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Methods to extract impervious surface areas from satellite images

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Impervious surface area (ISA) is an important parameter for many environmental or socioeconomic relevant studies. The unique characteristics of remote sensing data made it the primary data source for ISA mapping at various scales. This paper summarizes general ISA mapping procedure and major techniques and discusses impacts of scale issues on selection of remote sensing data and corresponding algorithms. Previous studies have indicated that ISA mapping remains a challenge, especially in urban–rural frontiers and in covering a large area. Effectively employing rich spatial information in high spatial resolution imagery through texture and object-based methods is valuable. Data fusion of multi-resolution images and spectral mixture analysis are common approaches to reduce the mixed pixel problem in medium spatial resolution images such as Landsat. Coarse spatial resolution images such as MODIS and DMSP-OLS are valuable for national and global ISA mapping but more research is needed to effectively integrate multisource/scale data for improving mapping performance. Development of an optimal procedure corresponding to specific study areas and purposes is required to generate accurate ISA mapping results.

Keywords: satellite images; impervious surface area; mapping; modeling

1. Introduction

The urban landscape is regarded as a complex combination of different land covers such as buildings, roads, grass, trees, soils, and water. Depending on spatial resolutions of the remotely sensed data, urban landscapes have considerably different spectral signatures and spatial patterns. In high spatial resolution images such as QuickBird and Worldview-2 having sub-meter spatial resolution, individual objects such as building roofs and trees can be clearly identified. These features become indiscernible in relatively coarse spatial resolution such as Landsat Thematic Mapper (TM) with 30 m spatial resolution (see Figure 1). Strahler, Woodcock, and Smith (1986) proposed H- and L-resolution scene models to explain the relationships between landscape complexity and the capability of discernible objects in remotely sensed data. In an H-resolution scene model, the elements can be directly identified because the scene elements are larger than the resolution cell. Conversely, in an L-resolution scene model, the elements in the scene become

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increasingly smaller than the resolution cell size, thus, the elements are not detectable and no longer regarded as individual objects. Hence, the reflectance measured by a sensor can be regarded as a combination of various classes of scene elements (i.e. mixed pixels) as weighted by their relative proportions (Strahler, Woodcock, and Smith 1986). In urban landscapes, QuickBird and Worldview-2 images can be regarded as an H-resolution scene model, and Landsat TM imagery is attributed to an L-resolution model, as illustrated in Figure 1. Therefore, the mixed pixels in medium and coarse spatial resolution images become a problem for mapping and monitoring urban land use/cover dynamic change (Cracknell 1998).

In order to explain the land cover composition in an urban landscape, Ridd (1995) proposed a vegetation, impervious surface, and soil (V-I-S) conceptual model, assuming that different land covers such as residential areas and forest are a linear combination of these three components. The V-I-S model provides a guideline for decomposing urban landscapes and a linkage for these components to remote sensing spectral characteristics. However, the V-I-S model cannot explain all land covers such as wetland and water. Shade/water is regarded as another important component in an urban landscape. Thus, four endmembers – shade, green vegetation, soil, and impervious surface can explain all land covers (Lu and Weng 2004). In reality, impervious surface is a complex land cover in that different kinds of construction materials have significantly various spectral signatures and spatial patterns (Figure 1), depending on spatial resolution of the remote sensing data. Generally, impervious surface areas (ISAs) are defined as man-made land surface areas that water cannot infiltrate into. They are primarily associated with human activities and habitation through the construction of transportation infrastructure and buildings (Slonecker, Jennings, and Garofalo 2001; Bauer, Loffelholz, and Wilson 2008). Because ISA is made of different construction materials in an urban landscape, no one individual ISA can represent all impervious surfaces. The high spectral variation within ISA category and their spectral confusion with other land covers make it difficult to automatically map urban land use/cover distribution, especially the ISA distribution (Lu and Weng 2006a; Lu, Moran, and Hetrick 2011). Previous research has indicated that bright building roofs have very high spectral signatures (high-albedo objects) which are confused with dry soils; and dark roads and dark building roofs have very low spectral

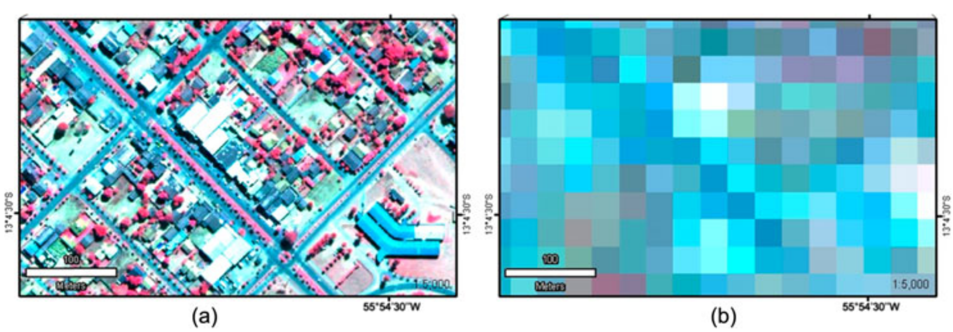

Figure 1. (a) The QuickBird image (bands 4, 3, 2 as RGB) with 0.6 m spatial resolution after data fusion of multispectral and panchromatic data showing the complexity of urban landscapes in a urban-rural frontier in Lucas do Rio Verde, Mato Grosso State, Brazil and (b) Landsat Thematic Mapper image (bands 4, 5, 3 as RGB) with 30 m spatial resolution showing the mixed pixel problem in the same location.

signatures (low-albedo object) which are confused with water/wetland and shadows (Lu and Weng 2004). Since ISA is concentrated on high- and low-albedo fraction images, it can be regarded as a combination of high- and low-albedo fraction images (Wu and Murray 2003; Lu and Weng 2006a, 2006b; Lu, Moran, and Hetrick 2011).

