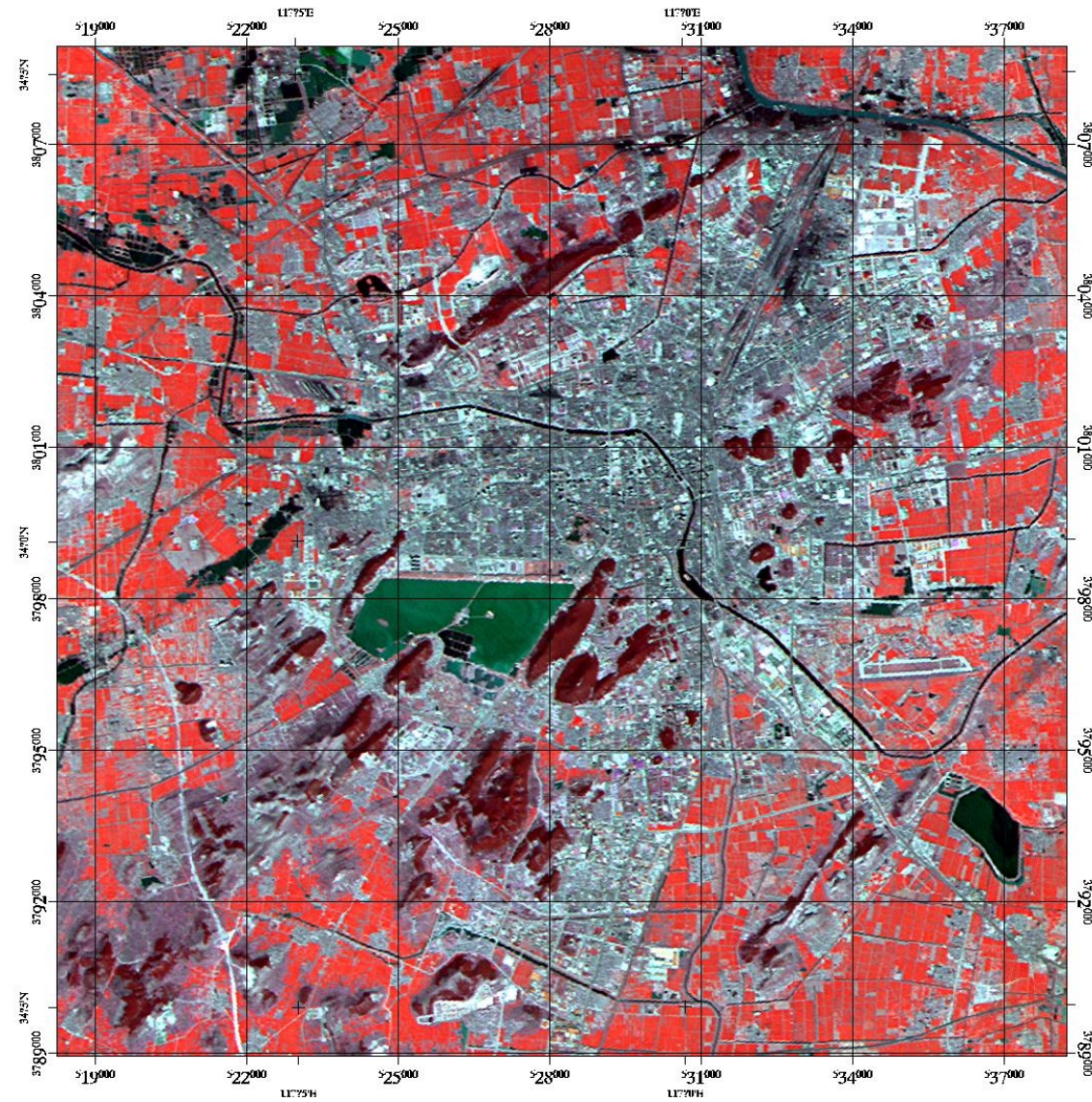
	2002			2005			2009		
	MLC	RBF	POL	MLC	RBF	POL	MLC	RBF	POL
OA	80.3960	87.5428	87.6238	76.8046	79.6920	79.4033	79.5026	88.4220	88.5077
Kappa	0.7543	0.8439	0.8452	0.7109	0.7455	0.7419	0.7413	0.8540	0.8550

The accuracy of SVM is higher than MLC

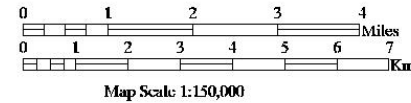
The accuracy of two kernel functions :RBF and Pol is similar

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

Classification Map of Xuzhou, China



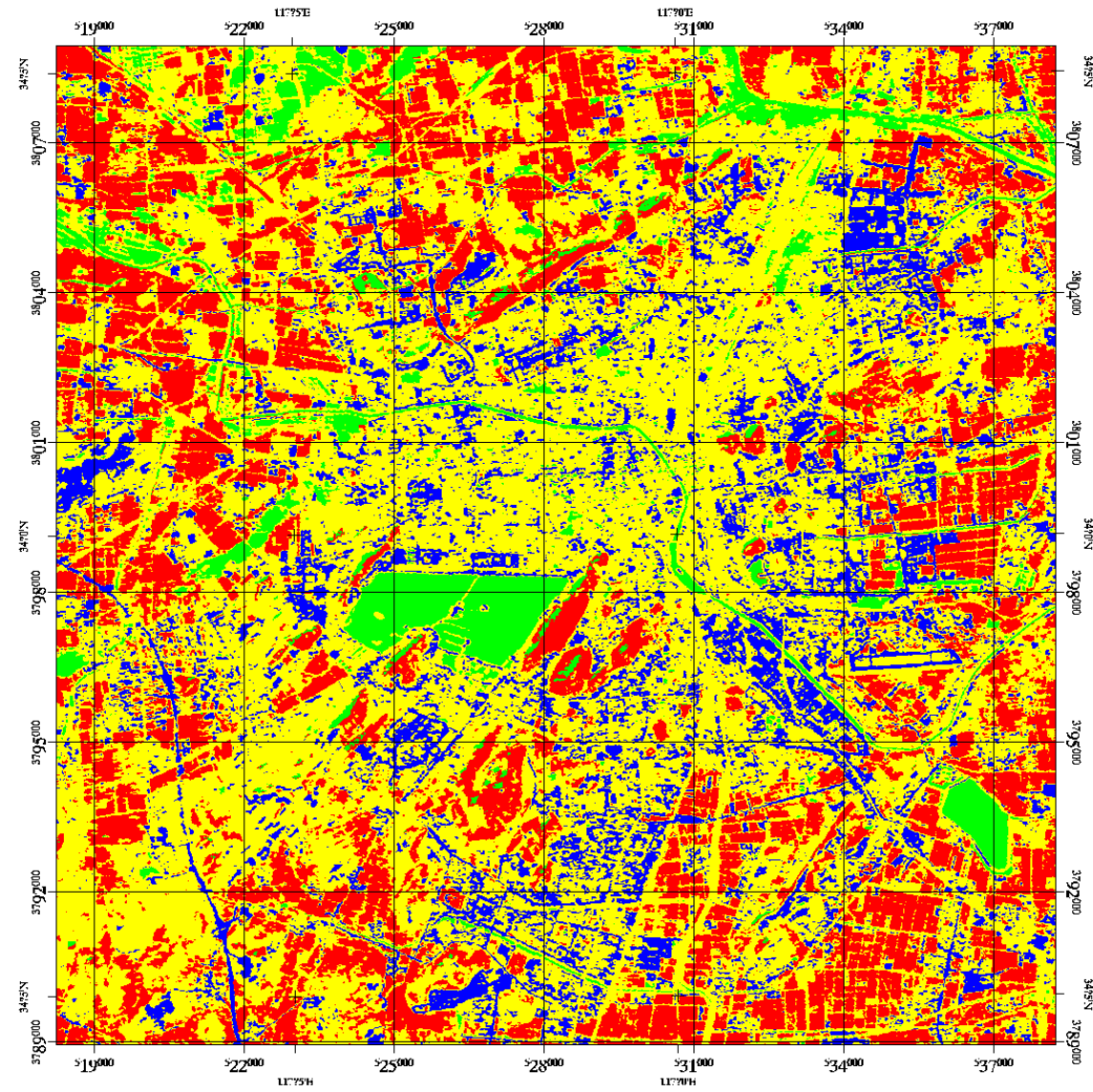
Projection: UTM, Zone 50N
Pixel Size: 20 Meters
Datum: WGS-84
Ellipsoid: WGS_1984



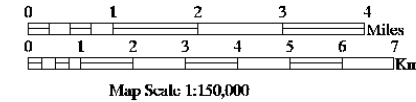
18–23 November 2019



Classification Map of Xuzhou, China



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



- vegetation
- low-albedo
- high-albedo
- soil



Content

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- 2 Technical flow of urban mapping
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- 5 Urban thematic mapping**
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Vegetation:

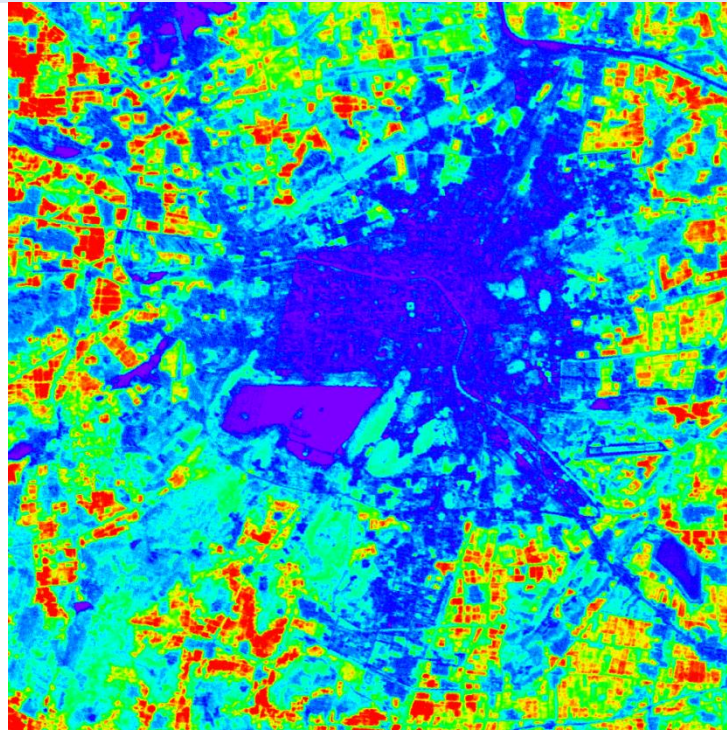
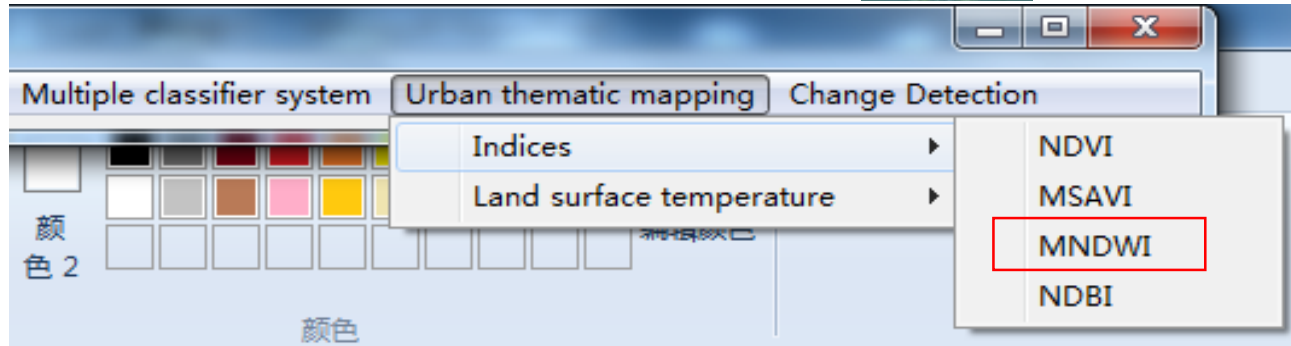
- Accuracy of derived layers will be highly dependent on the spectral differences of the targeted vegetation types
- Attributes such as biomass, leaf area index, and structural complexity have been estimated in forest environments – more work is needed in urban environments to determine whether these are achieved given the mix of species
- Maybe assessed using ratio's of re (chlorophyll absorption), near infrared (cellular structure) or mid-infrared (water absorption) reflectance

Mapping methods:

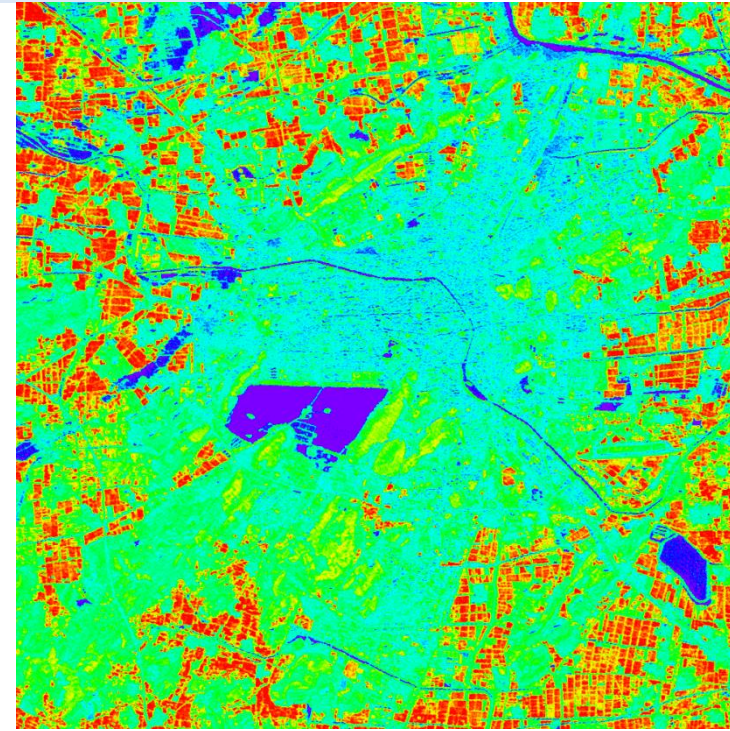
- Vegetation index (RVI, DVI, **NDVI**, GEMI, MSAVI, GEMI)
- Classification
- Spectral mixture analysis

Land surface temperature(LST)

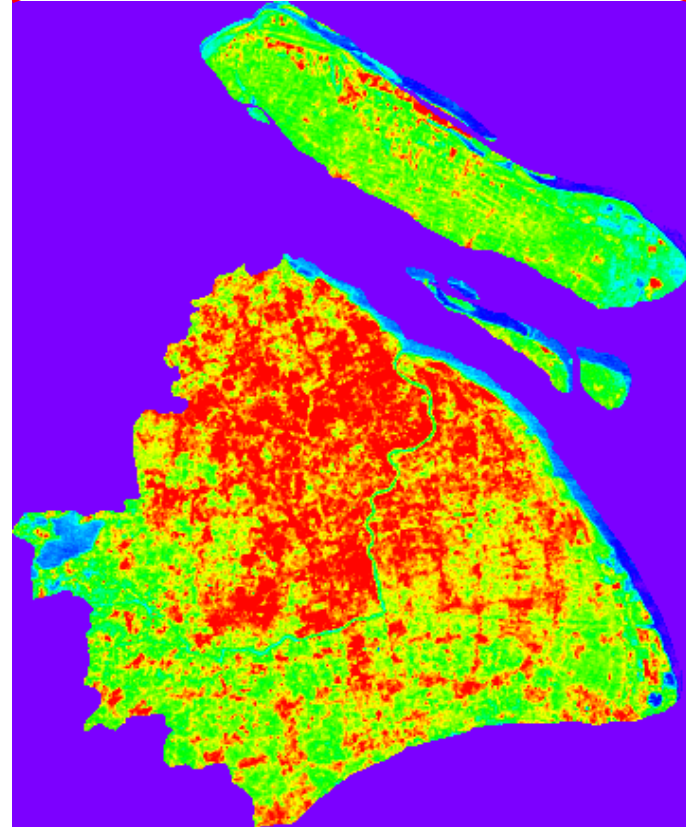
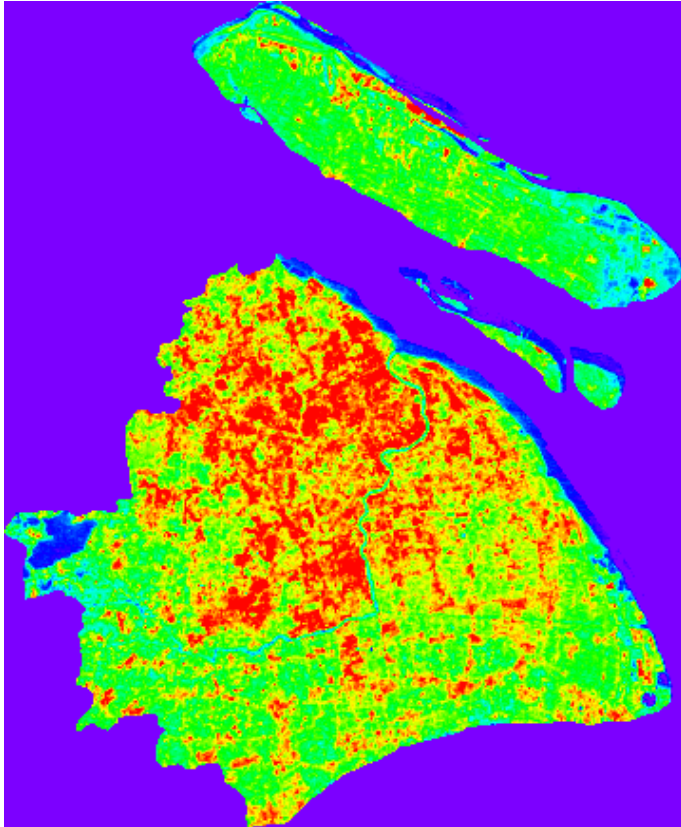
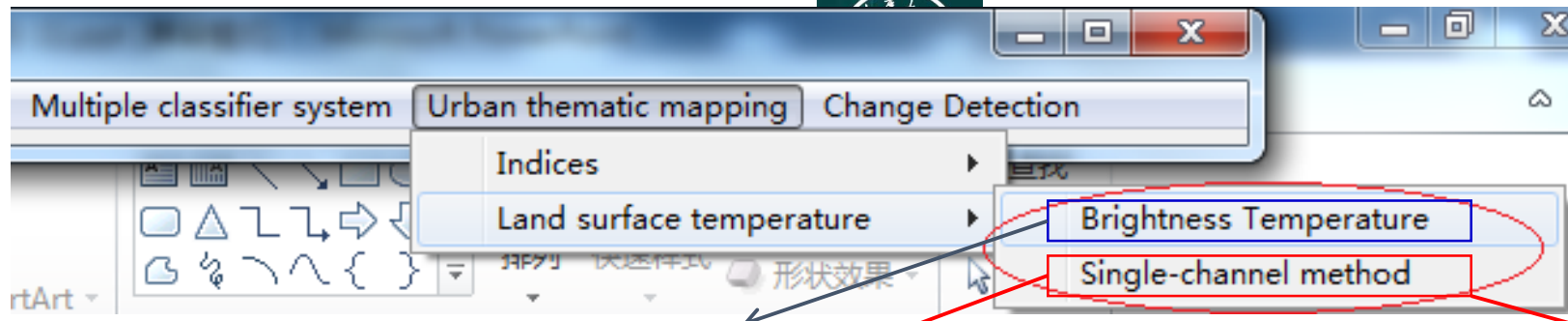
- Key parameter in the surface energy budget and controlled by the complex interplay of topography, incoming radiation, atmospheric processes, as well as by the soil moisture distribution and the different land covers and vegetation types.
- plays significant roles in urban heat island, climate change, vegetation ecology and environmental monitoring in the studies of urban thermal environment and dynamics



