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Remote sensing technology for mapping and monitoring land-cover and land-use change

John Rogan[a], DongMei Chen[b]

[a]*Clark School of Geography, Clark University, 950 Main Street, Worcester, MA 01610, USA*
[b]*Department of Geography, Queen's University, Kingston, Ont., Canada K7L 3N6*

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E-mail address: jrogan@clarku.edu (J. Rogan).

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Introduction

In the last three decades, the technologies and methods of remote sensing have evolved dramatically to include a suite of sensors operating at a wide range of imaging scales with potential interest and importance to planners and land managers. Coupled with the ready availability of historical remote sensing data, the reduction in data cost and increased resolution from satellite platforms, remote sensing technology appears poised to make an even greater impact on planning agencies and land management initiatives involved in monitoring land-cover and land-use change at a variety of spatial scales. Current remote sensing technology offers collection and analysis of data from ground-based, atmospheric, and Earth-orbiting platforms, with linkages to GPS data, GIS data layers and functions, and emerging modeling capabilities (Franklin, 2001). This has made remote sensing a valuable source of land-cover and land-use information. As the demand for increased amounts and quality of information rises, and technology continues to improve, remote sensing will become increasingly critical in the future. Therefore, the focus of this chapter is on the issues and challenges associated with monitoring land-cover and land-use change.

Planning and land management agencies have numerous and varied responsibilities and tasks (Jensen and Cowen, 1999). Further, their ability to complete these tasks is hampered by the paucity of comprehensive information on the types and rates of land-cover and land-use change, and even less systematic evidence on the causes, distributions, rates, and consequences of those changes (Loveland *et al*., 2002). For example, at the rural–urban fringe, large tracts of undeveloped rural land are rapidly converted to urban land use. This land-use dynamic makes it difficult for planners to obtain or maintain up-to-date land-cover and land-use information, where typical updating processes are on an interval scale of 5 years (Chen *et al*., 2001). Although the full potential of remote sensing technology for change detection applications has yet to be completely realized, planning agencies at local, regional and international levels now recognize the need for remote sensing information to help formulate policy and provide insight into future change patterns and trends (Jensen and Cowen, 1999).

Remote sensing information, in concert with available enabling technologies such as GPS and GIS, can form the information base upon which sound planning decisions can be made, while remaining cost-effective (Franklin *et al*., 2000). Clearly, however, the fast-paced developmental nature of remote sensing technology often overlooks the needs of end-users as it '…continues to outpace the accumulation of experience and understanding' (Franklin, 2001: 137). As a result, effective real-world operational examples of land-cover and land-use change remain relatively rare (Loveland *et al*., 2002; Rogan *et al*., 2003).

In the near future, the field of remote sensing will change dramatically with the projected increase in number of satellites of all types (Glackin, 1998). This will further compound the problems described above. In order to help create a better understanding of the rapid advancements in remote sensing technology that have occurred over the last three decades, we review the current state of remote sensing technology (i.e. sensors, data, analysis methods and applications) for monitoring land cover and land use. Specifically, we provide a brief history of the advances in remote sensing technology, and a review of the major technical considerations of land-cover and land-use monitoring using remote sensing data.

Evolution of remote sensing technology

Although coarse-spatial resolution meteorological satellite data have been available since the 1960s, civilian remote sensing of the Earth's surface from space at medium spatial resolutions (i.e. <250 m) only began in 1972 with the launch of the first of a series of Earth Resource Satellites (i.e. Landsat). This was the initiation of significant research activity in remote sensing technology, data analysis and applications, which continue today. The last 5 years have seen a proliferation of satellite platforms with a large number of sensors (e.g. Terra and ENVISAT) and increasing spatial resolutions (e.g. IKONOS and Quickbird). Indeed, the ever-expanding constellation of satellite platforms has acquired thousands of trillions of bytes of data invaluable for planning and land management applications (Jensen, 2000). It has been estimated that approximately 100 new satellites will be launched during the 10-year period between 1996 and 2006 (Fritz, 1996). Furthermore, high-resolution airborne data acquisition technology has developed rapidly in recent years. As a result, there is a large selection of remote sensing data of the Earth's surface with respect to spatial, spectral and temporal sampling. A summary of the key characteristics of selected satellite sensors is presented in Table 1. For comparison, the key attributes of urban/suburban and natural landscapes and their minimum spatial and spectral resolution requirements are presented in Table 2.