ISA has been recognized as an important parameter for environment-related studies such as water quality (Schueler 1994; Arnold and Gibbons 1996; Zug et al. 1999; Brabec, Schulte, and Richards 2002; Alberti et al. 2007), rainfall runoff (Lohani, Kibler, and Chanat 2002; Jacobson 2011; Dams et al. 2013), and climate change (Carlson and Arthur 2000; Jennings and Jarnagin 2002; Xian 2008; Imhoff et al. 2010). Although ISA only accounts for a small proportion in the earth surface (Elvidge et al. 2007; Schneider, Friedl, and Potere 2010; Kuang et al. 2013), it could be the most important land cover in the earth surface that closely relates to human's activities and well-being, and influences local climate change and environmental conditions. Therefore, much research has been conducted to develop methods and techniques to extract ISA distribution in past two decades (see reviewed papers by Slonecker, Jennings, and Garofalo 2001; Brabec, Schulte, and Richards 2002; Weng 2012; Wang et al. 2013). Due to the complexity of impervious surfaces and constraint of remote sensing data per se, accurate extraction of ISA from remotely sensed data is a challenge. It is still poorly understood which method is suitable for which kind of remotely sensed data or for a specific study area. Majority of ISA mapping studies are based on optical multispectral images, and single radar data have very limited application to ISA mapping due to its incapability in separating ISA from other land covers and its wavelength constraints.

Based on our experiments on ISA mapping using different spatial resolution images such as high- (e.g. QuickBird, IKONOS) (Lu and Weng 2009; Lu, Hetrick, and Moran 2011), medium- (Landsat, ASTER) (Lu and Weng 2006a, 2006b; Lu, Moran, and Hetrick 2011), and coarse spatial resolution images (MODIS, DMSP-OLS) (Lu et al. 2008), and using the integration of multi-scale and multi-senor data (Lu, Hetrick, and Moran 2011; Lu et al. 2011), this paper aims to provide a brief overview of the ISA mapping techniques and methods, discuss impacts of scale issues on selection of remote sensing data and corresponding algorithms, and discuss the needs to develop new methods to improve ISA mapping and estimation performance. Comparing to previous literature review papers (e.g. Slonecker, Jennings, and Garofalo 2001; Brabec, Schulte, and Richards 2002; Weng 2012; Wang et al. 2013) for providing a detailed description of specific methods, this paper provides a comprehensive summary of methods and techniques so that readers can quickly understand what methods are available for ISA mapping at different scales. This paper also provides a general procedure for mapping ISA distribution using remote sensing data, which is valuable for beginners to design a suitable procedure for conducting ISA mapping. Another contribution of this paper is to emphasize the important role of scale issues in designing a suitable procedure for ISA mapping, which has not been obtained sufficient attentions yet.

2. Overview of a general procedure for ISA mapping

ISA mapping and estimation is a complex procedure that requires careful design of each step, including statement of research problems, selection of suitable remote sensing data, image preprocessing and selection of suitable variables, development of ISA estimation models, and evaluation of the estimates. Each step may introduce errors into the ISA results. Thus, it is important to design an optimal procedure corresponding to a specific study area or purpose. The following subsections describe the major concerns for each step.

2.1. Consideration of biophysical conditions of the study area

Clearly understanding research problems, user's needs, and complexity of a study area is important for designing an ISA mapping/estimation procedure. Different characteristics of urban landscapes will affect the selection of remote sensing data and corresponding ISA mapping methods (Van der Linden and Hostert 2009). Previous research has indicated that ISA mapping has better performance in urban landscapes than in urban–rural frontiers because of different complexity (Lu and Weng 2006a; Li et al. 2013). The urban landscape in an individual city is relatively simpler than in multiple cities covering a large area. Difference in cultures and races may affect the use of construction materials and colors, as well as spatial patterns of buildings, thus affecting the ISA spectral signatures. Even within the same megacity, different geographic locations such as commercial area and urban–rural frontiers, and different population density and economic conditions will affect the complexity of urban landscapes. ISA mapping in a vegetation-growing season has better performance than in other seasons (Weng, Hu, and Liu 2009) because of the spectral confusion between nonphotosynthetic vegetation, ISA, and bare soils in a leave-off season. However, street trees will affect ISA mapping (Van der Linden and Hostert 2009) because the ISA under shadows cast by tall trees with big crowns will be missing.

