A literature review, 2001-2008, of classification methods and inner urban characteristics identified in multispectral remote sensing images.

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ABSTRACT:

During the last, decade very high resolution images have become available for civilians and researchers, opening new possibilities and challenges for remote sensing studies. Until than, inner urban studies were supported mainly by density proxies to infer land cover characteristics, based on spectral information of satellite images, or by airborne photographs witch allowed identification of structural elements of the cities scenario, such as streets network, besides other important urban characteristics, such as buildings dimensions, pattern, among others. The possibility of accessing this level of detail with multi-spectral images, along with the development of personal computers processing and storing capacity, bring this two fields together to a new place. Many studies have been conducted testing and applying consolidated and new products and technologies. This paper contribution is to present 110 studies of urban characteristics that were published between 2001 and 2008 at some of the most important journals of the remote sensing area, providing new researchers a guide to direct their first surveys and also allowing an analysis of possible trends on this field of study.

1. INTRODUCTION

Very high resolution multi-spectral images are revolutioning the possibilities of studding the inner urban areas, bringing up a mix of spectral information, well known by those who work with pixel based techniques since the 70's, and geometrical information, each day more close to what we have been studding at photogrammetric science. Despite the conceptual debate among these areas of study, it is now put on challenge how should we deal with this unique and each day more abundant product. Some, Walker e Blaschke (2008, p. 2036, 2037) for example, say that pixel based analysis for inner urban studies has not the desirable efficiency, while image segmentation and other context tools will become standard for mapping urban land cover with RS images.

On the other hand, an average student seeking for references in this area will find many papers published in the last ten years referring to a pixel based technique that well achieved the author's goal, suggesting that object based methods may not be a common sense for all kind studies.

The present paper main objective is to identify RS techniques recognized by scientific community that are used to analyze the inner urban space through multiresolution satellite or airborne images. We expect to guide researches on their first approach to the matter by presenting a systematic literature review held on some of the main RS journals. The systematic survey allows also exploratory analysis of the papers sample suggesting some trends for the study of urban characteristics.

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2. THE 2001-2008 LITERATURE REVIEW

2.1 Methodology

All articles that had the word "urban" in its title or as its keyword published between January 2001 and October 2008 was first selected from the scientific journals: Transaction in Geocience and Remote Sensing of Institute of the Electrical and Electronics Engineers (IEEE), Geocience and Remote Sensing Letters also of IEEE, Remote Sensing of Environment, published by Elsevier, International Journal of Remote Sensing (IJRS) of the Remote Sensing and Photogrammetry Society and the American Society for Photogrammetry & Remote Sensing Publication, the journal Photogrammetric Engineering & Remote Sensing. From this first selection, papers that used RS to investigate inner urban characteristics were selected and had information about RS procedures used organized in a synthesis table, a total of 110 articles.

2.2 The Literature Review Synthesis

An synthesis table presents basic information about the RS study used in each paper. Information such as image type used, urban characteristics explored (streets and building types, vegetation, pervious surfaces, change detection and others) classification method applied, pointing also what were the main image attributes considered. The accuracy obtained by the authors is also presented, when it was informed at the referred paper (Table 1).