Remote sensing technology has been driven by three interrelated factors: (1) advancements in sensor technology and data quality, (2) improved and standardized remote sensing methods, and (3) research applications (the least developed of the three, Franklin, 2001). The following sections focus on the evolution of sensors and data, with a brief discussion of methods and applications (for more detail on these issues the reader is referred to Jensen, 2000; Franklin, 2001).

Coarse-spatial resolution sensors

While coarse-resolution image data (i.e. spatial resolution >250 m) fall outside of the minimum spatial resolution requirements outlined in Table 2, a brief evaluation of the contribution of coarse scale, large-area sensors to monitoring land-cover and land-use change is warranted. Coarse-resolution data have been used for many years to acquire basic land-cover and land-use information over large areas. Spatial resolution is the obvious limiting factor in these studies, especially when urban and suburban land-cover and land-use change is considered. For example, Stow and Chen (2002) examined the sensitivity of anniversary-date multitemporal AVHRR[1] data to map land-cover and land-use change and found significant confusion between changed and unchanged areas, even with the application of a geometric mis-registration model. Recently, Zhan *et al*. (2002) described the monthly 250 m resolution Vegetative Cover Conversion (VCC) product generated from Moderate Resolution Imaging Spectroradiometer (MODIS) data. This product is designed to serve as a global alarm for land-cover change caused by

[1] The Advanced Very High Resolution Radiometer (AVHRR) sensor is a critical component of the National Atmospheric and Oceanic Administration (NOAA) series of polar orbiting satellite systems (Table 1). Although designed for meteorological purposes, they are providing critical image data for global climate change research.

Table 1
Characteristics of selected satellite sensors

Sensor mission	Organization	Operation period	Spatial resolution (m)	Swath (km)	Spectral coverage (μm)	Number of channels
MSS (Landsat 1-5)	NASA, USA	1972–1983	79 (MS) 240 (TIR)	185	0.50–12.6	4
AVHRR (NOAA 6-15)	NOAA, USA	1978–	1100	2700	0.58–11.50	5
TM (Landsat 4, 5)	NASA, USA	1982–	30 (MS) 120 (TIR)	185	0.45–2.35	7
HRV (SPOT 1, 2, 3)	SPOT Image, France	1986–	10 (PAN) 20 (MS)	60	0.50–0.89	3
LISS-I (IRS-1A)	ISRO, India	1988–	72.5	148	0.45–0.86	4
AVIRIS	JPL, USA		20	20	0.4–2.5	224
LISS-II (IRS-1B)	ISRO, India	1991–	36.25	146	0.45–0.86	4
SAR, AMI (ERS-1)	ESA	1991–2000	26	102	NA	NA
SAR, OPS (JERS-1)	NASDA, Japan	1992	18	75	0.43–1.7	7
LISS-III (IRS-1C, 1D)	ISRO, India	1995–	23, 70 188 (WiFS)	142	0.52–1.70	4
SAR (RADARSAT-1)	Canada	1995–	8–100	45–500	NA	NA
Panchromatic (IRS-1D)	ISRO, India	1997–	5.8	70	0.50–0.75	1
GOES-8, 10	NESDIS, USA	1994–	1000 (VNIR) 8000 (SWIR) 4000 (TIR)	8	0.52–12.5	5
SAR, OPS (ERS-2)	ESA,	1995–	26	102	NA	NA
EarlyBird	DigitalGlobe, USA	1997–	3 (PAN) 15 (MS)	6, 30	0.45–0.89	3
HRVIR (SPOT 4)	SPOT Image, France	1998–	10 (PAN) 20 (MS)	60	0.50–1.75	3
Vegetation (SPOT 4, 5)	SPOT Image, France	1998–	1150	2250	0.43–1.75	5
SeaWiFS (OrbView-2)	OrbImage, USA	1997–	1130	2800	0.40–0.88	8
MODIS (EOS)	NASA, USA	1999–	250 (PAN) 500 (VNIR) 1000 (SWIR)	2300	0.620–2.155, 3.66–14.385	36
ASTER (EOS Terra)	NASA and MITI USA	1999–	15 (VNIR) 30 (SWIR) 90 (TIR)	60	0.52–0.86, 1.60–2.43, 8.125–11.65	14
MISR (EOS Terra)	JPL and NASA USA	1999–	275	360	0.425–0.886	4
ETM^+ (Landsat 7)	NASA, USA	1999–	15(PAN) 30(MS) 60(TIR)	185	0.450–2.35, 10.4–12.5	7
IKONOS	Space Imaging, USA	1999–	1(PAN) 4(NIR)	11	0.45–0.90	4
QuickBird	DigitalGlobe, USA	1999–	0.82 (PAN) 3.2 (MS)	6, 30	0.45–0.90	4
Hyperion and ALI (EO-1)	NASA, USA	2000–	10(PAN) 30(MS)	185	0.433–2.35	9