2.2. Selection of suitable remote sensing data

Selection of suitable remote sensing data requires consideration of different factors, such as the complexity of an urban landscape, extent of the study area, requirement of user's needs, and data availability. In general, if a study area is relatively small and the ISA result is used as reference data, high spatial resolution remote sensing data are required to produce accurate results. Conversely, if a study area is very large and the requirement is to update ISA data quickly, coarse spatial resolution data may be a good choice. Most previous studies of ISA mapping in an individual city used medium spatial resolution multispectral data. Since different sensor satellite data are available (Guo et al. 2012), clearly understanding different features (e.g. radiometric, spectral, spatial, and temporal) of major remote sensing data is a prerequisite for selection of suitable data for a specific study. Optical sensor data mainly capture land surface features, and the multispectral information is critical to distinguish ISA from other land covers; in contrast, radar data reflect the surface roughness and the use of individual radar data is difficult to separate buildings from other land covers (Li et al. 2012a). However, integration of optical and radar data is valuable for improving ISA mapping performance (Yang et al. 2009; Leinenkugel, Esch, and Kuenzer 2011; Lu et al. 2011). Because LiDAR data can provide height information, incorporation of LiDAR-derived height information and optical sensor data may effectively separate buildings from other land covers (Im et al. 2012; Singh et al. 2012).

The spectral, spatial, temporal, and radiometric resolutions are important characteristics in optical sensor data and these characteristics will affect the selection of remote sensed data for ISA mapping at different scales (Weng 2012). Spatial resolution is especially an important factor in determining the use of remote sensing data in an urban landscape. Increasing spatial resolution through data fusion of different spatial resolutions data provides a new way to improve ISA mapping (Lu et al. 2011). The radiometric resolution in Landsat TM or ETM+ data with 8 bit may not enough to separate different ISA materials from other land covers because of the complexity of ISA materials. The improved radiometric resolution in Landsat 8 LDCM data with 12 bits may provide new capability to map more detailed ISA types. Spectral resolution is an important consideration for the selection of ISA mapping methods. Very high spatial resolution data with a limited number of spectral bands generate the difficulty in automatic separation of ISA from other land covers. Although hyperspectral data overcome this problem, its large data redundancy and limitation in data availability constrained its extensive application. Temporal resolution affects the availability of specific remote sensing data, especially in moist tropical regions because of the cloud cover problem (Asner 2001). Therefore, selection of suitable remote sensing data is one of the critical steps in ISA mapping.

2.3. Selection of suitable algorithms for ISA mapping

Although many methods and techniques are available (Weng 2007, 2012; Lu et al. 2012; Wang et al. 2013), developing a method suitable for a specific study is critical, depending on the complexity of a study area and characteristics of the selected remote sensing data. In general, per-pixel based methods are commonly used for high and medium spatial resolution images but they are criticized because of relatively poor results. Object-based methods are preferable for high spatial resolution images for reducing the heterogeneity of the urban landscape. The spectral mixture analysis (SMA)-based methods are commonly used for medium spatial resolution images, and regression tree or multiple regression models are valuable for coarse spatial resolution images. Detailed description for each category of methods is provided in Section 3.

2.4. Post-processing

Effective use of ancillary data is valuable for improving ISA mapping performance (Elvidge et al. 2007; Luo and Mounntrakis 2011). In general, these data can be used in three ways: the initial stage of ISA mapping by stratification of major non-ISA covers from vegetation; during the ISA modeling stage as extra variables; and post-processing of the ISA results. In particular, post-processing through use of expert rules is a valuable way to improve ISA mapping results. Since population density is closely related to ISA spatial patterns (Lu, Weng, and Li 2006), its use may improve ISA mapping performance. For example, commercial area and high-density residential area are confused with bare soils in remote sensing spectral signatures, and low-density residential area is confused with forest. Use of expert rules by analyzing the population density and ISA relationship can separate them (Lu and Weng 2006a). Also dark ISA is confused with water or shadows in spectral signatures, but their land surface temperatures vary, thus expert rules can be established to distinguish the low-albedo ISA and water/wetlands based on their different temperatures (Lu and Weng 2006a).

2.5. Evaluation of ISA results

Evaluation of ISA results is an important part in an ISA mapping or estimation procedure. Different methods such as error matrix, regression coefficient, root mean square error (RMSE), system error, and residuals are used in previous research (Wu and Murray 2003; Lu and Weng 2006a). When per-pixel based methods are used to map ISA distribution using high or medium spatial resolution images, the error matrix approach is used to evaluate the per-pixel based results using suitable sampling techniques, such as random sampling or stratified random sampling (Congalton and Green 2008). When medium or coarse spatial resolution images are used, the ISA results are in a fractional format, that is, the proportion of ISA in a pixel; thus, RMSE, residual analysis, system error, and regression coefficient are common methods to evaluate the fractional ISA estimates. During the evaluation of ISA results, proper collection of sample plots is required, including determination of a sampling technique, number of samples, size of sample plots, etc. Selection of a suitable unit (e.g. single pixel, cluster, polygon, and administrative units) is especially important but lack of standards, depending on the researchers (Lu and Weng 2006a). In a large area such as national and global scales, accuracy assessment is much difficult comparing with regional and local scales because of the consideration of collecting sufficient reference data with robust sampling techniques (Wulder et al. 2006; Herold et al. 2008). Uncertainty analysis is valuable for examining which factors influence ISA mapping performance in order to refine the procedure or to improve the selection of variables and modeling algorithms, but uncertainty analysis for ISA estimates has not obtained sufficient attention yet.