References	Plataform[1]						accuracy test[2]	Urban characteristics[3]																					Classification methods[4]							
											building						ways		areas				vegetation						pixel based				main atributes			
	airborne photograph	QUICKBIRD	SPOT	IKONOS	LANDSAT	other imaging satellites	accuracy test[2]	change detection	shadow	water	general	large	small	red	gray	white	roads	streets	open**	build up density	barren	impervious	general	trees	arbustive	grass	land use	other	supervised	unsupervised	object based	other methods	spectral	texture	geometric	topologic
Alberti et al. (2004)					√		.90	√		√											√	√		√	√				√			su	√			
Al-Khudhairy et al. (2005)				√			= .64		√		√						√				√	√	√								√		√		c l f t	
Bassani et al (2007)	h						= .89								90														√				√			
Belward et al. (2007)						MODIS	-	73																					√				√			
Benediktsson et al (2003)				√		IRS	=		99			94	85					94	94							√ 90					√	mnn	√			
Bhaskaran et al. (2004)	h						= .90							√	√	√													√				√			
Bian (2003)	f						-					√																			√	wl	√	√		x
Bruzzone et al. (2006)		√					k .91		√	√			√	√	√	√	√							√					√		√		√			x
Cablk and Minor(2003)				√			= x															93							√				√			
Carleer and Wolff(2006)		√					k		78	√	50			√	√	√		√						√	√	√					√		√	√	c l	
Chan et al. (2001)			√				-	√		√												√	√						√				√			
Chanussot et al. (2006)				√			x		85			96	57				33	19	55												√				t	s
Chen et al. (2004)	m						= .50																	√		√	r c/i		√							
Chen et al. (2007)						ASTER	= .81			90										86	80			93		86					√				c l	
Chou et al. (2005)	f		√				=	√		√							100	100			87			90	85	86	i/c 83		√				√	√		
Dare (2005)		√		√			-		√																					√			√			
Doucette et al. (2004)				√			.82										√															ss				
Emerson et al. (2005)					√		= .77			80										87				61		74			√					√		
Fauvel et al. (2006)				√			=		90			95	34				94	23	74										√		√	n	√			x
Frey et al. (2007)						ASTER	=			100								80			98				96	86	c l83 r70	T	√				√			
Gluch et al (2006)	m						= .87		86	100											71	90		100		100		T	√				√			
Greenhill et al. (2003)				√			=													90			√90							√						
Guindon et al (2004)					√		k .78			97															92	86	r78 c/i72		√		√		√			x
Herold et al. (2003)				√	√		k .68			√				√	√	√	√				√		√						√				√			
Herold et al. (2003)				√			k .73													80			70				r c/i 74				√			√	c l f	
Hester et al. (2008)		√					k .87			77											79	92		85	85	61	r63 c97 t92		√	√						
Hu and Tao (2007)		√		√			= .90										90															√			l f	x
Hu et al. (2005)		√		√			-			√														√		√	r				√		√	√		
Hung and Ridd (2002)					√		-														√						r c		√				√			
Islam and Metternicht (2005)					√		k .75													78				90		76			√				√			
Jain (2006)				√			=														√	√	√						√				√			
Kaya (2005)			√					√		√						√					√		√					D		√			√			
Kim (2006)				√			.83					83																				hu	√		f	
Kosugi *et al.* (2004)	fd						=	90																												
Lee (2003)				√			x			√	64				√	√	√				√			√		√			√	√			√			
Lee (2006)					√		= R															90		80		80			√							
Lee and Lathrop (2006)					√		=															85		74		74			√				√			
Li (2005)	fd						-				√																					√	√			
Liu (2006)				√			R .55													√			√						√					√		
Lo (2002)					√		-	√		√										√	√			√		√				√			√			
lo (2003)					√		= .85	√		√										√	√			√		√				√			√			
Lo (2004)					√		k .90			98										94				88	98	84			√	√			√			
Lu and Weng (2004)					√		k .85			100	√										√			100	69	87	r84		√				√			
lu and Weng (2005)					√		k .73			100										√				89	63	49	c/i88 r98		√				√	√		
Lu and weng (2006)					√		= .87			100										√		91	95				r70 c/i97					√	√			
Lu et al. (2006)	m						=				85																		√			√	√	√		
Madhavan et al. (2001)					√		-	√		√										√			√				c r			√			√			
McMahon (2007)	m						=			95										74	52	78		85	80			P								
Mennis (2006)					√		-																√				r c/i		√				√			
Myeong et al (2006)					√		-	√																√					√				√			
Myint (2003)					√		= .78			√															√	√	c r		√				√			
Myint et al. (2004)	m						= 100		√															√			c r	√				√		√		
Myint et al. (2007)				√			k .69		√															√		√	c r					√	√	√		
Nichol and Lee(2005)	m			√			R .80		√													√		√	√	√			√				√			
Orun (2004)						IRS	= .86																					N U								
Ouma et al. (2006)	h						=														√			96	√	√				√			√			
Pathak and Dikshit(2006)						IRS	k .88			95											√			90	93	70	r80 c95					nn				
Phinn et al. (2002)	fa				√		= .43			92											14	57	74							√						
Potere et al. (2008)	m				√	MODIS	-	√															√									√	√			
Powell et al (2007)					√	Video-grafia	R														√	√	√						√				√			
Pu et al (2006)						MODIS ASTER TABI	R			√					√	√	√				√	√		√	√	√		T		√			√			
Puissant et al. (2005)			√				k .92		96	99							99			89				87		97	r82		√				√	√		
Rashed et al. (2003)					√		=		86	√											94	92	94						√				√			
Rashed et al. (2005)					√	IRS	-	√		√										√	√				√		r c		√				√			
Schiefer et al. (2006)	h						-	√		√					√			√					√						√				√			
Shaban and Dikshit (2001)			√				k .86			√	√															√	c l r		√				√	√		
Shaban and Dikshit (2002)			√				k .75			√																√	c l r		√				√	√		
Shackelford et al (2003a)				√			x		√	100	93						86				100			√99		√100					√			√	c l	x
Shackelford et al (2003b)				√			x		√	95	87										96	80		93		100					√		√	√	c l f	x
Small (2001)					√		Q -																√	√		√			√				√			