(*continued on next page*)

Table 1 (*continued*)

Sensor mission	Organization	Operation period	Spatial resolution (m)	Swath (km)	Spectral coverage (μm)	Number of channels
MERIS (EnviSat-1)	NASA, USA	2001–	300, 1200	1150	0.39–1.04	Up to 15
ASAR (EnviSat-1)	NASA, USA	2001–	30	400	Radar	1
HRG (SPOT 5)	SPOT Image, France	2002–	5 (PAN), 10 (VNIR), 20 (SWIR)	60	0.48–1.75 VNIR, SWIR	3
OrbView-3	OrbImage, USA	Planned	1 (PAN), 4 (MS)	8	0.45–0.90	4

Detailed information on most sensors can be found in Jensen (2000) and the following WebPages: www.nasa.gov, www.digitalglobe.com, www.orbimage.com, www.spot.com; ALI, advanced land imager; ASTER, advanced spaceborne thermal emission and reflection radiometer; AMI, active microwave instrument; ASAR, advanced synthetic aperture radar; AVHRR, advanced very high resolution radiometer; AVIRIS, airborne visible infrared imaging spectrometer; ETM^+, enhanced thematic mapper plus; EOS, earth observing system; ERS, European remote sensing; GOES, geostationary operational environmental satellite; HRV, high resolution visible; HRG, high resolution geometric; HRVIR, high-resolution visible infrared; IRS, Indian remote sensing; ISRO, Indian Space Research Organization; JPL, jet propulsion laboratory; LISS, linear imaging self-scanning sensors; MERIS, medium resolution imaging spectrometer; MISR, multi-angle imaging spectroradiometer; MODIS, moderate resolution imaging spectrometer; MS, multi-spectral; MSS, multispectral scanner; NOAA, National Oceanic and Atmospheric Administration; NIR, near infrared; OPS, optical sensor; PAN, panchromatic; SAR, synthetic aperture radar, SeaWiFS, sea-viewing wide field of view sensor; SPOT, Le Systeme Pour l'Observation de la Terre; SWIR, short wave infrared; TIR, thermal infrared; VIR, visible infrared; WiFS, wide field sensor.