3. A brief overview of ISA mapping methods and techniques

Since the 1970s, remote sensing has become an important tool for urban relevant studies (Patino and Duque 2013). Many approaches such as per-pixel based classification (Hodgson et al. 2003; Jennings, Jarnagin, and Ebert 2004; Lu, Hetrick, and Moran 2011), regression tree models (Yang et al. 2003; Xian and Crane 2005; Xian, Crane, and McMahon 2008; Yang et al. 2009), and SMA-based approaches (Wu and Murray 2003; Wu 2004; Lu and Weng 2006a; Weng, Hu, and Liu 2009; Lu, Moran, and Hetrick 2011) have been used for ISA mapping. Slonecker, Jennings, and Garofalo (2001) grouped the ISA mapping techniques into three basic categories – interpretive applications, spectral applications, and modeling applications. Brabec, Schulte, and Richards (2002) grouped the techniques into four categories – using a planimeter to measure ISA on aerial photography, counting the number of intersections on the overlain grid on an aerial photography, conducting image classification, and estimating ISA through the percentage of urbanization in a region. Weng (2012) also summarized major techniques and discussed the impacts of spectral, spatial, temporal and geometric features on ISA mapping and estimation performance. Table 1 provides a summary of major ISA mapping methods using satellite images, which is grouped into six categories based on the use of remote sensing variables and techniques, and provides major references which were published in recent decade. Since the specific techniques have been described in details in previous publications, this section will only offer a brief overview of each category so that readers can understand major characteristics of different techniques, and understand how to select a proper technique for a specific purpose.

3.1. Per-pixel based classification methods

Classification algorithms can be unsupervised cluster analysis, supervised statistical-based algorithms such as maximum likelihood, and supervised nonstatistical-based algorithms such as neural network, decision tree, and support vector machine (Lu and Weng 2007). In theory, different land covers have their own spectral signatures, thus, they can be distinguished from remotely sensed data using proper classification algorithms. Previous research has examined the use of supervised classification methods such as

Table 1. A summary of major methods for mapping ISA distribution.

Category	Major methods	Data-sets	References
Per-pixel based classification methods	Maximum likelihood classifier; decision tree classifier; expert rules	IKONOS, QuickBird, Landsat	Goetz et al. (2003); Powell et al. (2008); Lu and Weng (2009); Lu, Hetrick, and Moran (2011)
Object-based methods	Segmentation-based classification	QuickBird, IKONOS	Hu and Weng (2011); Lu, Hetrick, and Moran (2011)
Sub-pixel classification methods	ERDAS sub-pixel classifier; Artificial neural networks; ISA as one endmember	Landsat, ASTER, IRS-1C	Ji and Jensen (1999); Rashed et al. (2001); Phinn et al. (2002); Weng and Hu (2008); Hu and Weng (2009); Van de Voorde and De Roeck (2009)
SMA-based methods	Addition of low- and high-albedo fractions; modified approach based on low-albedo, high-albedo, and land surface temperature; Spatially adaptive SMA; MESMA; temporal mixture analysis	Landsat,CHRIS/ Proba, HyspIRI, MODIS	Wu and Murray (2003); Rashed et al. (2003); Wu (2004); Lu and Weng (2006a, 2006b); Powell et al. (2007); Weng, Hu, and Liu (2009); Demarchi et al. (2012); Roberts et al. (2012); Yang, Matsushita, and Fukushima (2010); Yang et al. (2012); Deng and Wu (2013)
Regression-based methods	Regression-based models which the ISA reference is used a dependent variable and different remote sensing bands were used as independent variables. An alternative is to use vegetation related variables, such as tasseled cap greenness and fraction vegetation cover	Landsat, SPOT, inSAR, QuickBird, MODIS, DMSP	Gillies et al. (2003); Xian and Crane (2005); Elvidge et al. (2007); Bauer, Loffelholz, and Wilson (2008); Lu et al. (2008); Esch et al. (2009); Sutton et al. (2009); Yang et al. (2009); Van de Voorde et al. (2011); Im et al. (2012); Kuang et al. (2013); Sexton et al. (2013)
Threshold-based methods	Threshold based on NDISI; hybrid method based on NDVI and cluster analysis	QuickBird Landsat	Xu (2010); Lu, Hetrick, and Moran (2011)

Note: NDISI represents normalized difference impervious surface index figure captions.

maximum likelihood and decision tree for mapping ISA distribution (Goetz et al. 2003; Lu, Hetrick, and Moran 2011). High and medium spatial resolution images such as QuickBird and Landsat images are common data source (Lu, Moran, and Hetrick 2011; Lu, Hetrick, and Moran 2011). For high spatial resolution images, high spectral variation within ISA and the similar spectral signatures between ISA and other nonvegetation land covers make it difficult to select suitable training samples for an ISA class, resulting in high misclassification. In medium and coarse spatial resolution images, overestimation occurs in urban extents and underestimation occurs in rural landscape due to the limitation of spatial resolution in remotely sensed data and heterogeneity in an urban environment (Lu and Weng 2004). The per-pixel based classification algorithms are criticized because of relatively poor classification results. In reality, they are not commonly used for ISA mapping.