CBERS2001



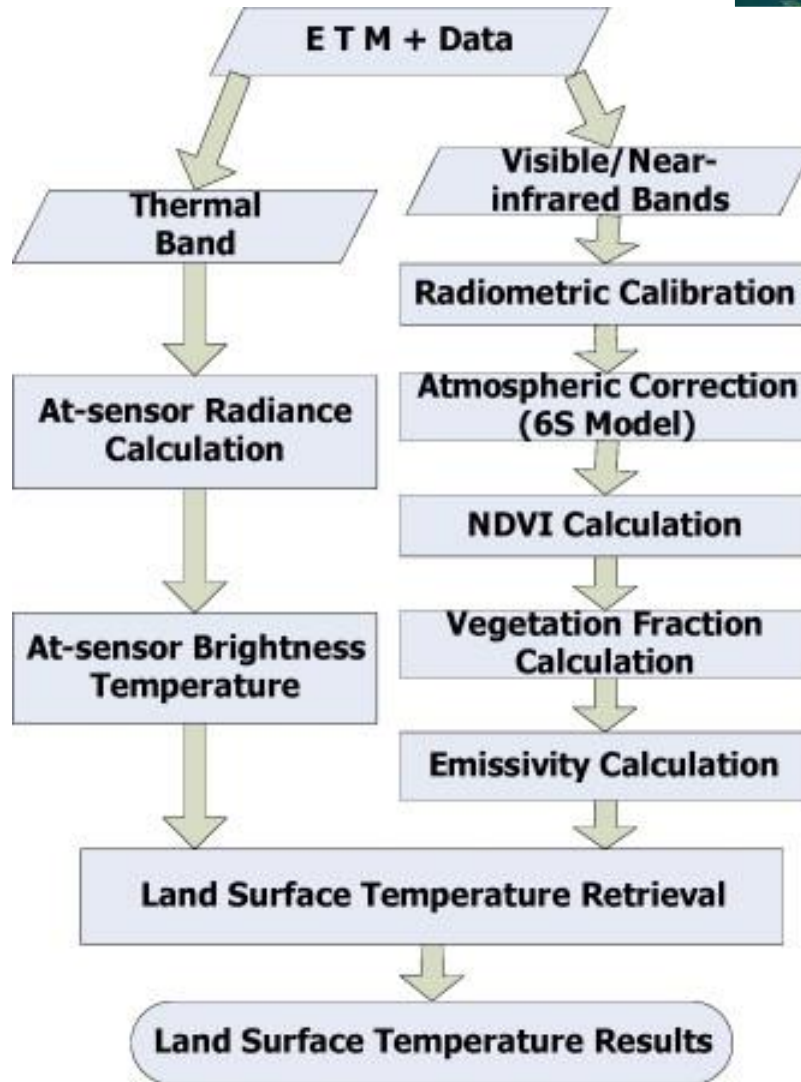
CBERS2005



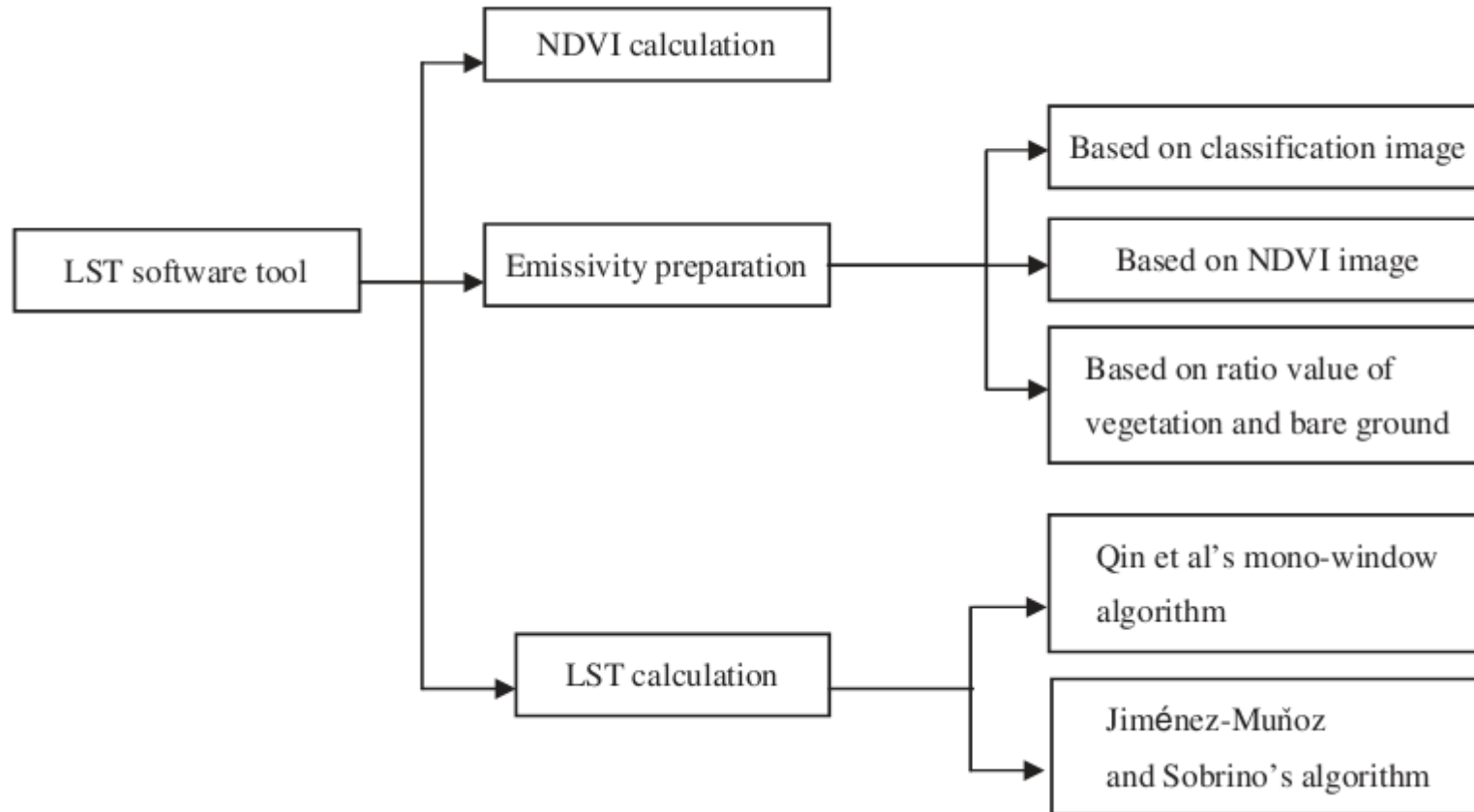
HJ1-B
IRS

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

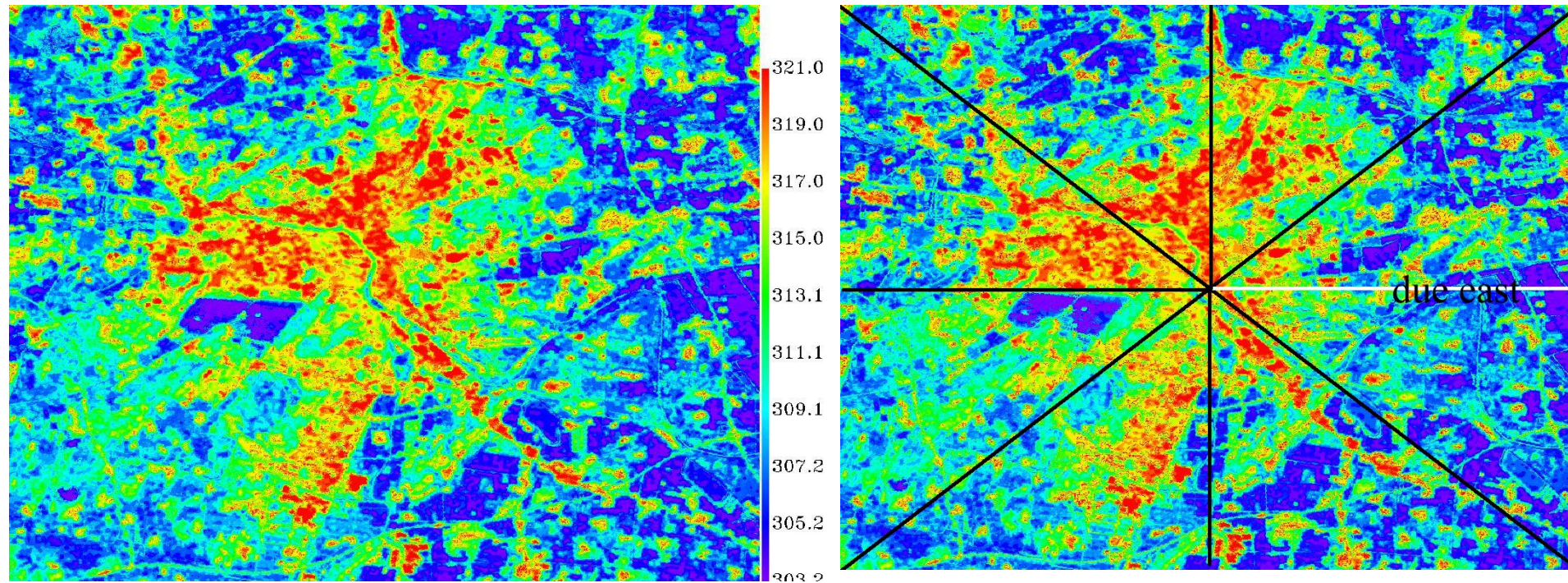


Qin et al. Geothermal area detection Using Landsat ETM+ thermal infrared Data and its mechanistic analysis- A case Study in Tengchong, China. JAG, 2011



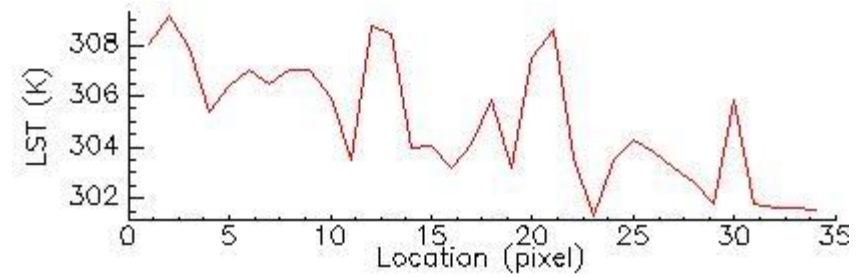
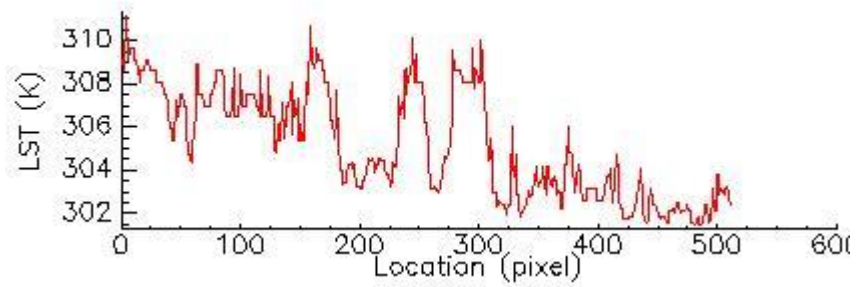
Zhang et al. A C++ program for retrieving land surface temperature from the data of Landsat TM/ETM+ band6. *Computer & Geoscience*, 2006

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

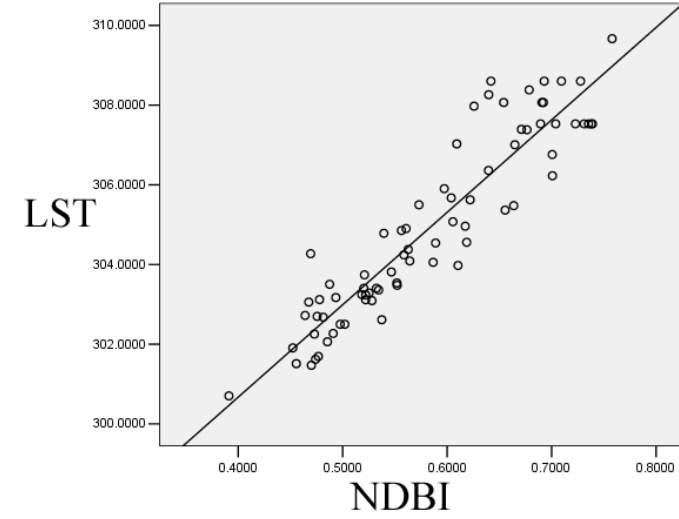
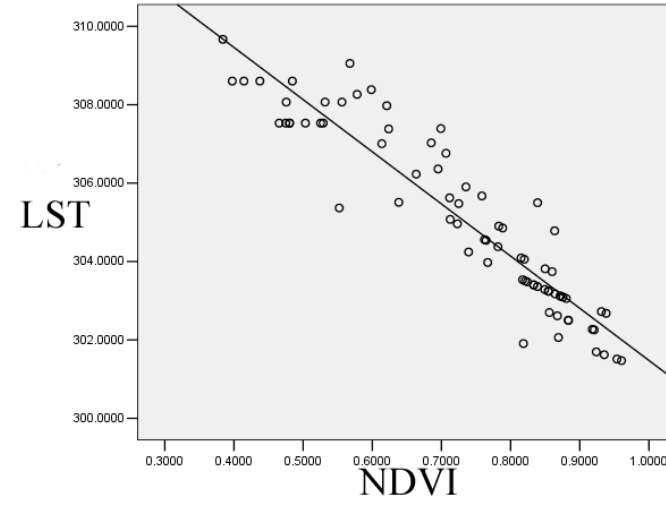
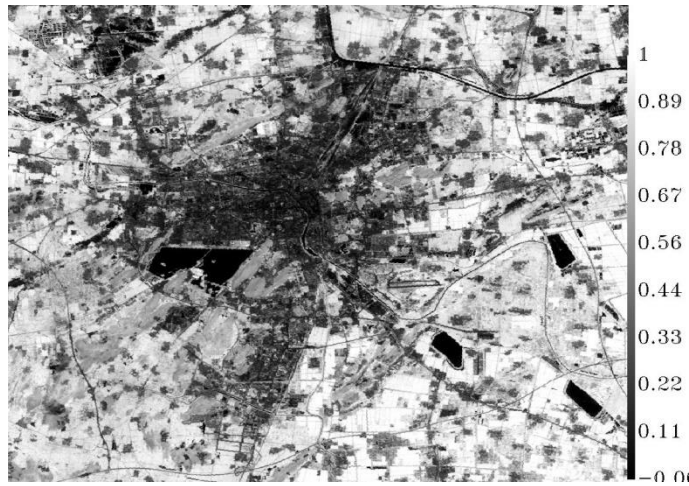