Continue

References	Plataform[1]						accuracy test[2]	Urban characteristics[3]																					Classification methods[4]							
											building						ways		areas				vegetation						pixel based				main atributes			
	airborne photograph	QUICKBIRD	SPOT	IKONOS	LANDSAT	other imaging satellites	accuracy test	change detection	shadow	water	general	large	small	red	gray	white	roads	streets	open**	build up density	barren	impervious	general	trees	arbustive	grass	land use	other	supervised	unsupervised	object based	other methods	spectral	texture	geometric	topologic
Small (2002)					√		-	√															√						√				√			
Small (2003)				√			-																√						√				√			
Small and Lu (2006)		√			√		-																√	√		√			√				√			
Soegaard and Jensen(2003)					√	NOAA	= .84	√										√					√				c/i r		√				√	√		
Song and Civco (2004)				√			-										√														√	SVM	√		f	
Stefanov et al (2001)					√		k .83	√		82											94		70			97	c/r46 r82	√	√				√	√		
Su et al. (2008)		√					k .89		√	√	√						√		√							√					√		√	√		
Sugumaran et al (2003)	m			√			=																	√93												
Tang et al. (2007)				√	√		k .77										√	√			√			√		√	c/l t			√			√			
Taubenböck et al. (2006)				√			=													94													√		f	
Thanapura et al. (2007)		√					k .83												90			92								√			√			
Thomas et al. (2003)	m						= .81			√	√										√		√					T	√	√	√		√	√	c f	x
Tobin et al. (2006)						VHR	-			√												√			√	√	i r	√		√			√	√	f	
Voorde et al. (2007)		√					k .86		89												75			92	90	84		√	√			pc	√		t	x
Walker and Blaschke (2008)	fd						k .80				82										75	79		89		69					√		√		f t	
Walker and Briggs (2007)	m						k .63		√								88				100				76	86					√		√			x
Weber et al. (2005)			√				= x			100											√		√	100			r90 c/i10		√				√			
Weng et al. (2006)					√		k .89			√														√	√	√	c/l r	T	√				√			
Weng et al. (2008)	h					EO-1	R .74														√	√	√													
Wu (2004)					√		R SE		√												√	90	√						√				√			
Wu and Murray (2003)					√		R .89													√	√	√	√	√		√	r i			√			√			
Wu et al. (2006)	m						k .72				√																c r i			√				√		
Wu et al. (2007)	m						k .70																				c r i			√			√			
Xian (2007)					√		-															√	√						√				√			
Xian et al (2006)					√		-													√		√						T	√				√			
Xian et al. (2008)					√	ASTER	R .86	√												√		√							√							
Xiao et al. (2008)			√		√		-													√								T				√	√		l	
Xu (2007)					√		= 98			√												√	√									√	√			
Yang et al. (2003)					√		R .75	√														√							√				√			
Yuan (2008)	fd fa	√					k .87	√		90												94		95							√		√			h x
Yuan and bauer (2007)					√		-															0,9						T				√	√			
Zha et al. (2003)					√		k .92													√	√			√					√				√			
Zhang (2001a)			√		√		k	√		95	85																r90			√				√		
Zhang (2001b)	m						k																	97						√			√	√		
Zhang et al. (2002)					√		= .80	√												89									√						f	
Zhang et al. (2003)			√				= .72			√							√							√		√		A E	√					√		
Zhang et al. (2006)		√					x		97	92	89						85				75			85		61			√		√		√		f	
Zhou and lam (2008)				√			= .95			√														√			ci r					√		√		
Zhu and Blumberg (2002)						ASTER	= .89				84							100			87		97				i90		√						f	
Zhu et al. (2006)						OMISI	= .86		√	√												√	√					T	√						f	