3.2. Object-based classification methods

Object-based classification methods have been extensively used for high spatial resolution image classification (Blaschke 2010; Lu, Hetrick, and Moran 2011). In general, object-based methods involve two key steps: producing a segmentation image and classifying the segments into meaningful classes (Jensen 2005). Previous studies have indicated that object-based classification methods are effective in reducing spectral variation inherent in the same land cover, thus improving classification results (Thomas, Hendrix, and Congalton 2003; Laliberte et al. 2004; Wang et al. 2004; Mallinis et al. 2008). However, this method cannot solve spectral confusion and shadow problems in high spatial resolution images and the mixed pixel problem in medium spatial resolution images (Lu, Hetrick, and Moran 2011). The difficulty in optimizing parameters (e.g. minimum value distance, variance factor, minimum size of pixels in a segment) for developing segmentation images is another factor affecting its extensive application.

3.3. Sub-pixel based classification methods

If research is only on ISA distribution, an urban landscape can be regarded as a combination of ISA and background. Previous research has examined techniques to mapping ISA using ERDAS sub-pixel classifier (Ji and Jensen 1999), matched filtering method (Lu, Hetrick, and Moran 2011), and standard SMA by directly selecting ISA as an endmember (Rashed et al. 2001; Phinn et al. 2002). In reality, the complexity of ISA materials results in high variation of spectral signatures, and thus identifying an individual ISA to represent complex ISA materials is not feasible (Lu and Weng 2004). An alternative is to select different ISA endmembers, and multiple endmember SMA (MESMA) is used to develop all ISA fractional images, and the final result is a combination of all ISA fractional images (Rashed et al. 2003). In practice, sub-pixel based classification method cannot provide satisfactory ISA results because of heterogeneity of ISA materials and the spectral confusion between ISA and other nonvegetation land covers (e.g. soils, water/wetland).

3.4. SMA-based methods

Of the many methods for ISA mapping (Lu et al. 2012; Weng 2012; Wang et al. 2013), the SMA-based methods have been regarded as one of the most appropriate ones, especially for medium spatial resolution multispectral images (Wu 2004; Lu and Weng 2006a; Lu, Moran, and Hetrick 2011; Weng 2012). In an urban landscape, four endmembers – high albedo object, low-albedo object, vegetation, and soil – are used to unmix the multispectral images into these fraction images. As an example illustrated in Figure 2 (Li et al. 2013), ISA is mainly concentrated on high- and low-albedo fraction images, and thus ISA can be developed from the combination of both fractions (Wu and Murray 2003; Lu and Weng 2006a; Lu, Moran, and Hetrick 2011). One critical step in extracting ISA is to remove non-ISA pixels in both fraction images. Lu and his colleagues have explored different methods, such as use of land surface temperature and unsupervised cluster analysis, to remove non-ISA pixels (Lu and Weng 2006a; Lu, Moran, and Hetrick 2011). Previous studies have indicated that the SMA-based ISA estimates provide much higher accuracy of area statistics than the per-pixel based results, especially in the urban–rural landscape, as shown in Figure 3 (Lu, Moran, and Hetrick 2011). Comparing with traditional spectral-based SMA method, spectral normalization