Table 2
Attributes of urban/suburban and natural landscapes with their corresponding minimum spatial and spectral resolution requirements

	Minimum spatial resolution requirements	Minimum spectral resolution requirements
Urban/suburban attribute[a]		
Land cover/use		
Level I: USGS	20–100 m	V-NIR-MIR-Radar
Level II: USGS	5–20 m	V-NIR-MIR-Radar
Level III: USGS	1–5 m	Panchromatic-V-NIR-MIR
Level IV: USGS	0.25–1 m	Panchromatic
Natural attribute		
Forest class		
Level I: land cover	20–1 km	V-NIR-MIR-Radar
Level II: cover types	10–100 m	V-NIR-MIR-Radar
Level III: species dominance	1.0–30 m	Panchromatic-V-NIR-MIR-Radar
Level IV: species identification	0.1–2.0 m	Panchromatic

[a] Based on the hierarchical land-cover classification scheme of Anderson *et al*. (1976); adapted from Jensen and Cowen (1999) and Franklin *et al*. (2003).

anthropogenic activities and extreme natural events. While these data are too coarse for the purposes of local level planning and land management, they could serve as a general ‘change’ product for regional/national agencies.

Medium-spatial resolution sensors

Medium-resolution sensors are intended to provide appropriate scales of information for a wide-variety of Earth-resource applications. The continuity of the Landsat program since 1972 is recognized as a key milestone in the evolution of remote sensing technology (Franklin, 2001). For 12 years, the Landsat Multispectral Scanner (MSS) sensor provided image data with a spatial resolution of approximately 80 m, acquired across four spectral bands (i.e. visible and near-infrared). Although these data exhibited significant noise (Schowengerdt, 1997), they provided a unique opportunity for researchers to investigate and apply remote sensing data at regional scales. The MSS spatial resolution was also sufficient for general mapping efforts in urban/suburban and natural environments (Table 2). These data are invaluable today for historical change detection studies and form an important component of the North American Land Characterization (NALC) data set (Yuan and Elvidge, 1998).

The launch of the Landsat Thematic Mapper (TM) in 1984 produced a new remote sensing data source that provided higher spectral, spatial, and radiometric resolution data (Table 2). While the Landsat MSS spectral bands and bandwidths were selected by sensor designers for their general utility to map vegetation and geologic features, Landsat TM spectral channels were chosen specifically to map vegetation type, soil moisture, and other key landscape features (Jensen, 2000). Thus, the TM-era has permitted research to be conducted with greater precision, over large areas (i.e. the swath-width of a TM scene is

185×185 km^2). Landsat TM data have facilitated investigations with thematic demands on an order of magnitude greater than could be achieved with MSS (Table 2). However, despite these advancements, the planning and land management community still lacked large-area, high-spatial resolution remote sensing data from space. This situation improved somewhat with the launch of the Système Pour l'Observation de la Terre-1 (SPOT-1) satellite in 1986. This sensor provided multispectral data with a slightly higher spatial resolution (20 m) and a panchromatic channel (10 m). The panchromatic data are of such geometric fidelity that they can be photo-interpreted like a typical aerial photograph for planning needs (Jensen, 2000). Further, following the availability of these data, many projects began to employ image fusion techniques, using panchromatic and multispectral information for improved land-cover and land-use monitoring (e.g. Treitz *et al*., 1992; Muchoney and Haack, 1994; Pellemans *et al*., 1993). High-spatial resolution panchromatic information has also been used effectively as textural information for land-cover and land-use monitoring (Chen *et al*., 2001). A 15 m spatial resolution panchromatic band was added to the Landsat Enhanced Thematic Mapper (ETM$^+$). Overall, the widespread availability of high-spatial resolution panchromatic data allows for high-order investigation into urban/suburban and natural landscapes (Jensen and Cowen, 1999).

In addition to the panchromatic channel, the SPOT sensor presented a major breakthrough in sensor design. The SPOT sensor acquires information using a linear array of detectors. This approach is superior since there are no moving parts (i.e. a rotating mirror that scans back and forth across the orbit path). This design provides for a longer 'dwell-time' or radiance integration period over a target (Schowengerdt, 1997) and thereby provides increased sensitivity to radiometric contrasts between surfaces. The SPOT system's overall capability was enhanced significantly in 1998 with the addition of a mid-infrared channel on the SPOT-4 sensor, providing greater utility for land-cover and land-use monitoring (Stroppiana *et al*., 2002). The SPOT-5 sensor (launched in 2002) collects panchromatic, visible and near-infrared, and mid-infrared data at 5, 10 and 20 m spatial resolution, respectively (SPOT Image, 2002).