MWA

SCA

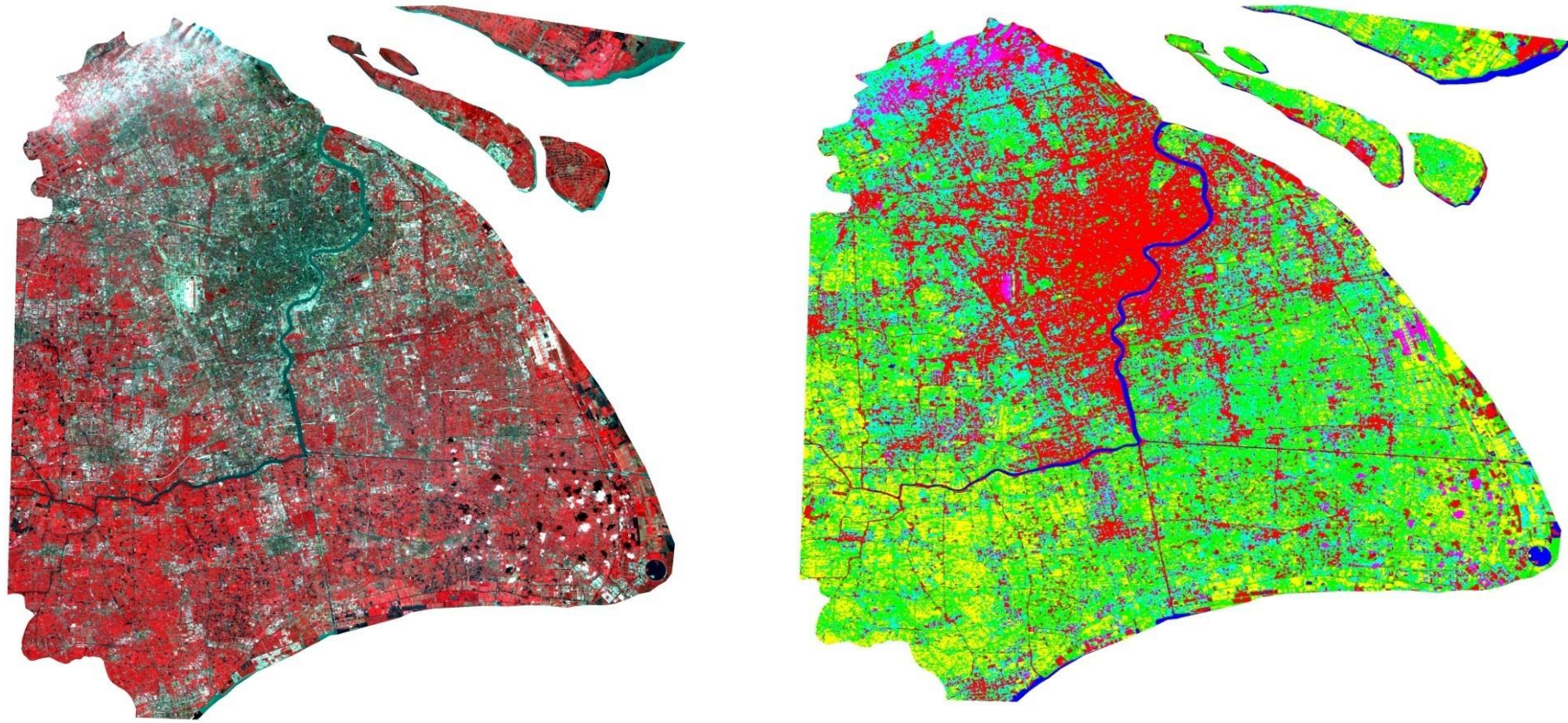


Transection derived from LST data at 60m and 900m scales



NDVI,NDBI, and their relationship between LST

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



Water Clouds Built-up Public Green Space Agriculture land Non-use land

HJ-1 Multispectral 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"	Newroad	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