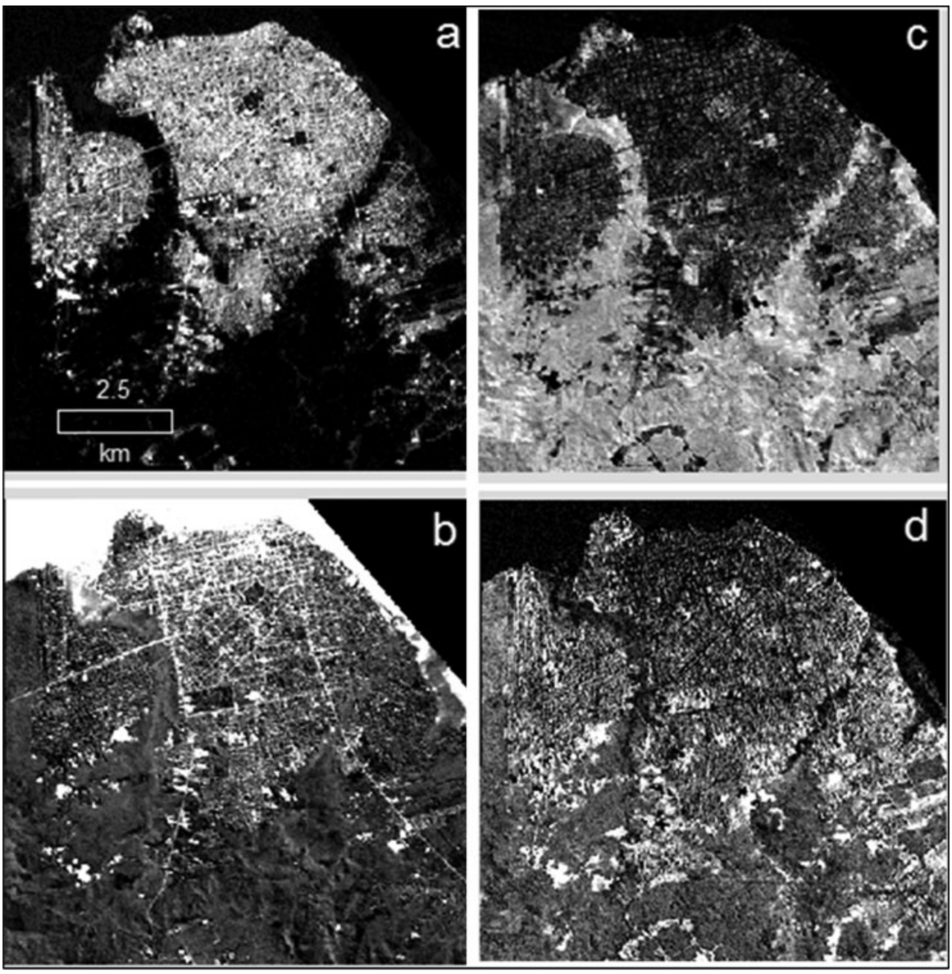

Figure 2. Four fraction images (a – high-albedo; b – low-albedo; c – green vegetation; and d – soil) which were developed from the 2010 Landsat TM multispectral image in Santarem, Para State, Brazil.

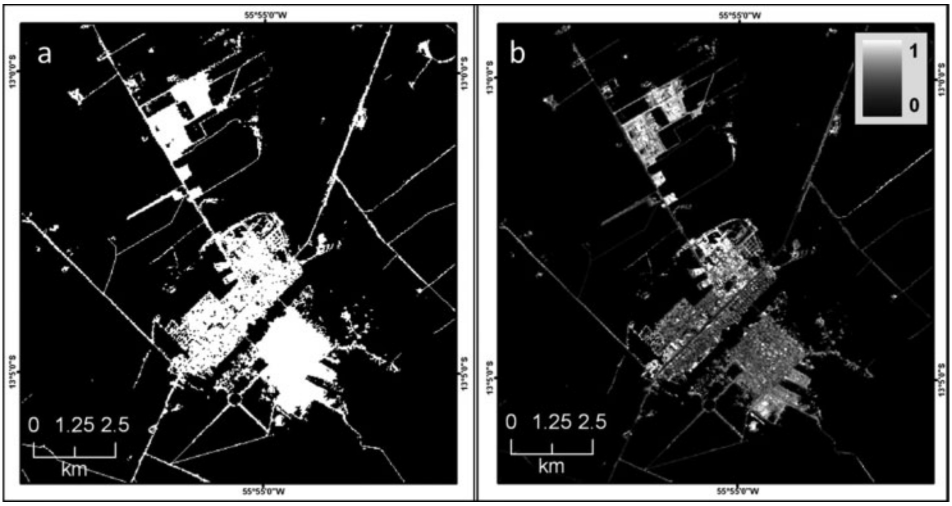

Figure 3. A comparison of ISA distributions which were developed using (a) per-pixel based and (b) spectral mixture analysis-based methods based on the 2008 Landsat TM imagery in Lucas do Rio Verde, Mato Grosso State, Brazil.

can further improve ISA mapping performance (Wu 2004, 2009; Yuan and Bauer 2007). Generally, the SMA-based method is used in individual cities based on medium spatial resolution multispectral images. When urban extent is accounted for a small proportion of a study area, the SMA-based method may not produce satisfactory results because of the difficulty in developing good-quality high-albedo and low-albedo fraction images (Lu, Moran, and Hetrick 2011).

3.5. Regression-based models

Although the SMA-based methods have been proven effective for ISA mapping in individual cities, its application to a large area was not successful due to the difficulty in identifying endmembers and the complexity of urban landscapes. In this case, a regression-based method is a good choice. For example, the regression tree model has been used for ISA mapping in the US based on Landsat images (Yang et al. 2003; Xian and Crane 2005; Xian, Crane, and McMahon 2008; Yang et al. 2009; Xian and Homer 2010). High resolution digital aerial photographs were used to produce ISA reference data, and Landsat multispectral bands were used as predictive variables. A regression tree model was developed to map ISA in a large area (Xian and Crane 2005; Xian, Crane, and McMahon 2008). Another example is to integrate coarse spatial resolution images such as MODIS and DMSP-OLS and a limited number of Landsat images for mapping settlement distribution in southeastern China (Lu et al. 2008), in which reference data were produced from Landsat images, and a regression model was developed through the combined MODIS normalized difference vegetation index (NDVI) and DMSP-OLS data and the settlement reference data. The regression-based models have proven effective for mapping national and even global ISA distribution (Elvidge et al. 2007; Kuang et al. 2013). The key is to select suitable variables from coarse spatial resolution images and high-quality ISA reference data from high or medium spatial resolution images.