The Indian Space Research Organization (ISRO) has also added to the suite of medium-resolution sensors. ISRO has launched four linear array sensors to date (IRS-1A, 1B, 1C and 1D). In general, the IRS sensors offer a combination of TM/ETM$^+$ spectral resolution, with SPOT sensor spatial resolution. The IRS-1C and 1D (launched in 1995 and 1997, respectively) offer visible and near-infrared bands at 23 m spatial resolution and a mid-infrared band at 70 m spatial resolution. Most significantly, these IRS sensors acquire panchromatic information at 5.8 m spatial resolution, which has significant implications for higher-order mapping capabilities (Table 2).

The contribution of medium-resolution sensors is expected to continue long into the future (Franklin, 2001). Indeed, follow-on sensors have already been launched. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), an instrument on the Terra platform, acquires visible and near-infrared information at 15 m spatial resolution and mid-infrared information at 30 m spatial resolution. Further, the Earth Observer (EO-1) platform includes the linear array Advanced Land Imager (ALI) with 10 bands, ranging from the visible to mid-infrared regions of the electromagnetic spectrum at 30 m spatial resolution and a panchromatic band acquired at 10 m spatial resolution (Jensen, 2000).

High-spatial resolution sensors

The discussion of medium-resolution sensors highlights a tendency among instrument designers to prolong the longevity of medium-spatial resolution image acquisition, yet planners and land managers require high-spatial resolution data to address land-cover and land-use problems at higher-order thematic levels where spatial resolutions of 5 m or higher are required (Table 2). From a spaceborne perspective, this became possible in 1994, when the United States government made a decision to allow civil commercial companies to market high-spatial resolution satellite remote sensing data (i.e. between 1 and 4 m spatial resolution, Glackin, 1998). This groundbreaking decision resulted in several new spaceborne high-resolution sensors (Table 1).

Technological advances in sensor design allow aerial photographic precision and quality in these satellite-based data, and permit the investigation of thematic information at the highest-order in both urban/suburban and natural landscapes (Table 2). The three most notable high-resolution spaceborne sensors are IKONOS-2 (Space Imaging Inc., launched in 1999), Quickbird-2 (DigitalGlobe Inc., launched in 2001), and Orbview-3 (ORBIMAGE Inc., planned). These sensors offer 11-bit visible and near-infrared information at 4 m spatial resolution, and panchromatic information at 1 m or higher (Jensen, 2000, Table 1).

Airborne systems have been in operation for many years and are increasingly reliable, cost-effective and available worldwide (Franklin, 2001). The flexibility of airborne platforms means that onboard sensors can acquire data at user-specified times, rather than those of scheduled satellite overpasses, and platform altitude can be reduced to provide high-resolution data (as good as, or better than that stated above). Multispectral sensors that record data spanning the ultraviolet through the mid-infrared parts of the spectrum have been in use for more than 20 years (Jensen, 2000). In addition, airborne high-fidelity digital frame cameras have seen wide use in land-cover and land-use applications (Coulter *et al*., 2000; Chen *et al*., 2002). For example, digital frame cameras are now capable of acquiring high-spatial resolution data at 0.2 m across visible and near-infrared wavelengths.

Hyperspectral sensors

Chapter 2.3 indicates that the majority of sensor research and development has been devoted to: (a) medium-resolution (i.e. spatial and spectral) large-area image acquisition, and (b) high-resolution small-area image acquisition. However, recent work has revealed a burgeoning interest in the field of imaging spectrometry for land-cover and land-use monitoring (Treitz and Howarth, 1999). Imaging spectrometry is defined as ‘the simultaneous acquisition of images in many relatively narrow, contiguous…spectral bands…" (Jensen, 2000: 227). These data show promise for identifying a range of surface materials or phenomena that cannot be identified with broadband imaging systems (Herold *et al*., 2002).