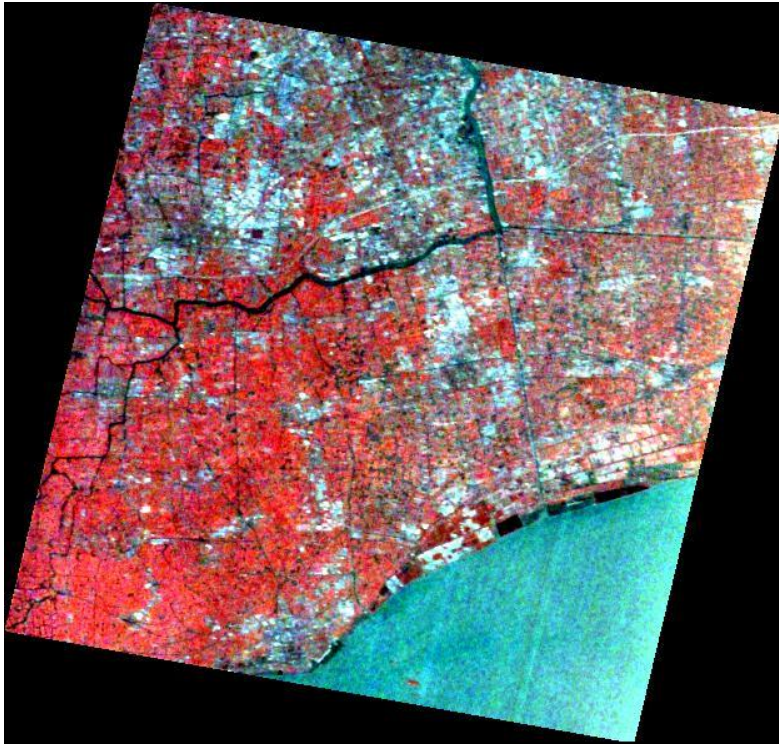


Buildings

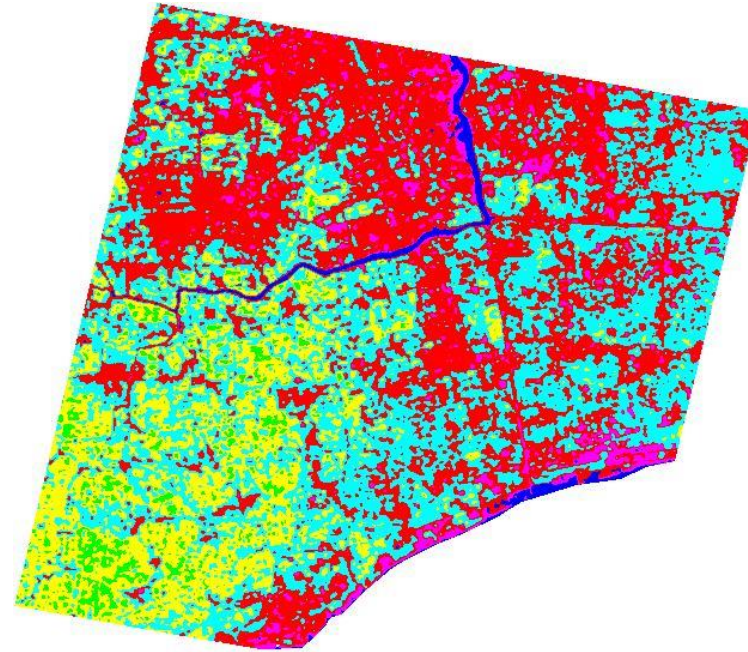


Non-use land

ground truth

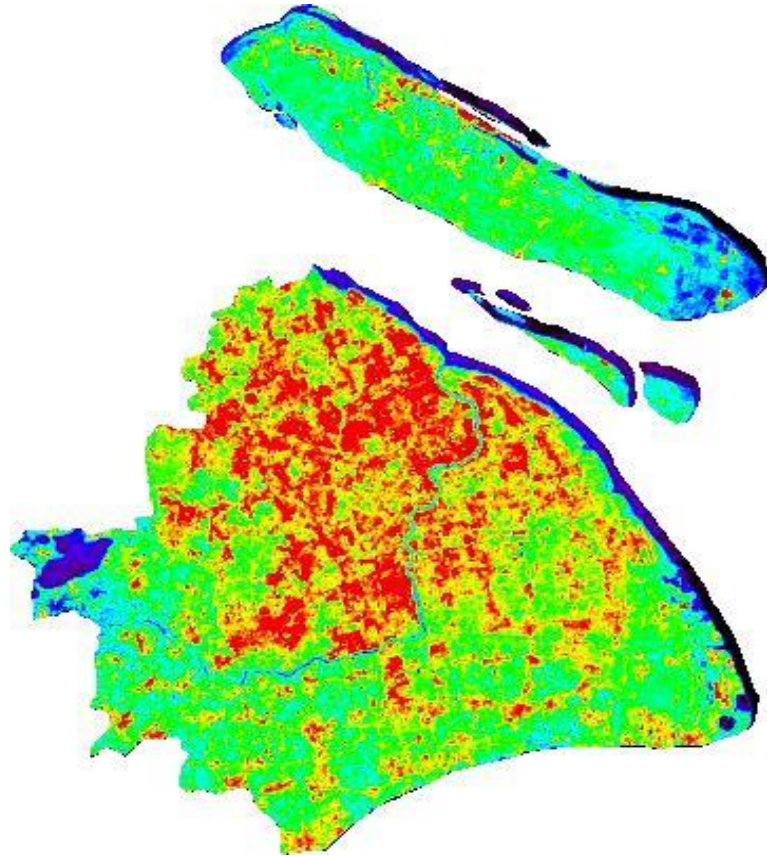


HJ-1 Hyperspectral Image(2009.05.01)
R: band 88, G: band 28, B: band 18

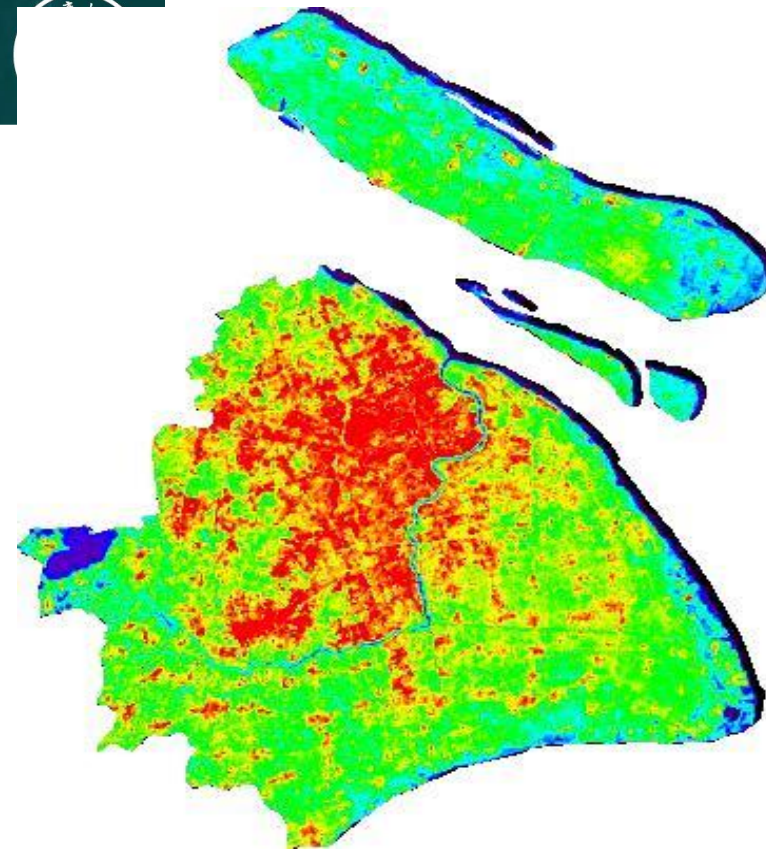


Water Clouds Built-up Public Green Space Agriculture land Non-use land

SAM Classification

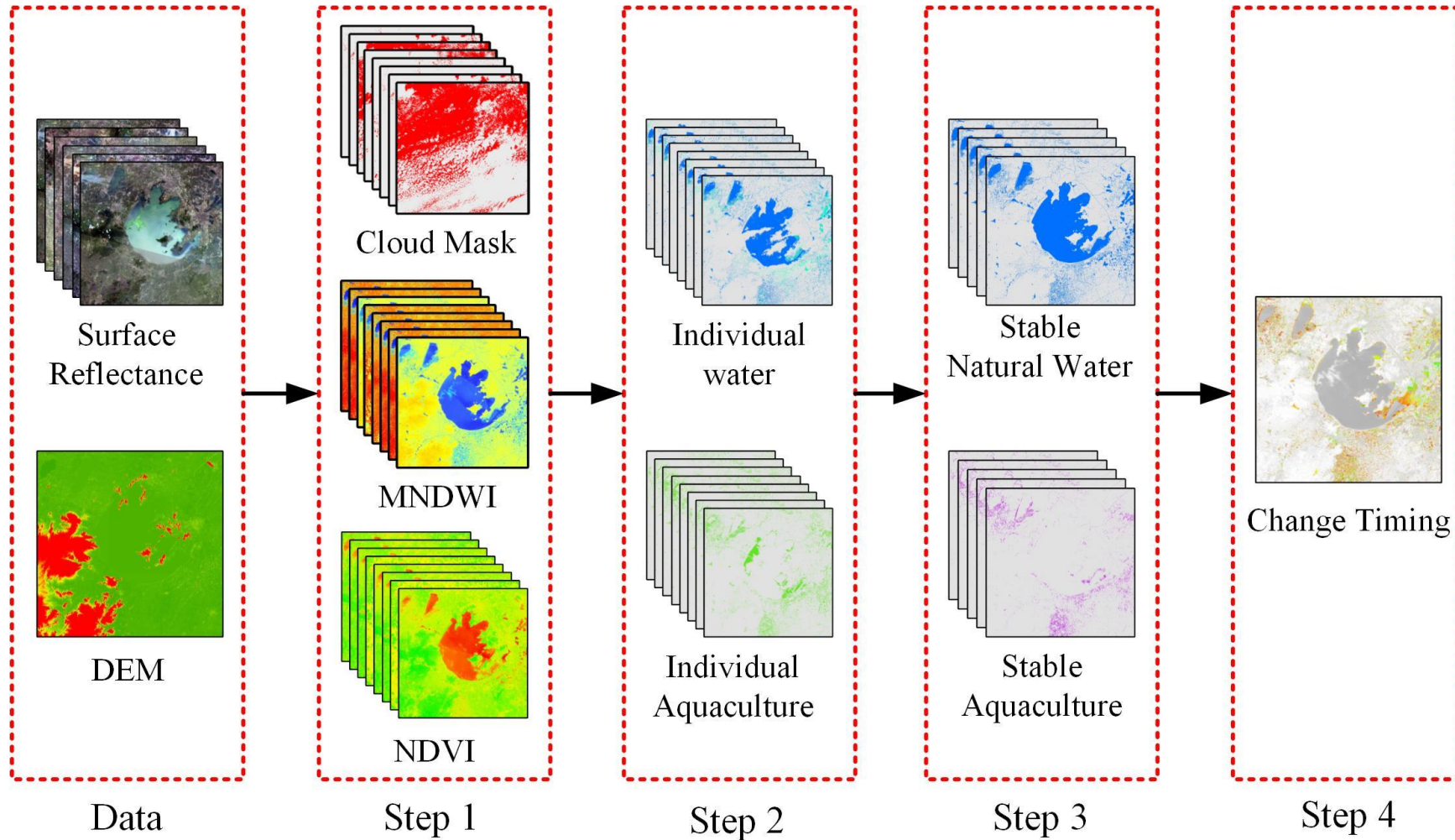


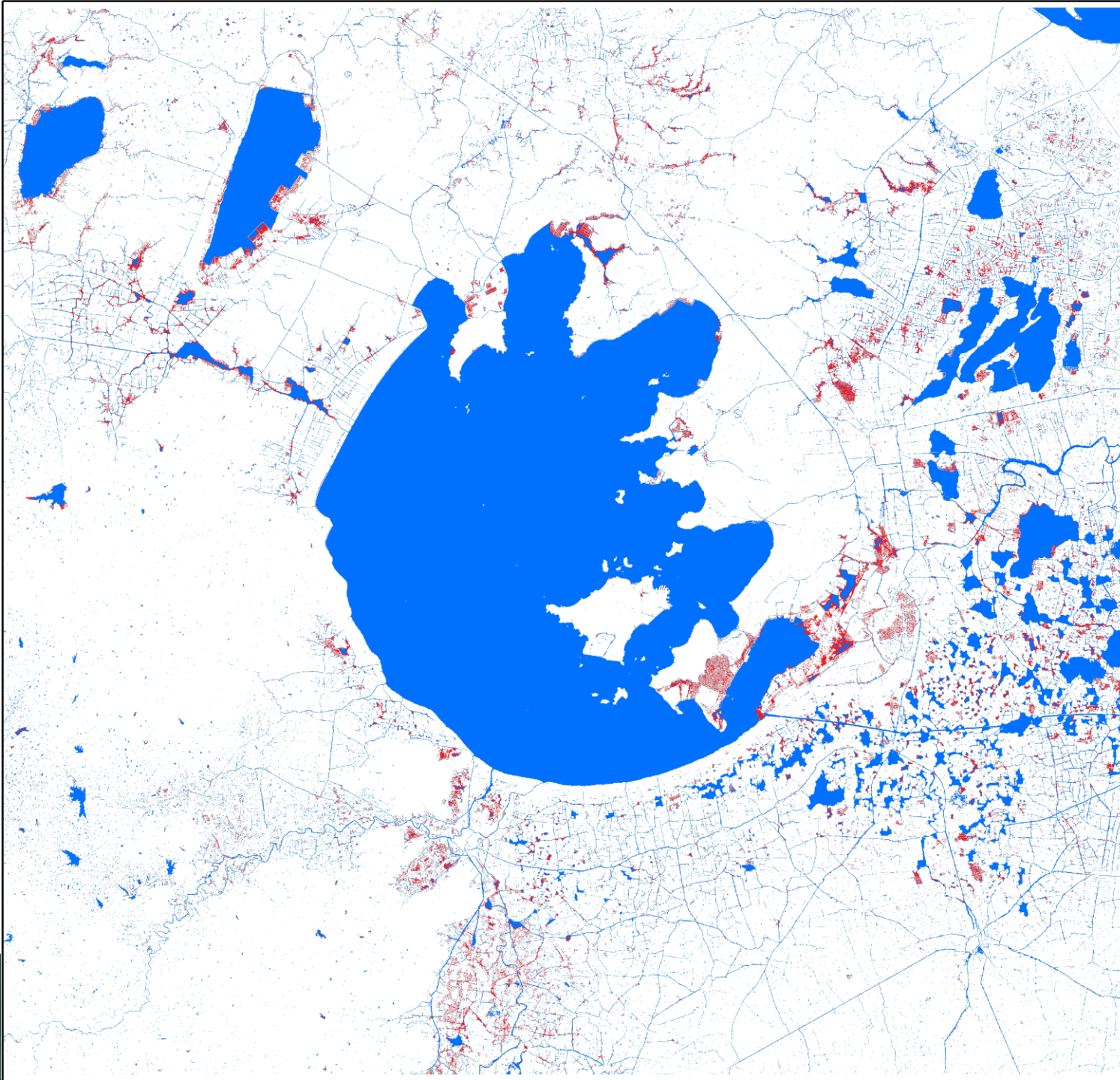
(a) 2009.10.21



(b) 2009.05.01

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





18–23 Novem

Content

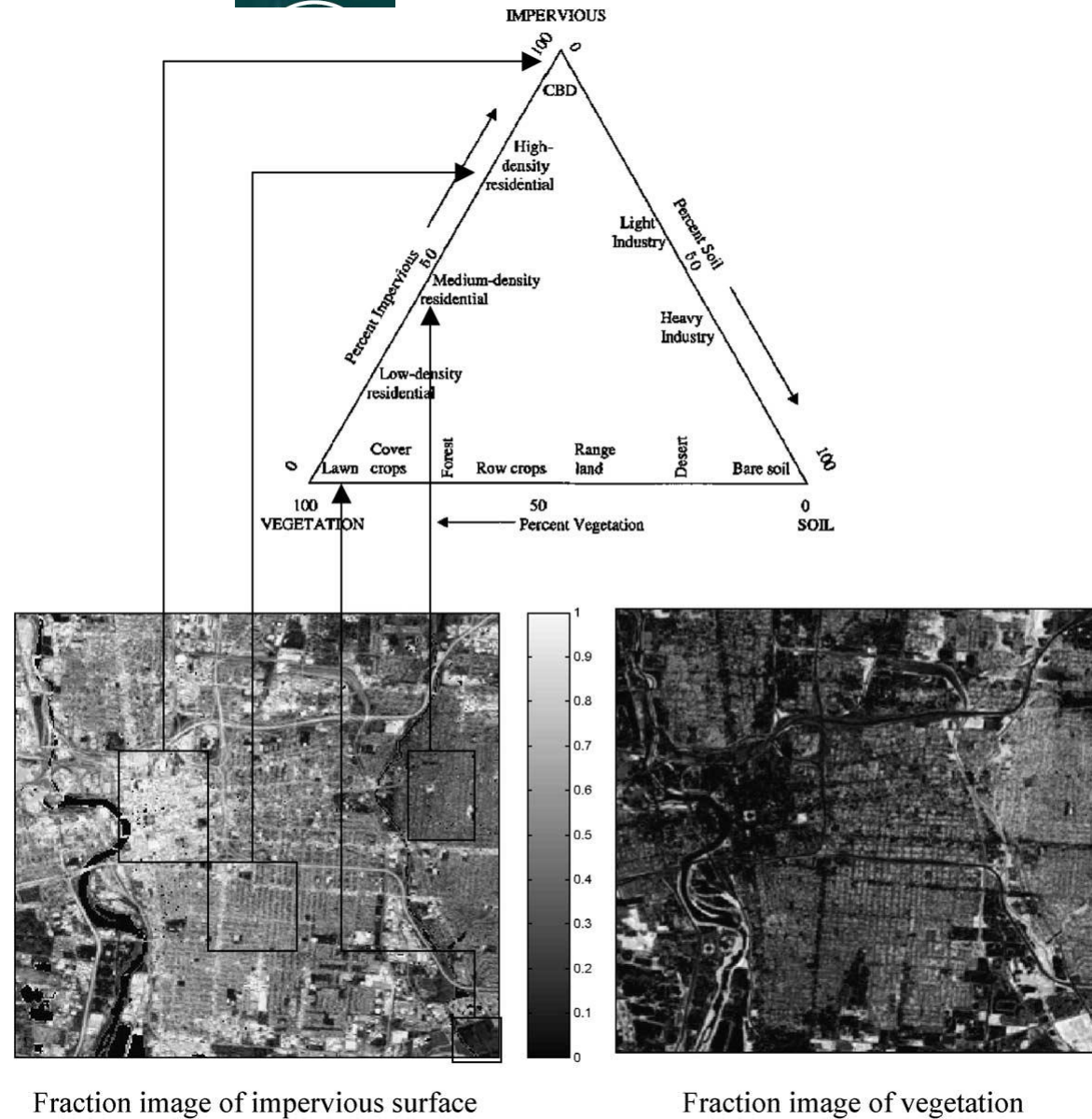
- 1 Urban remote sensing
- 2 Technical flow of urban mapping
- 3 Urban extent mapping
- 4 Urban land cover/land use mapping
- 5 Urban thematic mapping
- 6 ISA estimation and mapping**
- 7 Change detection
- 8 Conclusions and Advances

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

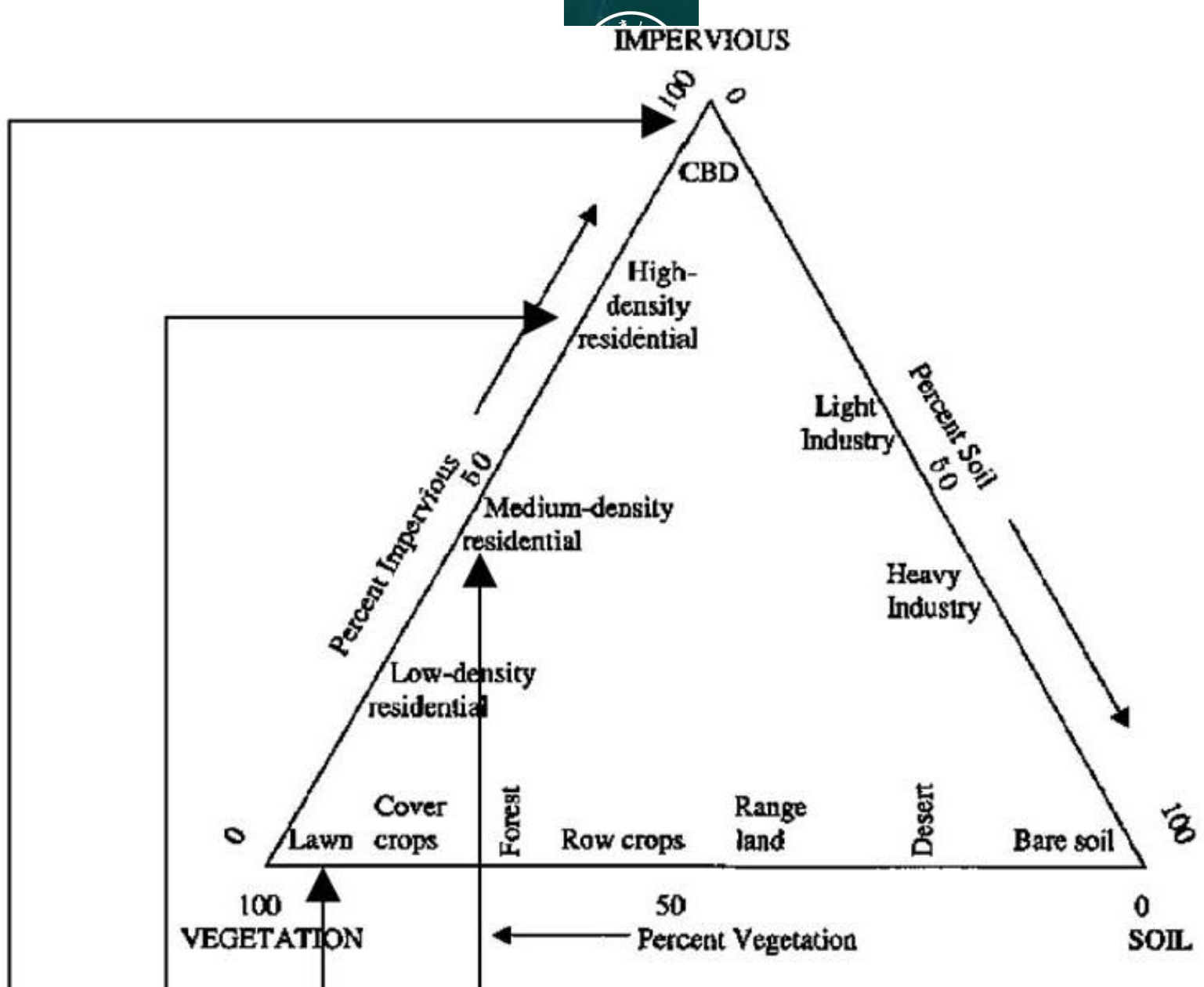
Vegetation – impervious surface- soil (V-I-S) model (Ridd, 1995)

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



Fraction image of impervious surface

Fraction image of vegetation



Extracting Impervious surface based on spectral mixture analysis

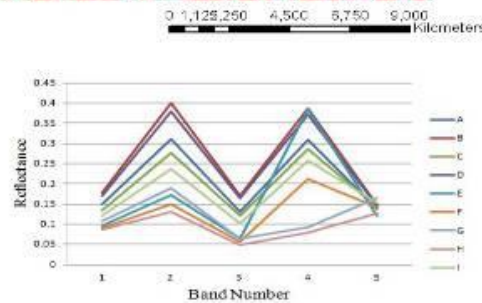
- Image preprocessing
- Endmember extraction
- Abundance estimation by spectral mixture model
- Impervious surface estimation.

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

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



- A: CBD
- B: High-density areas
- C: low-density areas
- D: Baren land in moutaion
- E: Cropland
- F: Forest
- G: Lake
- H: River
- I: Soil

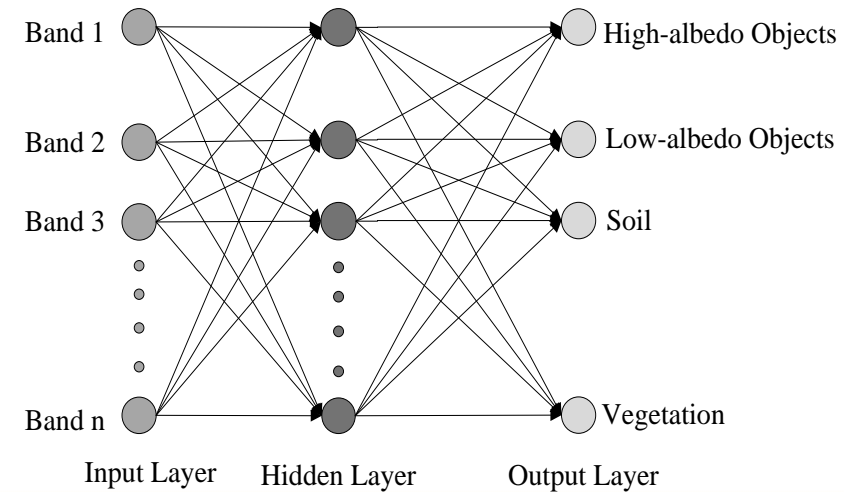


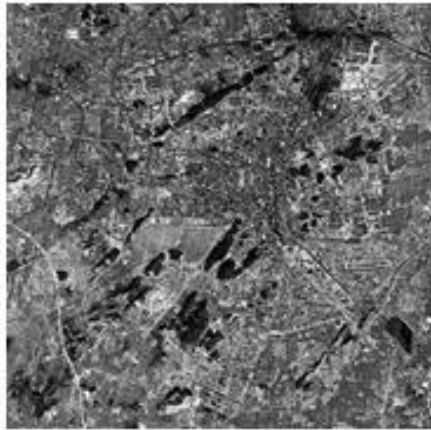
Linear spectral Mixture Model (LSMM)

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

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

MLP neural network

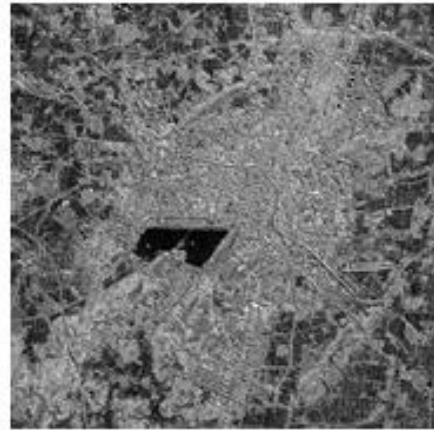




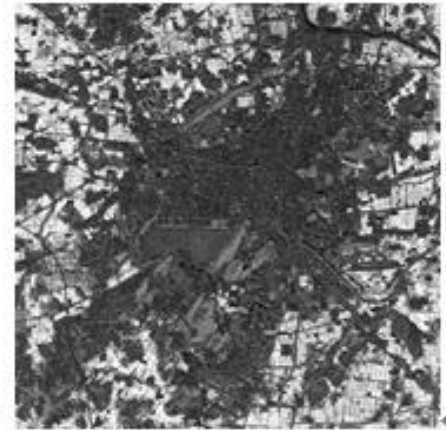
High-albedo



Low-albedo



Soil

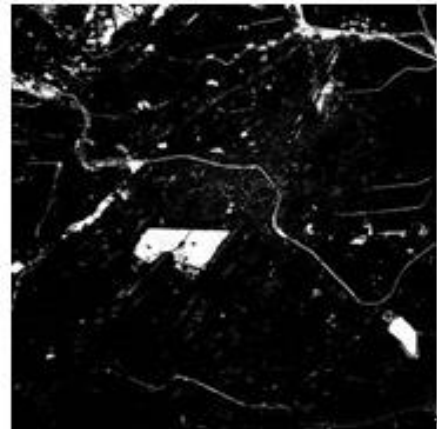


Vegetation

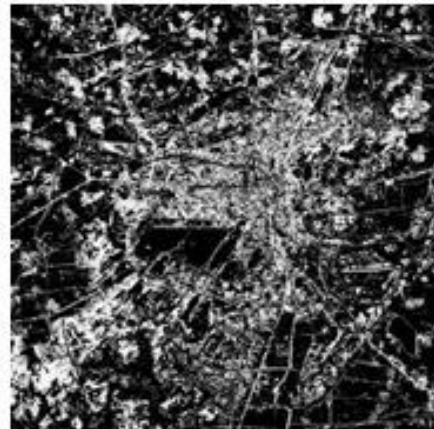
(a) 2005 CBERS LSMM four fraction images



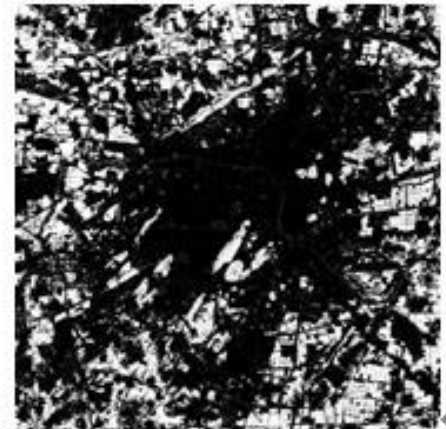
High-albedo



Low-albedo

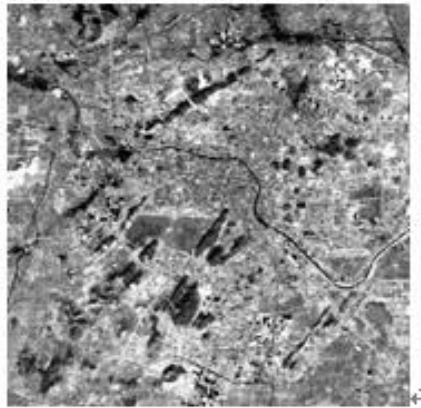


Soil

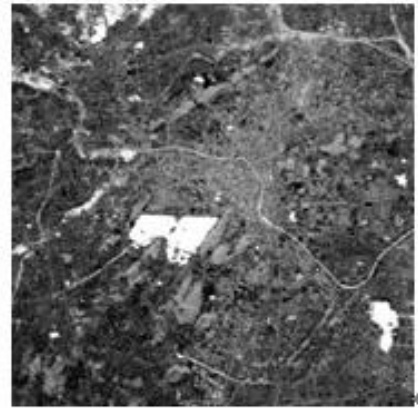


Vegetation

(b) 2005 CBERS MLP four fraction images



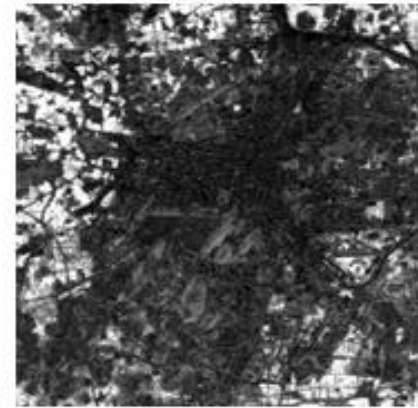
High-albedo



Low-albedo

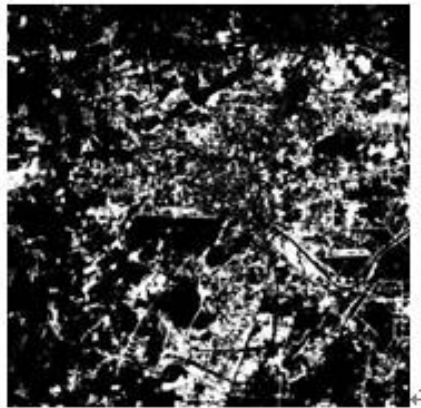


Soil

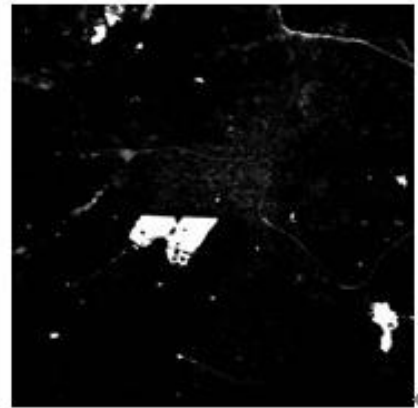


Vegetation

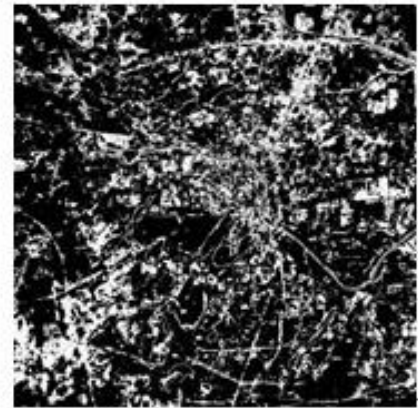
(c) 2009 HJ-1 LSMM four fraction images



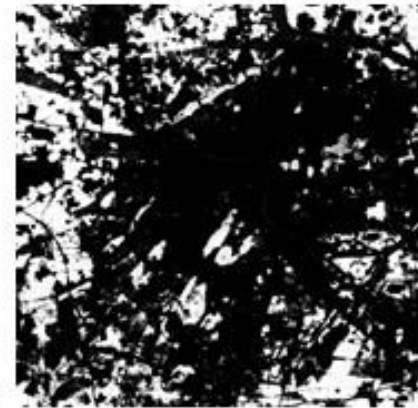
High-albedo



Low-albedo



Soil



Vegetation

(d) 2009 HJ-1 MLP four fraction images



SE , RMSE and R^2 results of accuracy assessment

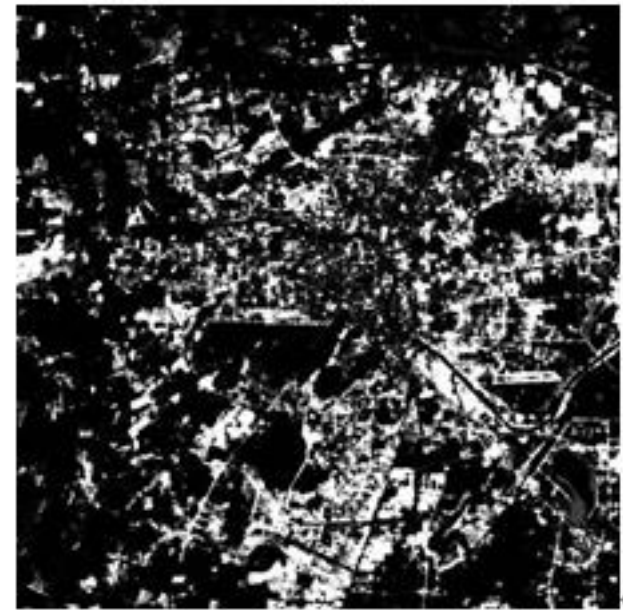
	RMSE	SE	R^2
2005-LSMM	0.153	0.131	0.693
2005-MLP	0.122	0.107	0.818
2009-LSMM	0.149	0.127	0.683
2009-MLP	0.147	0.126	0.735