In addition to the use of spectral or radiometric data as predictable variables, an alternative is to identify some variables that have strong correlation with ISA. Previous studies have indicated that ISA has highly negative correlation with vegetation cover and positive correlation with land surface temperature (Weng, Lu, and Schubring 2004). The ISA can be estimated from these variables through an established relationship between ISA and corresponding variables. For example, ISA was estimated with regression models using vegetation indices, such as the tasseled cap greenness (Bauer, Loffelholz, and Wilson 2008) and fractional vegetation cover from the NDVI (Gillies et al. 2003). Because of local specificities regarding phonologies and climate conditions, caution should be taken to directly transfer this method to other study areas or other dates of data-sets. Also economic conditions, cultures, and races may affect spatial patterns of vegetation and other land covers in an urban landscape.

3.6. Threshold-based methods

Vegetation and ISA have different spectral signatures, thus, vegetation indices such as NDVI can be used to separate nonvegetation and vegetation classes through the thresholding method. The nonvegetation classes mainly include bare soils, water/wetland and ISA. The key is to separate ISA from bare soils and water/wetland through a classification method such as cluster analysis. This method is valuable for ISA mapping from high spatial resolution images (Lu, Hetrick, and Moran 2011). For medium spatial resolution images such as Landsat, the thermal band is useful to assist the separation of ISA from other land covers by establishing new indices through incorporation of temperature into vegetation index. For example, Xu (2010) developed a normalized difference impervious surface index to map ISA through thresholding method. Another application of using the threshold-based method is on DMSP-OLS data for producing urban ISA or settlements in a large area (Imhoff et al. 1997; Elvidge et al. 2007). However, uncertainty is high due to coarse spatial resolution in DMSP-OLS data. It is difficult to identify an optimal threshold to separate ISA from other land covers (Lu et al. 2008).

4. Consideration of scale issues in the ISA mapping

A large number of previous studies used medium spatial resolution images, especially Landsat, for ISA mapping in individual cities (Wu 2004; Lu and Weng 2006a; Lu et al. 2012). Since very high spatial resolution images such as QuickBird and Worldview are available in the past decade, much research has been shifted to mapping ISA distribution at a local scale (Lu and Weng 2009; Lu, Hetrick, and Moran 2011) so that these results can be used as reference for evaluation or validation of other results. Another shift is on the use of coarse spatial resolution images such as DMSP-OLS and MODIS data for ISA estimation at national and global scales (Elvidge et al. 2007; Kuang et al. 2013) in order to timely update ISA data-sets for meeting research needs related to rapid urbanization and ISA impacts on environmental and socioeconomic conditions. As indicated in Section 2 that ISA mapping requires a careful design of each step, many factors can affect ISA mapping results and they have been discussed in previous literature (e.g. Weng 2012). Therefore, this section will mainly discuss the impacts of scale issues on ISA mapping, including selection of remote sensing data and corresponding variables.

4.1. ISA mapping at a local scale

ISA data at a local scale are generally extracted from very high spatial resolution images so that this result can be used for practical applications such as urban planning and design and as reference data for modeling or for validation of the ISA estimates from other sensor data at a large area. The major advantages of using high spatial resolution images are that individual objects can be clearly identified, which is very suitable for visual interpretation, and mixed pixel problem is significantly reduced. However, high spatial resolution images present new challenges for automatically mapping ISA distribution. These problems include high spectral variation within the same land cover type and spectral confusion between ISA and other land covers; and shadows caused by tall objects and confusion between dark ISA and water/wetland (Lu and Weng 2009; Lu, Hetrick, and Moran 2011). Cost of image purchase and data redundancy are another problem affecting its extensive applications.

Texture (Puissant, Hirsch, and Weber 2005; Aguera, Aguilar, and Aguilar 2008; Pacifici, Chini, and Emery 2009) and object-based methods (Mallinis et al. 2008; Zhou, Troy, and Grove 2008) are commonly used to reduce the impacts of high spectral variation within the same land cover. Both methods have been proven to provide better classification than per-pixel based methods (Lu, Hetrick, and Moran 2011). One challenge in selecting a suitable textural image is to determine the optimal combination of following parameters: choice of a spectral image, use of a suitable texture measure, size of a moving window, quantization level of an image, and inter-pixel distance (Shaban and Dikshit 2001; Pacifici, Chini, and Emery 2009). The difficulty in identifying a suitable textural image, the uniqueness of individual study areas, and high computation cost for calculating textures limit extensive applications. For the object-based methods, the key is to identify optimal parameters for producing a good segment image but remains a challenge due to the complexity of urban landscapes (Li et al. 2012b). Also more research is needed to automatically reduce shadow problem inherent in high spatial resolution images.

4.2. ISA mapping at a regional scale

Many ISA mapping studies are for megacities because of their importance in socioeconomic and political conditions and their impacts on environmental conditions. Medium spatial resolution satellites such as Landsat images are common data source for ISA mapping at a regional scale. The suitable spatial and spectral resolutions of Landsat images with a relatively long history of data availability and public access at no cost make it a primary data source for regional ISA mapping (Wulder et al. 2012). Many techniques as summarized in Table 1 are developed for the use of medium spatial resolution images. Because of the complexity of urban landscapes and user's requirement for accuracy and detailed spatial patterns, Landsat and other sensor data with medium spatial resolution are regarded too coarse for examining spatial patterns of ISA distribution (Lu et al. 2012). In order to improve ISA mapping performance, three potential techniques may be used: (1) using a data fusion method to integrate different spatial resolution images for enhancing spatial information (Pohl and van Genderen 1998; Zhang 2010; Leinenkugel, Esch, and Kuenzer 2011; Lu et al. 2012); (2) decomposing multispectral images into physically meaningful fraction images using unmixing methods (Lu and Weng 2006a; Lu et al. 2012); and (3) calibrating ISA estimates by establishing a regression model (Lu, Moran, and Hetrick 2011).