To date, government agencies and commercial firms have designed numerous linear and area array imaging spectrometers capable of hyperspectral imaging (Jensen, 2000,

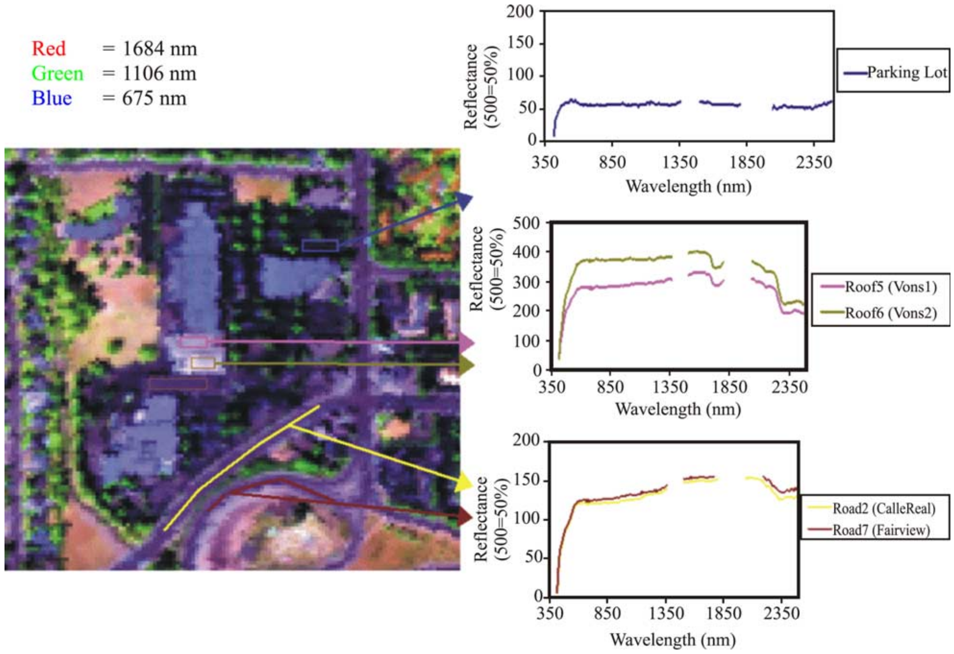

Fig. 1. AVIRIS (normal spatial resolution of 4 m) image of urban area with reflectance spectra for asphalt parking lot, roofs and roads in Santa Barbara, CA (Data provided by Dar Roberts, UCSB).

Fig. 1). Indeed, Franklin (2001) noted a significant increase in the number of airborne multispectral and hyperspectral data providers over the previous 10-year period. The Airborne Visible Infrared Imaging Spectrometer (AVIRIS) has been operating for 10 years and provides 12-bit data at ~20 m spatial resolution across 224 spectral bands. Another notable airborne hyperspectral sensor is the Compact Airborne Spectrographic Imager-2 (CASI-2), a programmable system (i.e. the user can program the sensor to collect a combination of high-spatial and spectral resolution data) that is capable of collecting up to 228 spectral channels. Current hyperspectral satellite sensors include the Moderate Resolution Imaging Spectrometer (MODIS) and the Earth Observer-1 Hyperion instrument (Table 1).

It is important to note that a large amount of research has examined and, as a result, developed an understanding of hyperspectral data in natural environments (Treitz and Howarth, 1999; Ustin *et al*., 1999). There remains a significant need for research within the context of assessing change in urban/suburban environments using hyperspectral remote sensing (Rashed *et al*., 2001; Herold *et al*., 2002). Recent studies that have applied hyperspectral data in urban/suburban areas have found this complex environment problematic due to the myriad of surface covers present, and highlight the need for more investigation. Hyperspectral data for various surfaces in an urban environment are illustrated in Fig. 1.