Table 1. Literature review, 2001-2008, of classification methods and inner urban characteristics identified in multispectral remote sensing images. Source: BRITO (2010). Notes: (1) Type of airborne sensor: m – multi-spectral, h – hyper-spectral, fa – analogical photography digitalized, fd – digital photography; VHR – very high resolution image not specified. (2) Accuracy tests used and approximate value of the best accuracy set presented by the author: (k) Kappa coefficient, (SE) Systematic error, (=) percent of accuracy, (R) root mean square error, values presented for studies that used the square root sum method is equal one minus the sum of the squares. (3) Urban characteristics and approximate accuracy value of the best accuracy set presented by the author: c - commercial, r - residential, i - industrial, t – transportation; others: A – ancient city, E – external city, D – damaged building, T - temperature, N - natural, U – urban, P - swamp; (**) Open areas are areas not classified as building, streets, parking lot, or garden, for example, public places between streets with grass or bare soil. (4) Other Classification Methods: Outros: SVM - suport vector machine, nn - neural network, hu - heads up building extraction algorith, ss - self- supervised, wl - wavelet transformation, su - spectral un-mixing, mm – mathematical morphology. Main basic geometric attributes used: c - length, l - width , f - form e t – size; and main topological attributes used: h - hierarchy, x - context, s – contrast.

2.3 Exploratory Analysis and Trends

Among all 110 papers, only 20 used strictly object based classification methods, 76 used pixel based classification methods considered conventional. A slight but sensible rise of the number of paper published using RS to study intra-urban characteristics was noticed. There is also noticed a high number of studies that are still using LANDSAT images. It may be justified by the easy access and more broaden knowledge of techniques applied to this product. Most of those studies use a pixel-based approach and presents, on the other hand a more restrict analysis, what can still be seen as a positive approach once it can cost-effective to the project.

As Fauvel at al. (2006) has already stated, we have found in the review that most of urban classification methods consists on feature extraction, followed by classifying algorithms, but it is not possible to affirm that one method is in all circumstances superior the other, because each method has its own characteristic and specific applications. But the systematic literature review shows that object based classification method offer more tools to work with very high resolution images for inner urban studies, particularly because of its capabilities to manage complex information of context and shape, characteristics that help differ important urban defining structures.

Brito (2010) presents in detail other analysis, considering comparative studies, more frequently used techniques and approaches, spatial resolution of most used satellite products and other highlighting aspects, that are also based on the synthesis table and on other relevant information present at the papers.

3. CONCLUSIONS

Although the number of very high resolution images available has significantly increased the last 10 years, studies approaching qualitative aspects of the urban environment are still needed. Studies considering urban defining elements, such as buildings and streets, represent a small parcel of the papers found. The difficulty to digitally recognize those elements is justified by its complexity, especially where dealing with poor areas of undeveloped countries, but this is a challenge that ought to be faced. We believe science already has in those RS products the means to achieve this goal.

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