4.3. ISA mapping at national and global scales

Mapping national and global ISA distribution has obtained increasingly attention due to the impacts of human-induced activities on global environmental change (Elvidge et al. 2007). Use of high or medium spatial resolution images requires prohibitive time and labor costs for national and global urban mapping, thus, coarse spatial resolution images such as MODIS and DMSP-OLS become a major data source (Cao et al. 2009; Schneider, Friedl, and Potere 2009; Zhang and Seto 2011; Liu et al. 2012; Ma et al. 2012; Yang et al. 2013). However, the coarse spatial resolution images results in high estimation uncertainty. Previous research has explored the ISA estimates using time series MODIS NDVI with SMA-based approach (Knight and Voth 2011; Yang et al. 2012) and DMSP-OLS data with multiple regression analysis (Elvidge et al. 2007). Because of the difficulty in ISA mapping using single MODIS or DMSP-OLS data, integration of both data sources has been proven valuable for improving ISA estimation accuracy (Lu et al. 2008; Cao et al. 2009; Zhang, Schaaf, and Seto 2013). The advantage of using coarse spatial resolution images is the potential to rapidly update national or global ISA data. However, the complex mosaic of different landscapes in a large area makes most of the methods used successfully in high and medium spatial resolution images unsuitable for coarse spatial resolution image.

5. Summary

Mapping ISA distribution is a comprehensive procedure. It is critical to identify major factors influencing ISA estimation performance, especially in a large study area through uncertainty analysis. Figure 4 illustrates the relationships among spatial resolution of selected remote sensing data, extent of a study area, and potential variables and

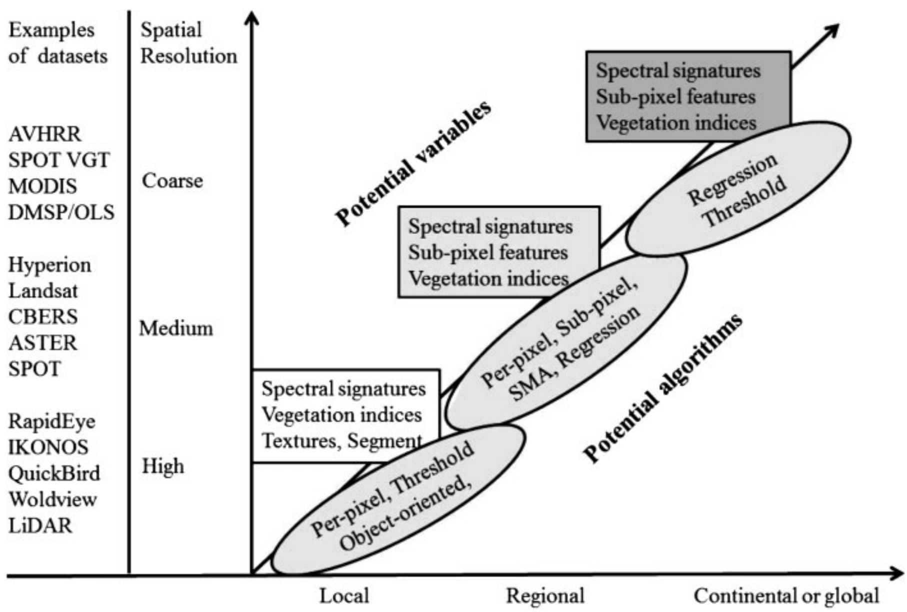

Figure 4. Relationships among spatial resolution of remote sensing data, scale issue, and the selection of potential variables and corresponding algorithms.

algorithms. Scale is an important concern in selecting remote sensing data and corresponding variables and thus the design of an optimal procedure. At a local scale, very high spatial resolution image is an important data source for ISA mapping. Using spatial information through textures or segmentation is an effective way to improve ISA mapping performance. It is necessary to automatically identify optimal textural or segment images and to reduce the shadow problem. Integration of LiDAR-derived height information and high spatial resolution optical sensor images is an important research aspect for improving ISA mapping performance.

Many medium spatial resolution images are used for ISA mapping for individual cities. Integration of multi-resolution/sensor data has been proven valuable in improving ISA spatial patterns and the SMA-based methods can considerably improve ISA area estimates. It is necessary to use suitable data fusion techniques to enhance the difference between ISA and other land covers. Post-processing by effectively using ancillary data such as population density and land surface temperature is valuable too. At national and global scales, timely updating of national and global ISA data-sets is needed for global environmental change, climate change, and population and economic research. Coarse spatial resolution images such as MODIS and DMSP-OLS have become a primary data source for this purpose but uncertainty may be high due to the complexity of biophysical conditions. Integration of MODIS (or SPOT VGT) and DMSP-OLS data has been proven valuable. More research is needed to integrate multi-scale data from high, medium, and to coarse spatial resolution images for mapping ISA distribution.

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