Microwave sensors

Active microwave remote sensing (i.e. radar) technology has been available for more than 50 years, but has not seen widespread use on the scale of optical remote sensing. Despite the theoretical precepts to its utility in urban/suburban and natural environments, there has been a paucity of applications of active radar to land-cover and land-use monitoring (Kasischke *et al*., 1997). This may be attributed to the lack of general understanding of radar data and to insufficient methods of analyzing them. However, for 20 years a number of synthetic aperture radar (SAR) systems have been developed, and five separate spaceborne SAR systems have been successfully deployed: SIR-C/X-SAR, ERS-1, ERS-2, JERS-1, and RADARSAT-1 (Table 1).

Of the SAR systems listed above, only RADARSAT-1 (launched by the Canadian government in 1995) and ERS-2 (launched by the European Space Agency in 1995) are still in continuous operation. C-band RADARSAT-1 is unique in that it provides a range of spatial resolutions and geographic coverages. For example, in *Fine Beam* mode, data are acquired over $50 \times 50\ \mathrm{km}^2$ areas at 10 m spatial resolution, whereas, in *ScanSAR Wide Beam* mode, data are acquired over $500 \times 500\ \mathrm{km}^2$ areas at 100 m spatial resolution (Jensen, 2000). ERS-2 collects data in C-band wavelengths at $26 \times 30\ \mathrm{m}^2$ spatial resolution. C-band data from these sensors have been used effectively in a number of forest mapping and forest change detection studies (Grover *et al*., 1999; Quegan *et al*., 2000). The remote sensing research community appears to have a better grasp of the potential of active SAR in natural environments, but work is continuing in urban/suburban environments, particularly around the synergistic application of SAR and optical data (Nezry *et al*., 1993; Gamba and Houshmand, 2001). Several new SAR satellites are planned for launch in the near future, adding polarization diversity and polarimetry to a range of resolutions and swath widths (e.g. ENVISAT, ALOS, PALSAR, and RADARSAT-2).

Evolution of methods and applications

Curran (1985) suggested that rapid technological advancements and improved sensor systems had propelled remote sensing into a stage of exponential growth toward an era, where reliable information can be generated and shared routinely for planning and land management applications. This rapid advancement has been facilitated by substantial improvements in remote sensing methods and applications (Franklin, 2001).

Image processing systems are a key component of the infrastructure required to support remote sensing applications (Schowengerdt, 1997) and have improved in number and capability in the last 15 years. Advancements in computer technology have obviously facilitated the development of image processing systems. Remote sensing applications have clearly benefited from the recent phase of development, which has focused on ease-of-use, interoperability with GIS, and increased availability of algorithms for automated processing of remote sensing data (Franklin, 2001). Further, increased availability and access to remote sensing data (i.e. long term and historical), GIS and spatial data sets from ever-multiplying digital libraries has been an invaluable aid to development in the last decade (Jensen, 2000). Also, the decision to discontinue *Selective Availability* in GPS receivers in 2000 allowed an increase in accuracy for use in remote sensing calibration and validation applications (Gao, 2002). Significant cost-sharing initiatives by consortia of federal agencies, such as the Multi-Resolution Land Characteristics (MRLC) have facilitated increased data availability, and therefore, increased numbers of remote sensing applications. These developments are leading to an emphasis on remote sensing end-user products. Concomitant to this is a reduction in costs at all levels of the image processing chain (e.g. cost of remote sensing data acquisition, computer support, and image processing software).

Factors affecting remote sensing data costs include: data acquisition platform, image spectral resolution and spatial resolution. Although the precise cost for remote sensing data has fluctuated over the past 30 years, some relative relationships have remained consistent (Lunetta, 1998). Coarse- (spectral and spatial) satellite data (e.g. AVHRR) are many orders of magnitude less expensive than medium- (spectral and spatial) resolution data (e.g. Landsat and SPOT). Further, high-resolution data (e.g. IKONOS, Quickbird) are approximately one order of magnitude greater in cost compared to medium-resolution data. Table 3 provides the estimated cost per unit area and preprocessing cost of remote sensing data. From a practical standpoint, costs are often the most important factor in a remote sensing application (Phinn, 1998).