(a) 2001 CBERS image



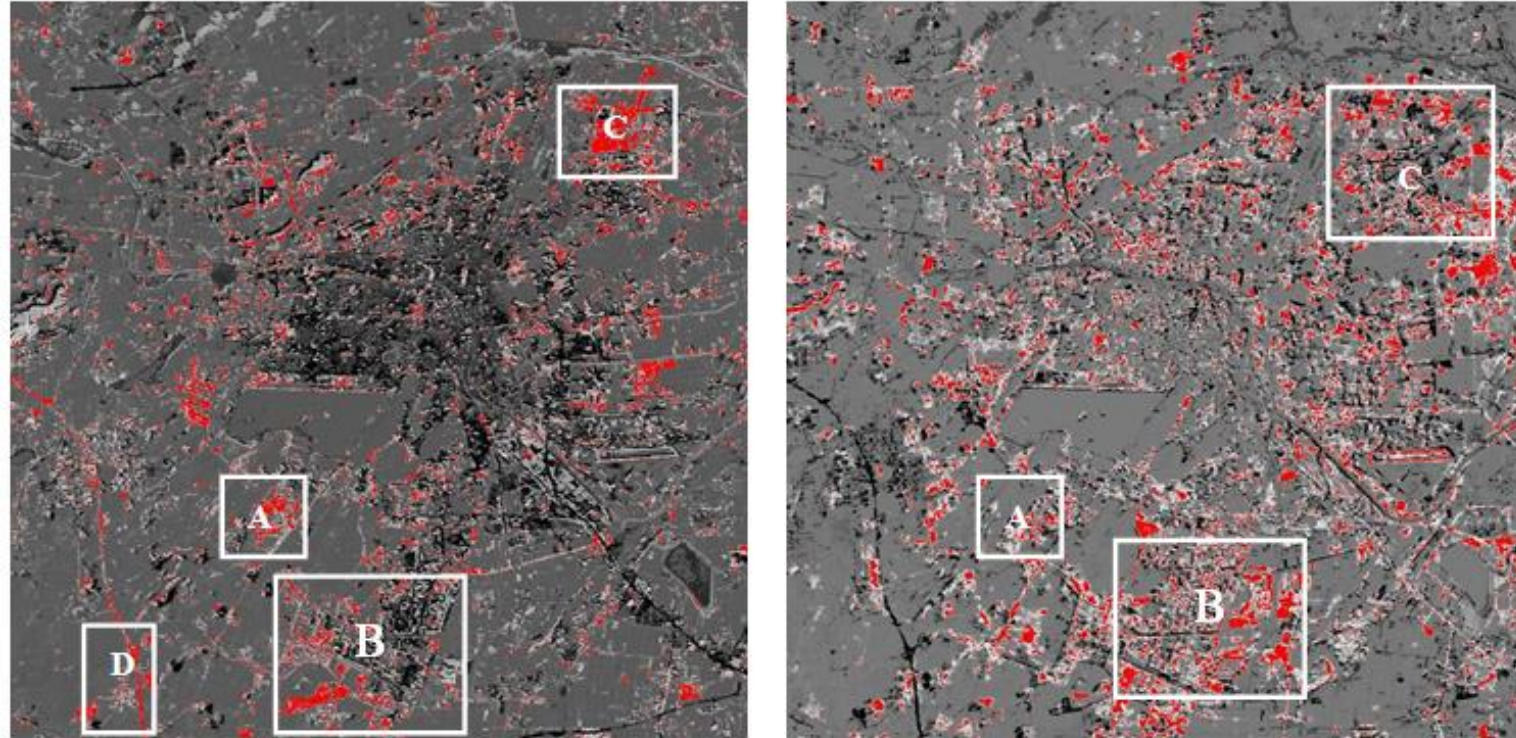
(b) 2005 CBERS image



(c) 2009 HJ-1 image



Figure 5. Impervious surface area results using MLP.



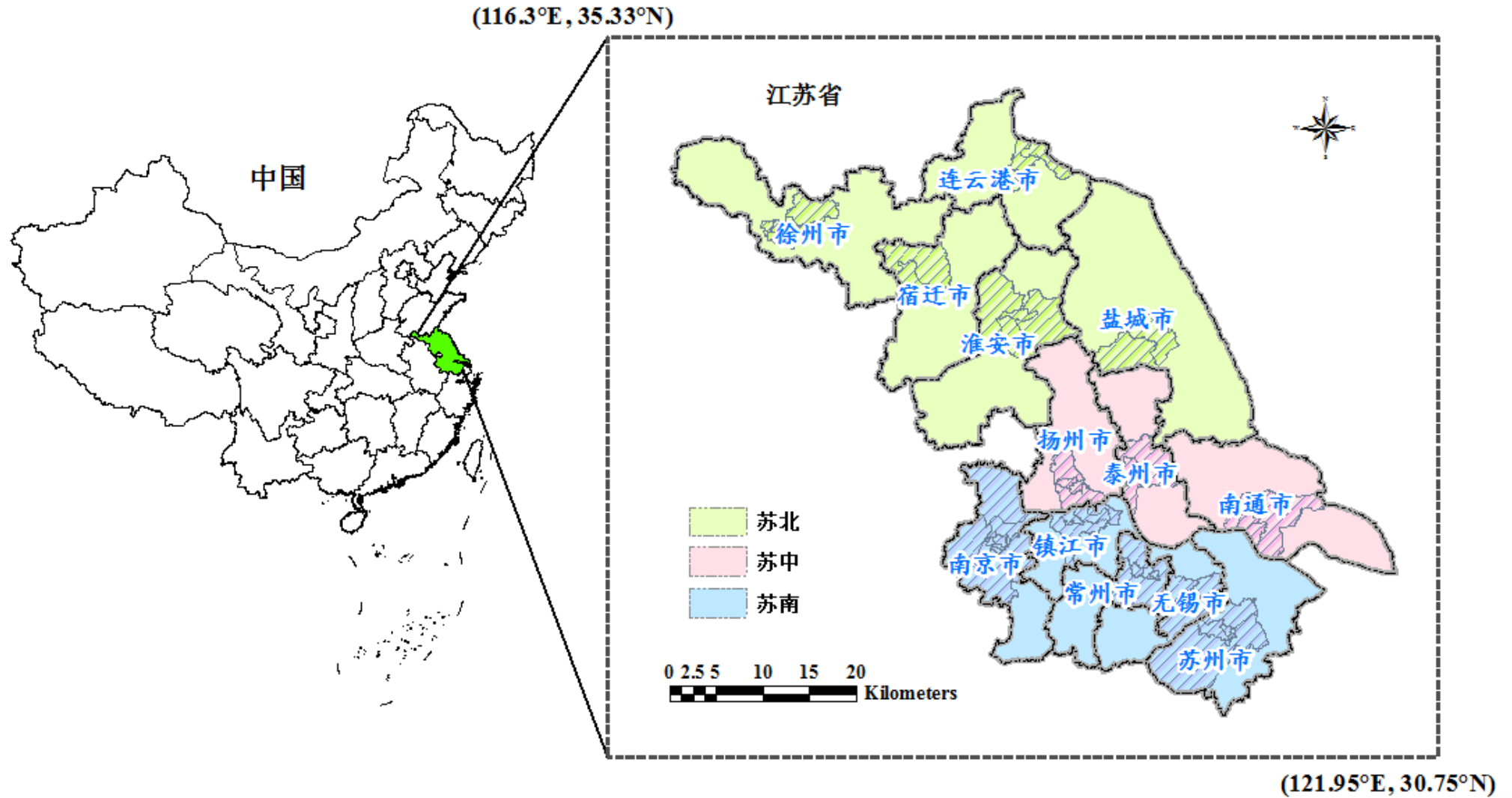
(a) growth area from 2001 to 2005

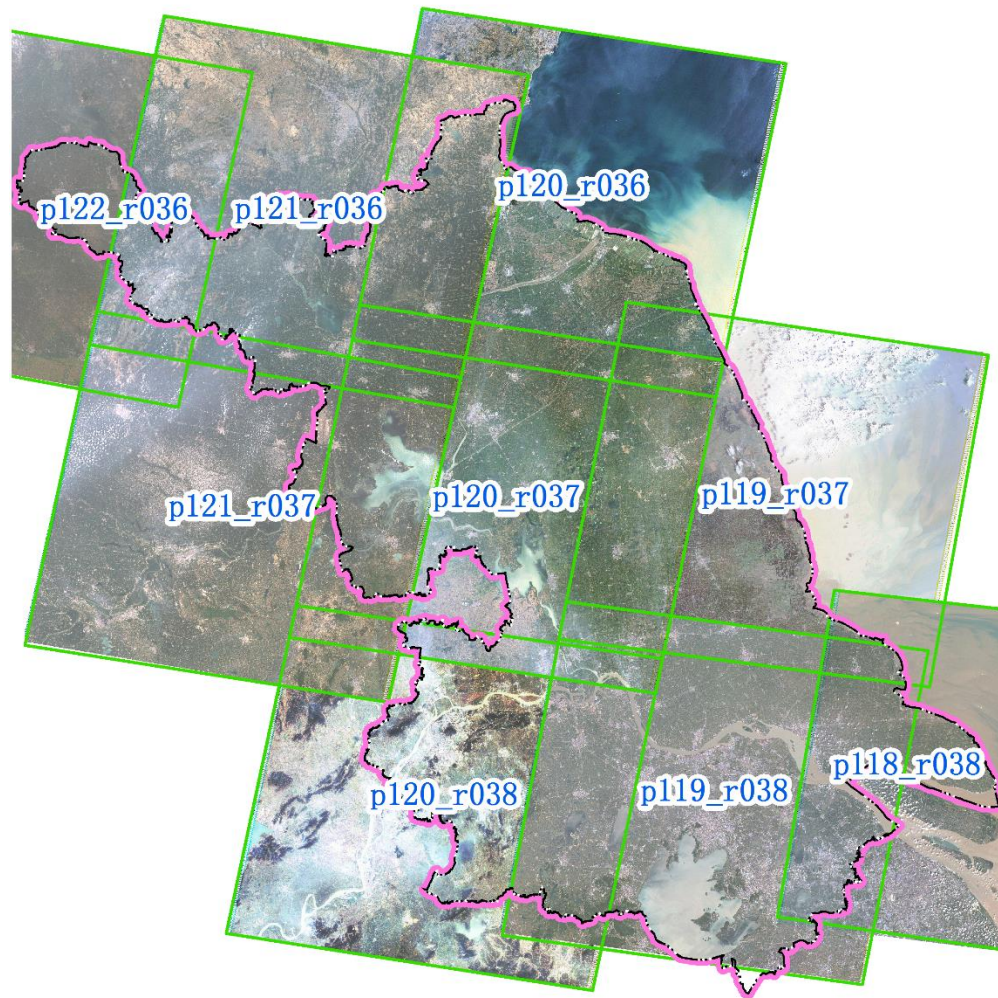
(b) growth area from 2005 to 2009⁺

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.⁺



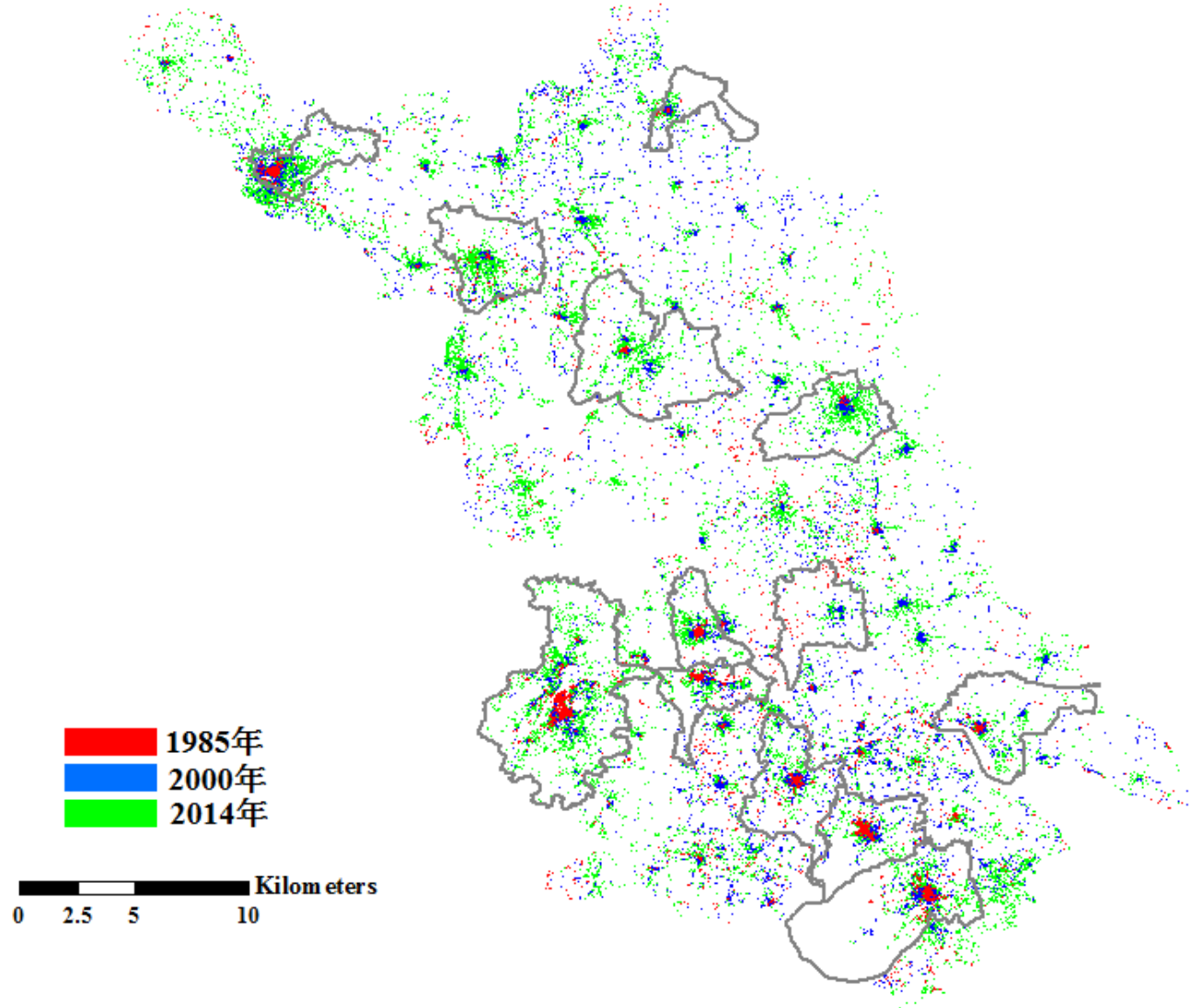


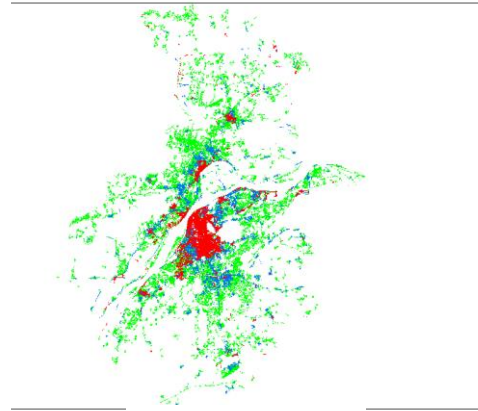
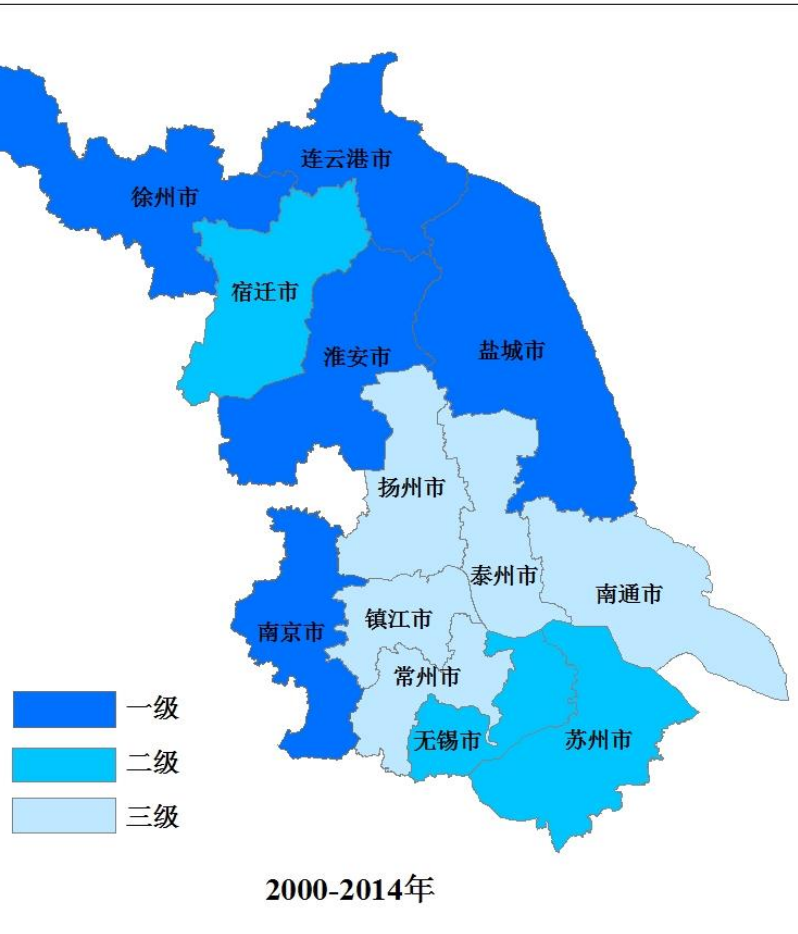
data:

1985, Landsat 5 TM

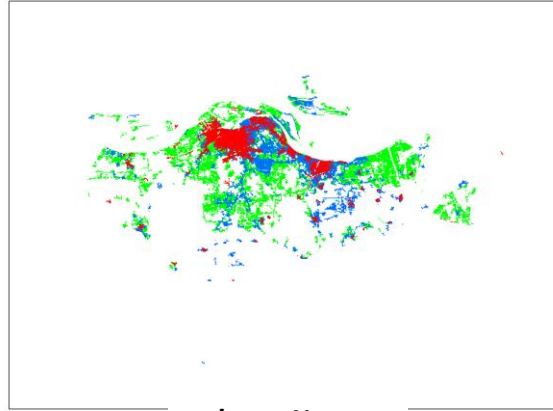
2000, Landsat 7 ETM+

2014, Landsat 8 OLI

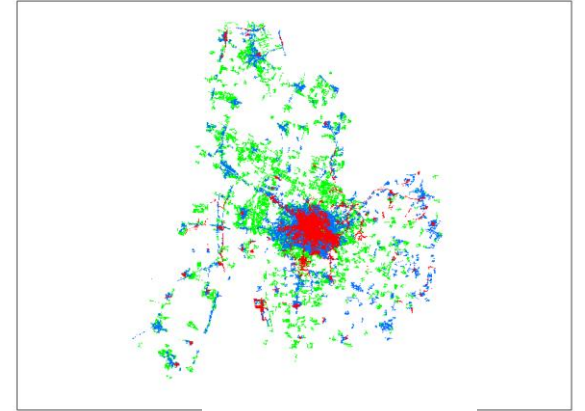




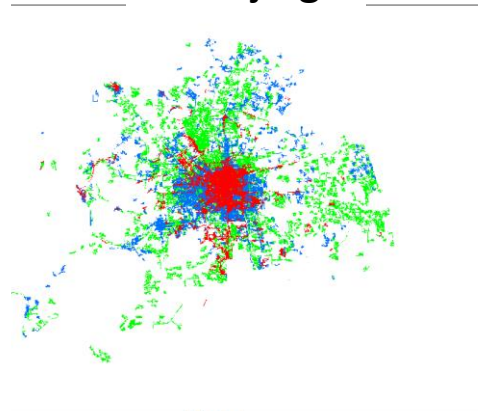
Nanjing



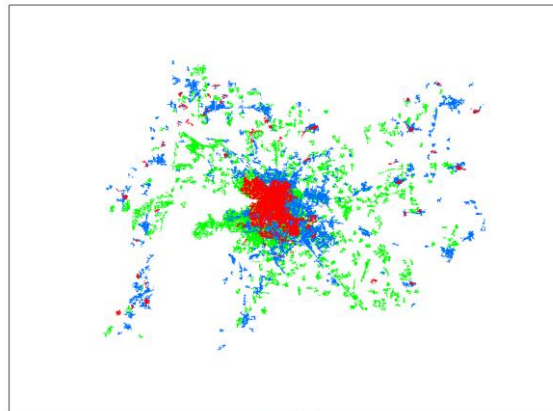
Zhenjiang



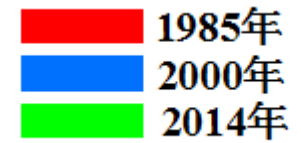
Changzhou

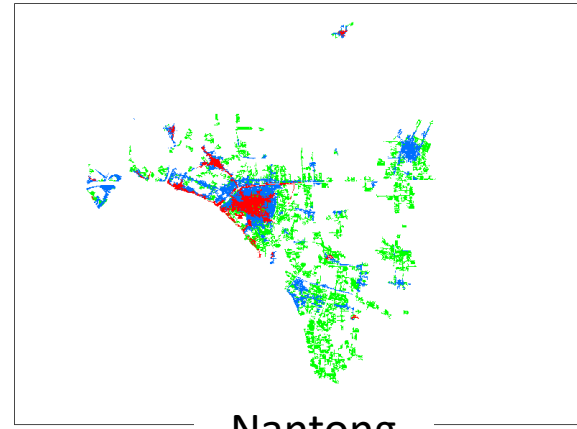
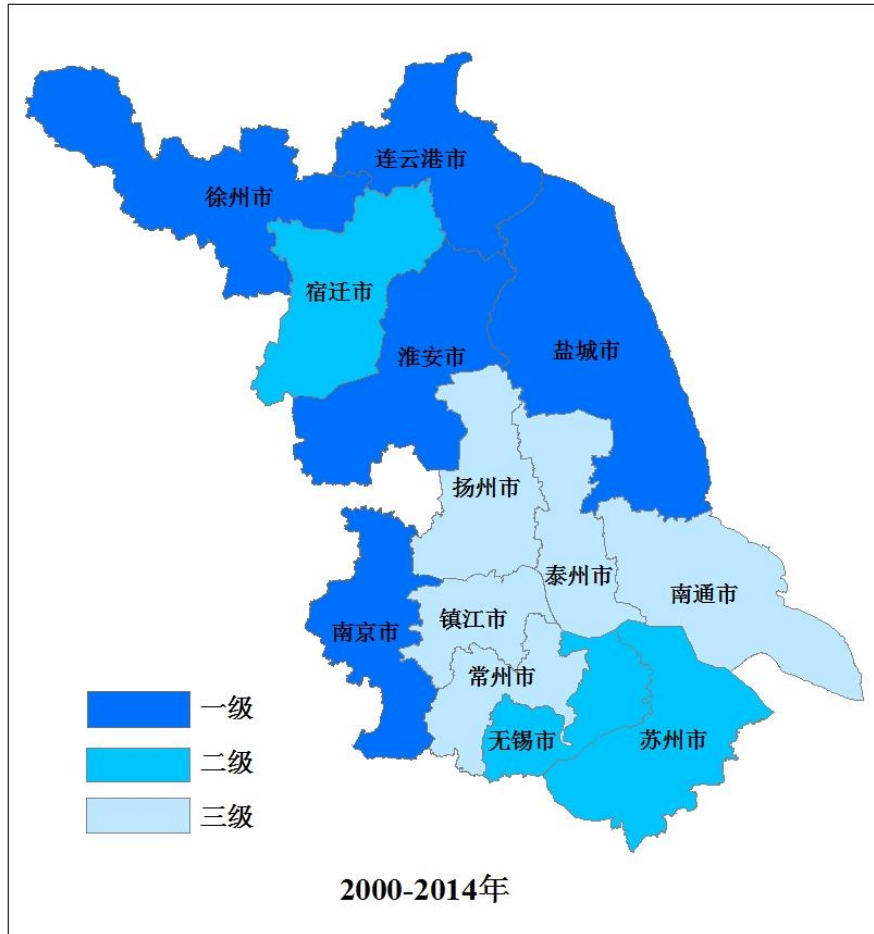


Suzhou

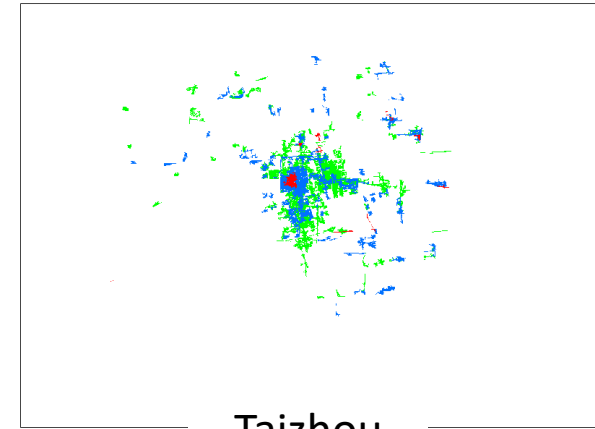


Wuxi

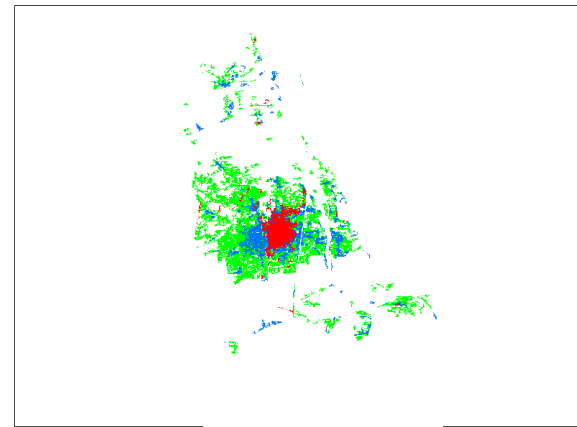




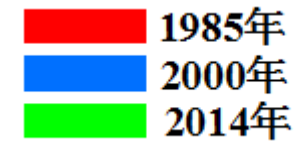
Nantong

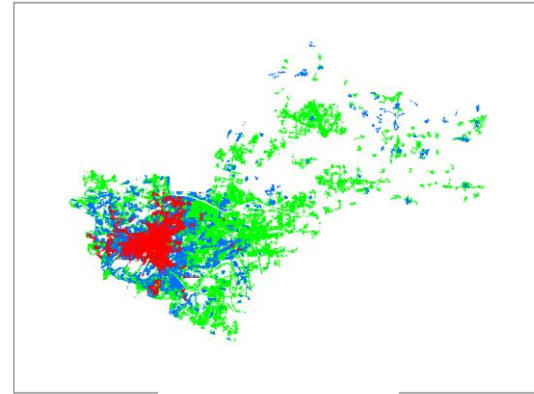
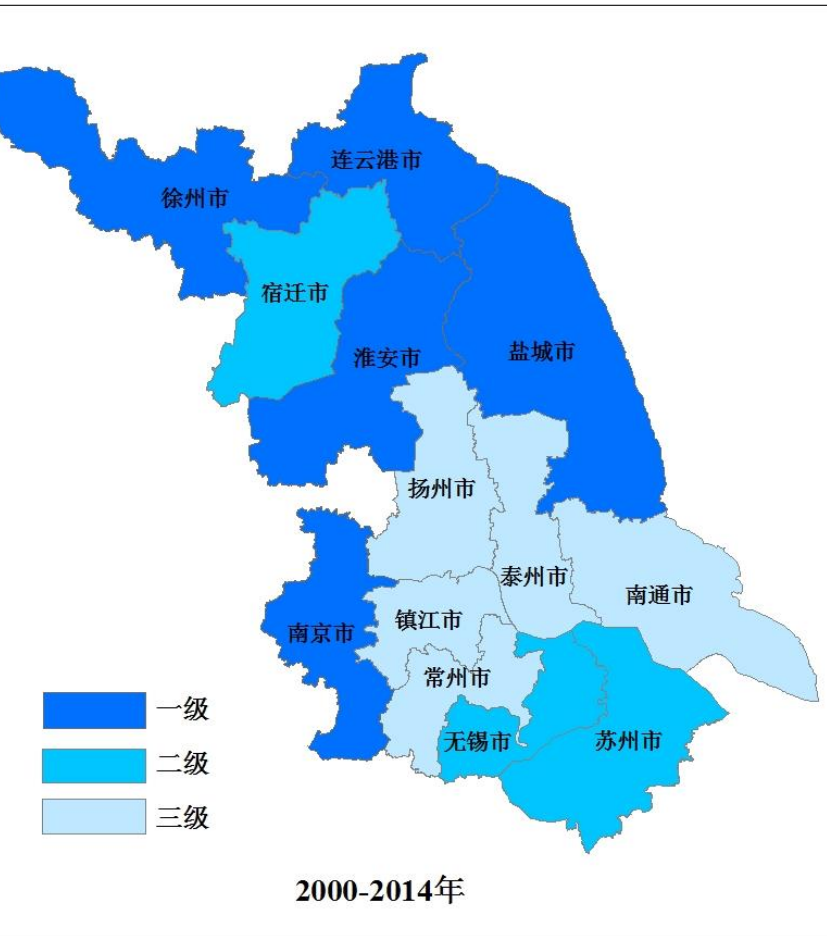


Taizhou

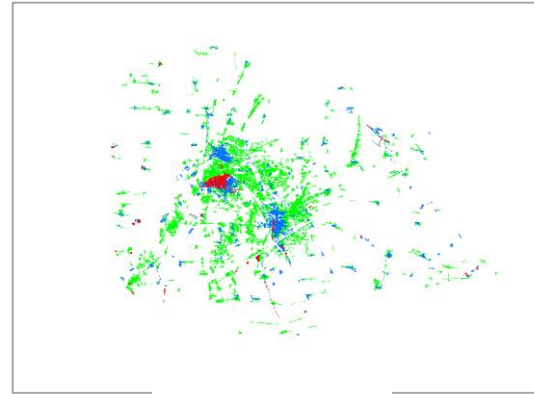


Yangzhou

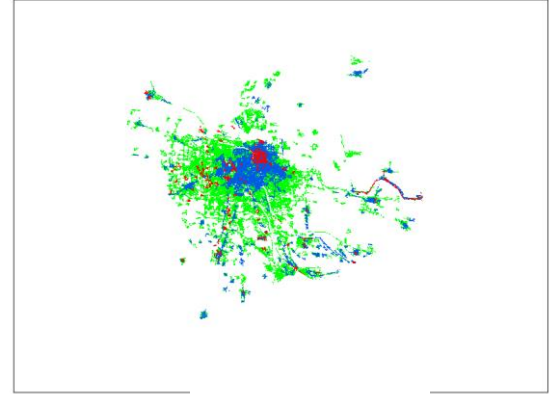




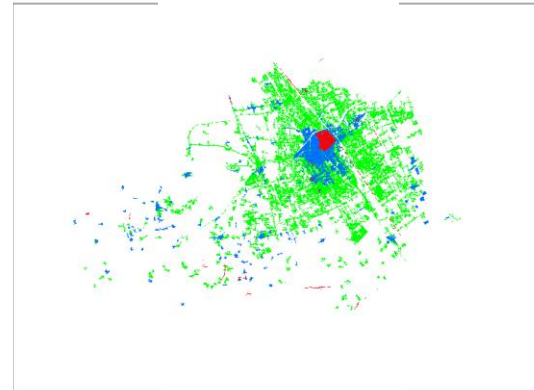
Xuzhou



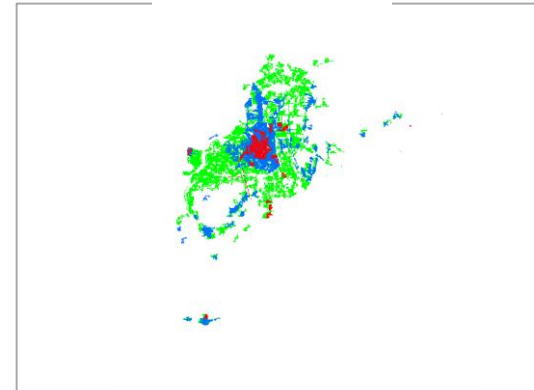
Huaian



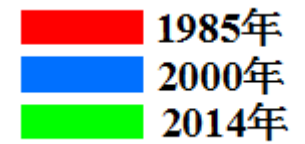
Suqian



Yancheng



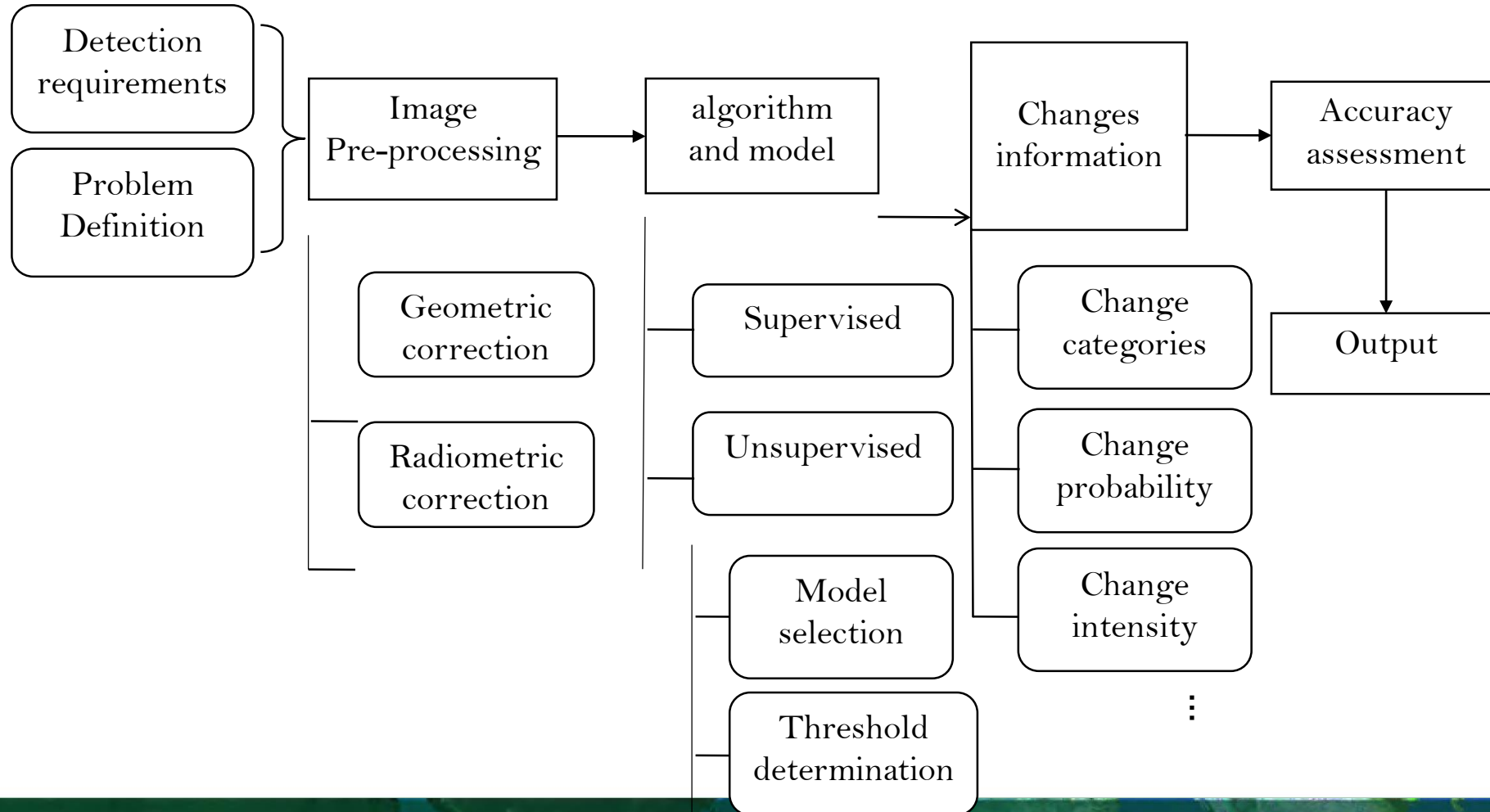
Lianyungang



Content

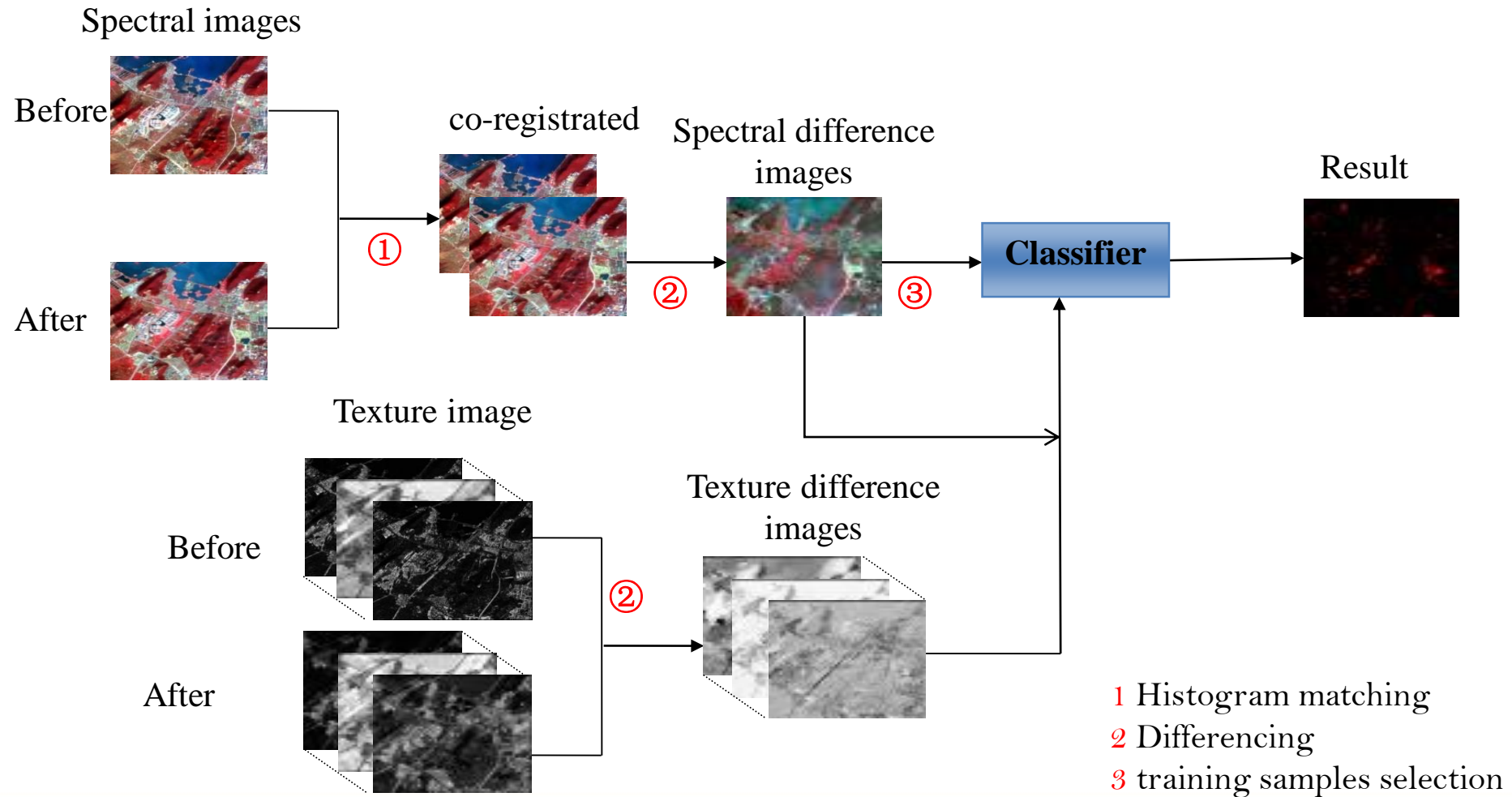
- 1 Urban remote sensing
- 2 Technical flow of urban mapping
- 3 Urban extent mapping
- 4 Urban land cover/land use mapping
- 5 Urban thematic mapping
- 6 ISA estimation and mapping
- 7 Change detection**
- 8 Conclusions and Advances

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

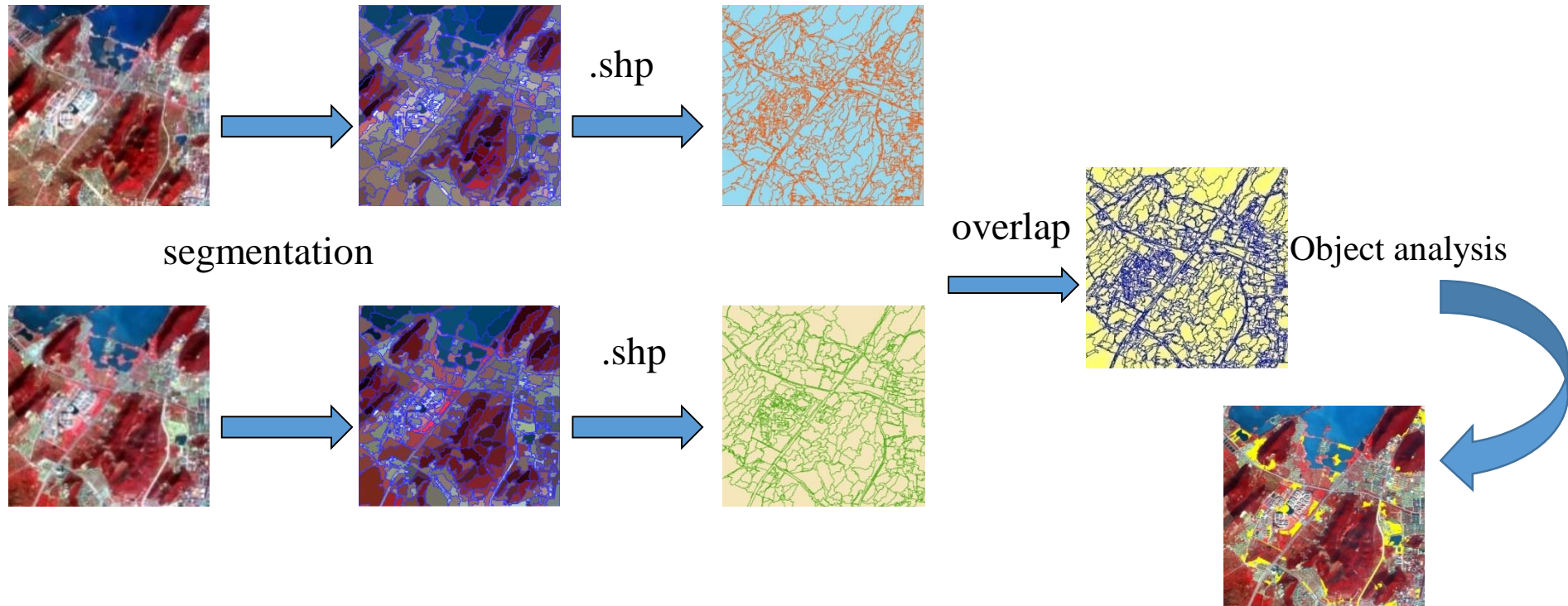


Unsupervised change detection/data			Single band	Multiple bands	
			Panchromatic, SAR, one band/feature of MS/HRS image	Medium-low multiple spectral image	Hyperspectral /Ultraspectral image
Binary detection	Image algebra	Difference	√		
		Ratio	√		
		Regression analysis	√		
		Distance or similarity measure	√		
	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)



Supervised: object oriented-based



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

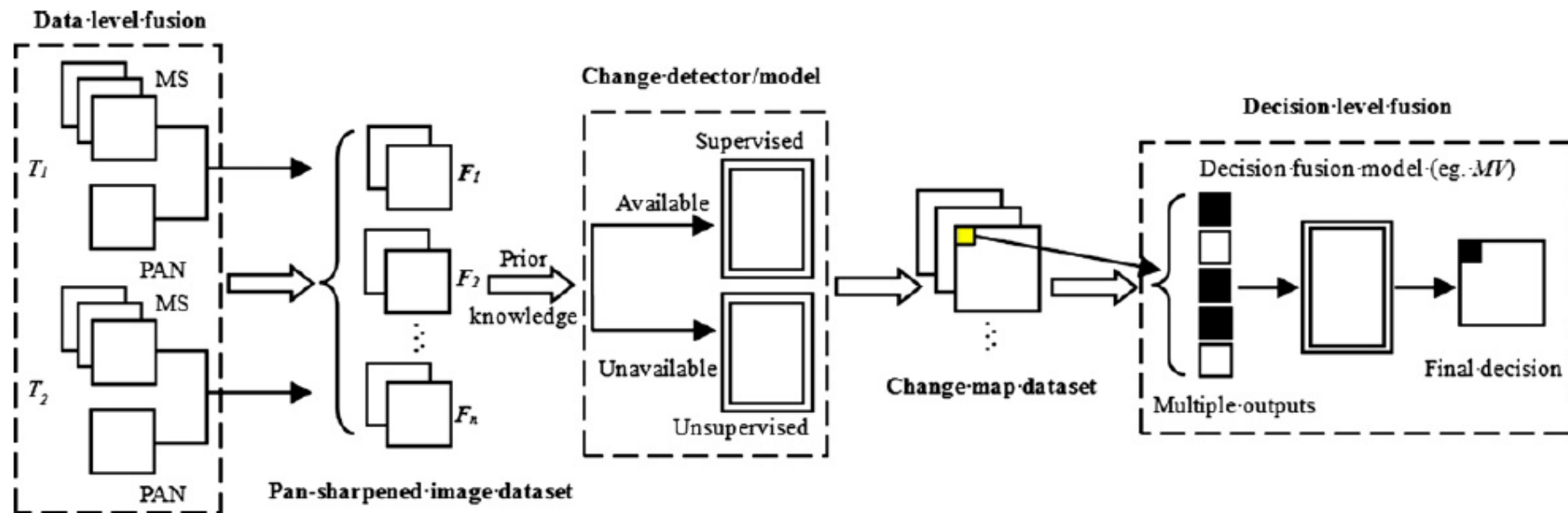


Fig. 1. Flowchart of the proposed change detection procedure based on information fusion techniques.

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

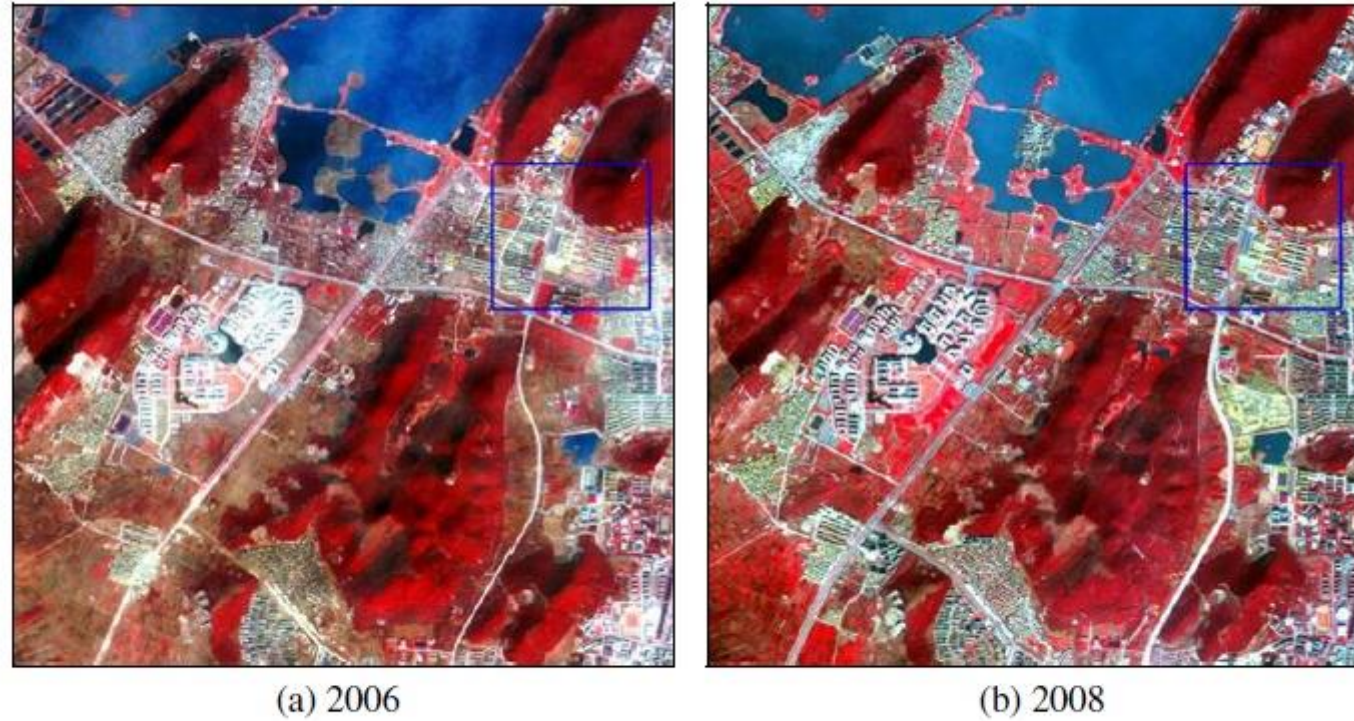


Fig. 6. False composite images of ALOS pan-sharpened data over the study area.

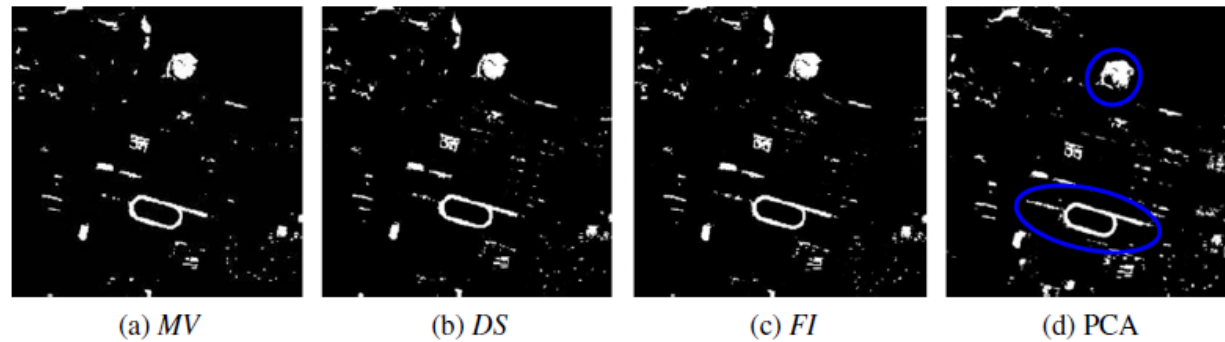
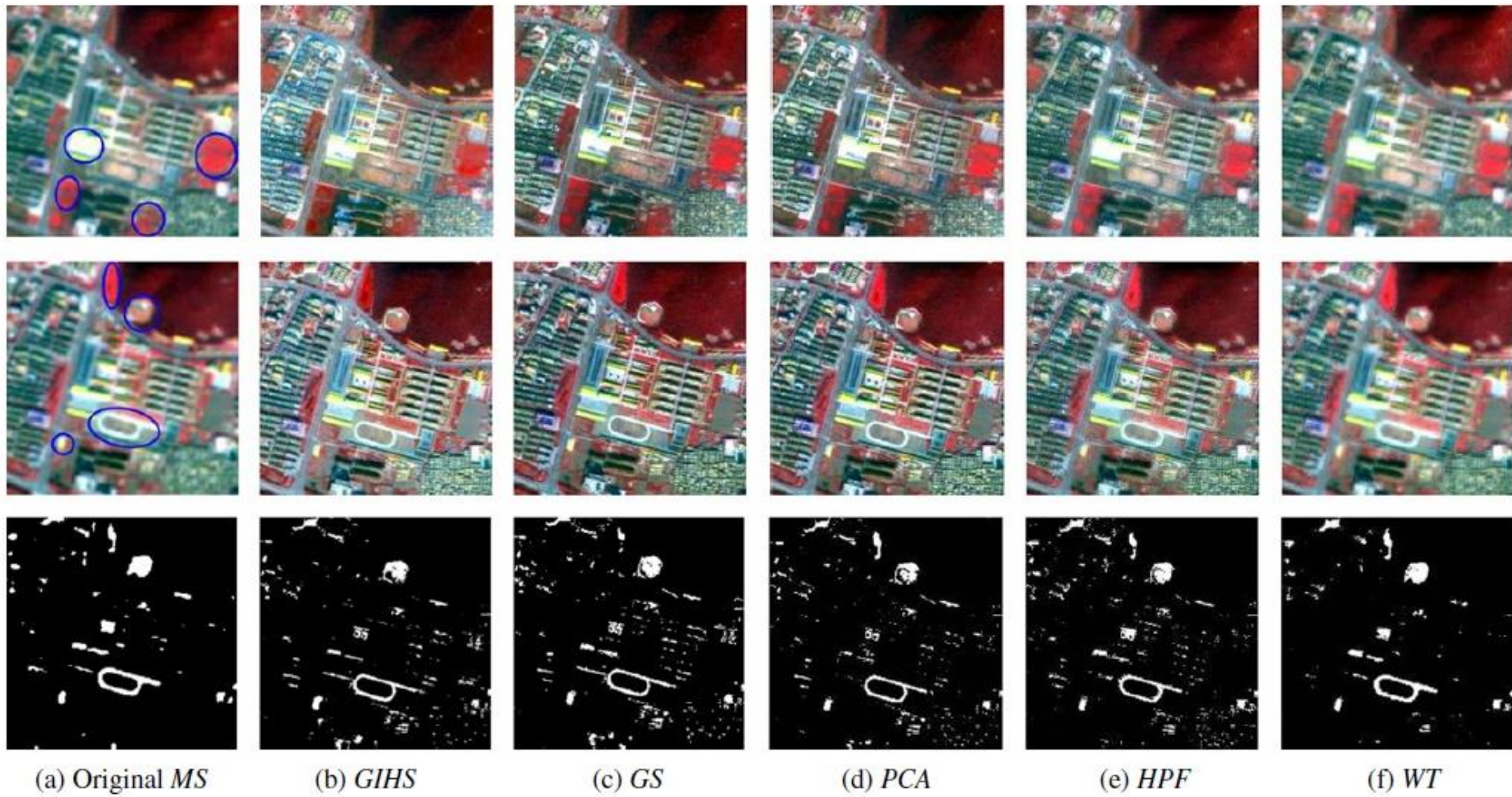


Fig. 8. Change detection results from decision level fusion strategy.

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	<i>MV</i>	89.44	0.7828	17.39	7.56	687	267	954
	<i>FI</i>	89.37	0.7820	16.35	8.68	646	314	960
	<i>D-S</i>	89.36	0.7817	16.38	8.68	647	314	961
First stage-data level fusion	<i>PCA</i>	88.29	0.7599	17.62	9.99	696	361	1057
	<i>GIHS</i>	88.33	0.7598	19.11	8.56	755	299	1054
	<i>GS</i>	88.22	0.7587	16.91	10.77	668	396	1064
	<i>HPF</i>	87.63	0.7458	19.27	10.04	761	356	1117
	<i>WT</i>	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

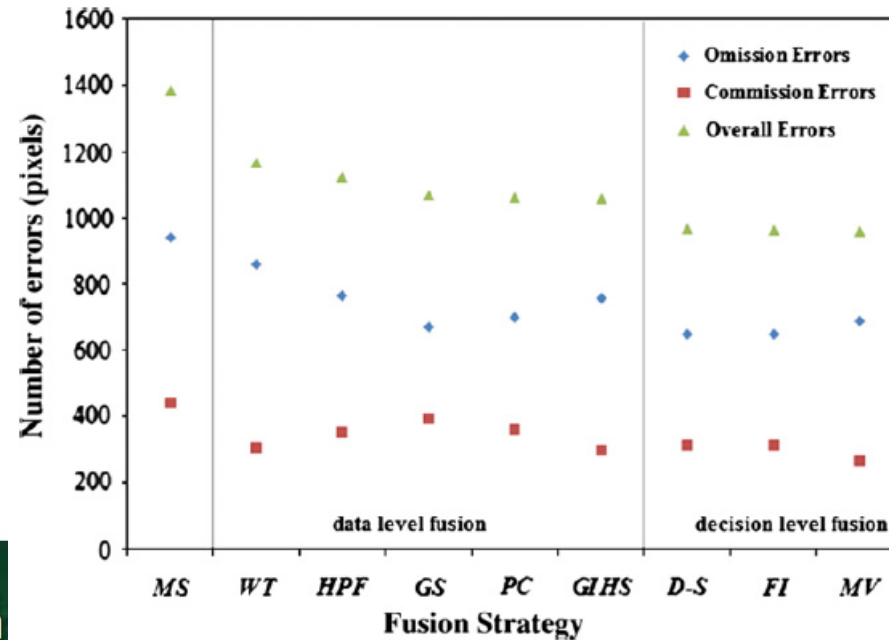


Fig. 9. Errors of change detection from different fusion strategies.

Fusion of Difference Images for Change Detection

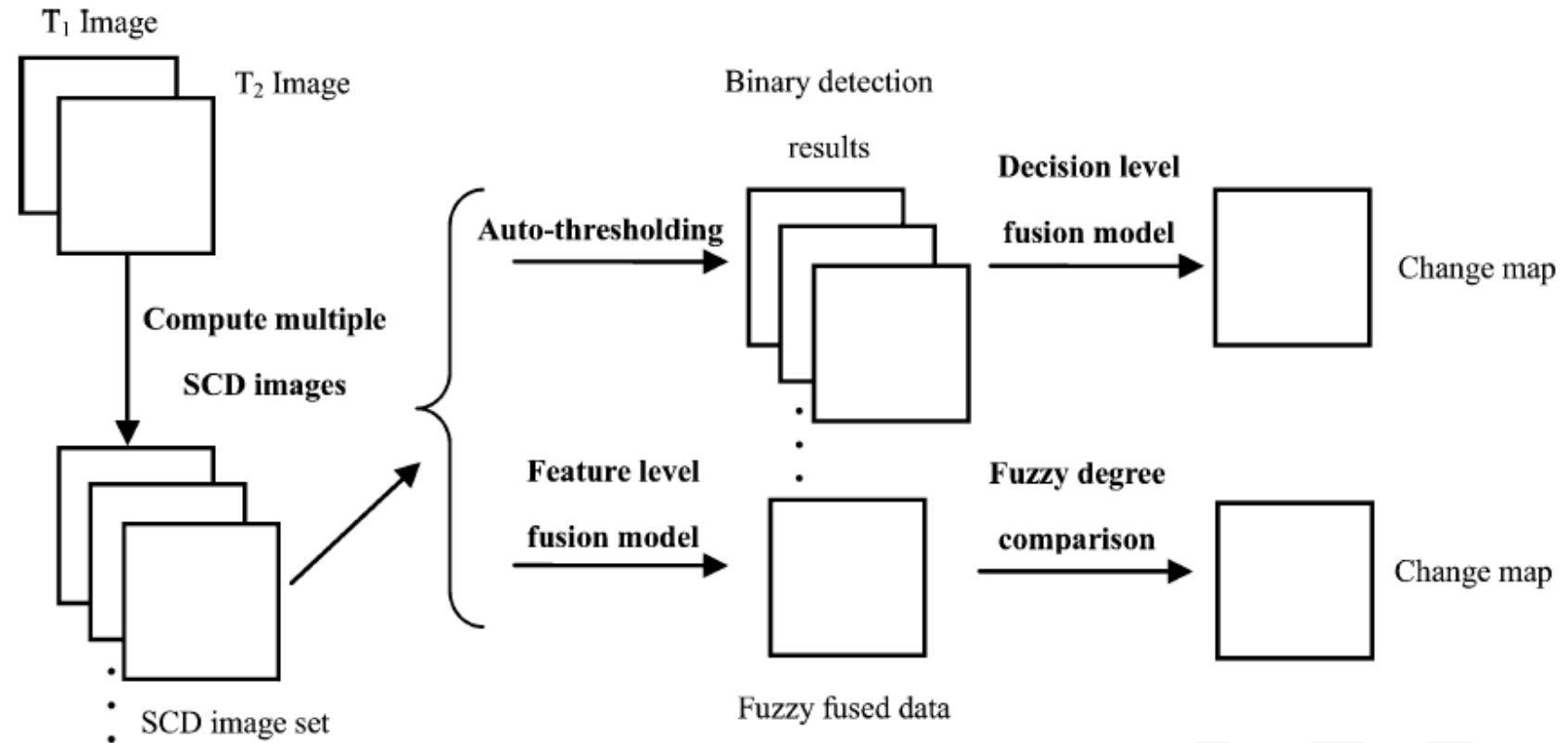


Fig. 1. Flowchart of the fusion procedure aimed at fusing multiple spectral change difference (SCD) images.

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



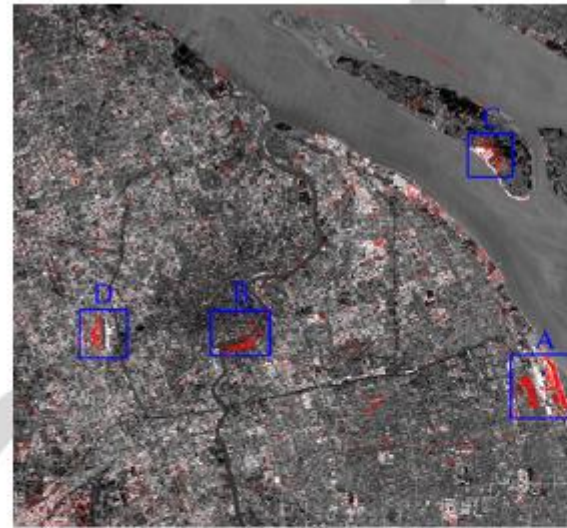
Fig. 2. False color composites of 2005 and 2009 CBERS images for the first test site (Shanghai). (a) 2005; (b) 2009.



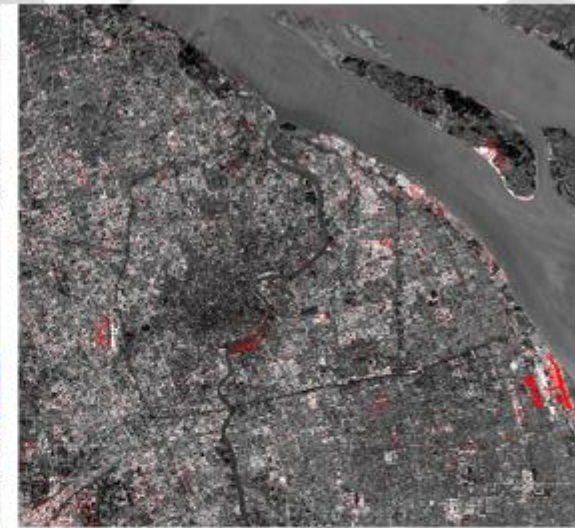
(a)



(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

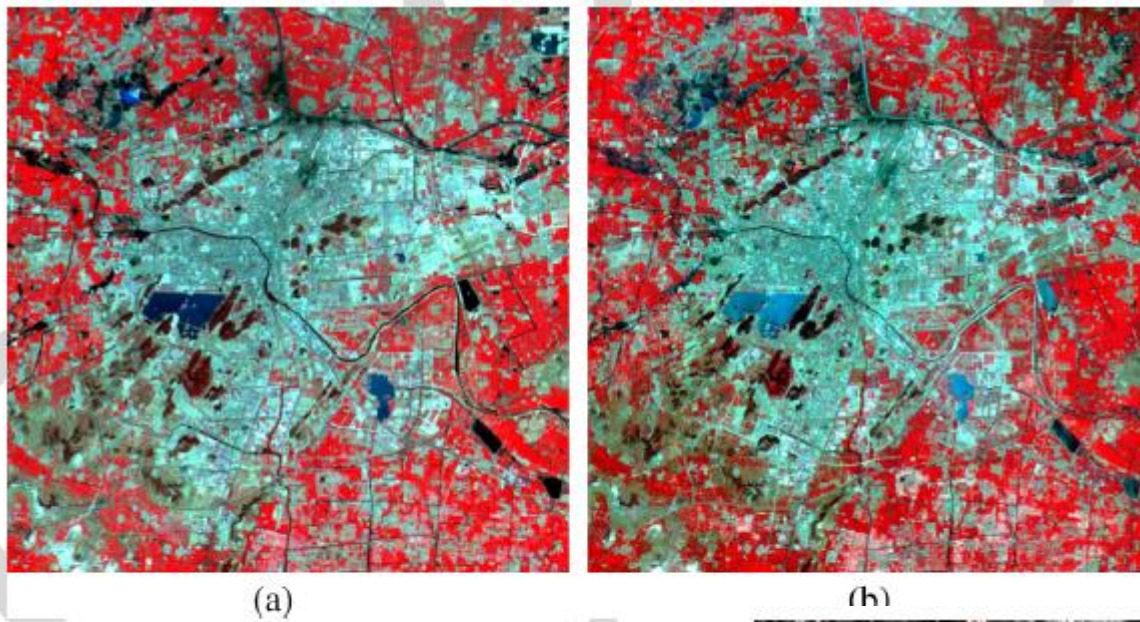


Fig. 5. False color composite images of the second HJ-1/B data; (b) 2011 HJ-1/A data.

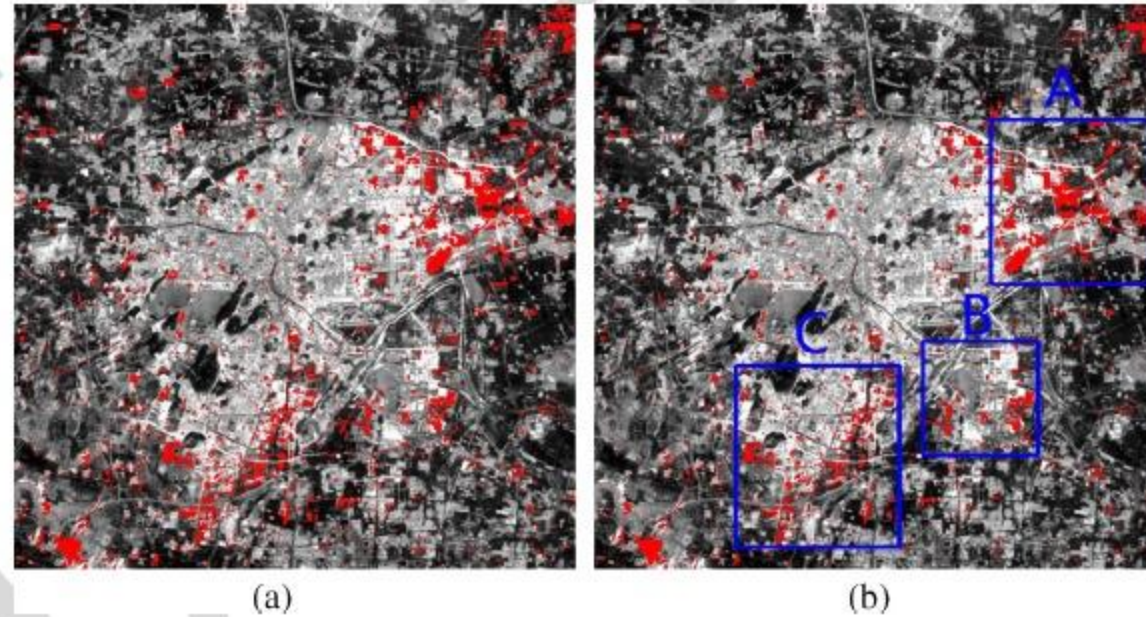


Fig. 6. Change detection results (in red) in the Xuzhou test site using two level fusion schemes: (a) feature level fusion; (b) decision level fusion using Majority Voting. In blue the areas highlighted in Fig. 7: A- Xuzhou Economic Development Zone, B- anew district of Xuzhou, C- Tongshan new area.

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

- 1 Urban remote sensing
- 2 Technical flow of urban mapping
- 3 Urban extent mapping
- 4 Urban land cover/land use mapping
- 5 Urban thematic mapping
- 6 ISA estimation and mapping
- 7 Change detection
- 8 Conclusions and Advances**

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