Early applications of remote sensing technology were largely experimental, but soon led to an expanding field of land-cover and land-use classification to establish baseline conditions for natural and urban/suburban areas (Lunetta, 1998). These efforts were aided by the hierarchical land-cover classification scheme developed by Anderson *et al*. (1976), which established guidelines for remote sensing mapping efforts, and its influence persists today (Franklin *et al*., 2003). With improved understanding of land-cover processes and improved means to observe them, researchers began investigating both the patterns and processes of land-cover and land-use change in a variety of environments, including; change in vegetation canopy and/or shrub cover (Singh, 1989; Levien *et al*., 1999); change in urban/suburban cover (Chan *et al*., 2001); wetland monitoring (Jensen *et al*., 1995;

Table 3
Comparison of typical costs for different types of remote sensing imagery per square kilometer (after Lunetta (1999) and Franklin (2001))

Spatial resolution	Sensor	Scene coverage (km^2)	Estimated acquisition cost per km^2	Estimated preprocessing cost per km^2
Coarse (>250 m)	MODIS	5 428 900	\$0.00	\$0.00005
	Orbview-1	3 750 000	\$0.00013	\$0.00006
	NOAA AVHRR	5 760 000	\$0.00015	\$0.000078
Medium (20–250 m)	Landsat MSS	34 000	\$0.0088	\$0.0044
	Landsat TM 4–5	34 000	\$0.0162	\$0.0081
	Landsat ETM 7	34 000	\$0.0213	\$0.01065
	IRS (XS)	21 900	\$0.114	\$0.028
	SPOT 1-3	3600	\$0.416	\$0.15
	ASTER	3600	\$0.0152	\$0.0076
	RADARSAT	1000	\$2.5300	\$1.20
High (<20 m)	IKONOS	121	\$29.00	\$14.50
	SPOT 5	3600	\$0.73	\$0.27
	IRS (Pan.)	4900	\$0.33	\$0.08
	Quickbird	400–1600	\$39.00	\$19.5
	Archive Color-IR Photography (1:40 000)	83	\$0.50	\$0.175
	New Color-IR Photography (1:40 000)	83	\$5.50	\$2.75
	Aircraft digital imagery (1 m)	Variable	\$50	\$25
	AVIRIS (20 m)	99	\$5.00	\$2.50
	LIDAR	Variable	\$74	\$37

Cost information applies to continental United States only (US dollars) for system-corrected data, as of February 2003.

Phinn and Stanford, 2001); and crop mapping and monitoring (Fang, 1998; McNairn *et al*., 2002). Recent applications have moved into the realm of land-cover and land-use modelling for ecosystem sustainability assessments in natural and agricultural areas (Moulin *et al*., 1998; Vine and Puech, 1999), and projected growth assessment of urban/suburban areas (Clarke and Gaydos, 1998).

Methodological issues in mapping and monitoring land-cover and land-use change

Chapter 3 demonstrates that remote sensing data users are, and will continue to be, inundated with an enormous variety of data that may, or may not be, useful for particular planning purposes (Phinn, 1998). Trade-offs exist in the resolving power of these remote sensing systems (i.e. spatial, spectral, radiometric and temporal), which will affect the quality, quantity, and timeliness of acquired imagery. Therefore, successful utilization of remotely sensed data for land-cover and land-use monitoring requires careful selection of an appropriate data set and image processing technique(s) (Lunetta, 1998). Chapter 2 summarizes the conceptual framework that links the information and environmental characteristics of a land-cover and land-use monitoring project to a suitable choice of remote sensing data. The main considerations are spatial, spectral and temporal resolution required for a specified monitoring purpose. An example of how different information can be revealed in images of different spatial resolutions is presented in Fig. 2, where a suburban area is depicted on a 1 m spatial resolution airborne digital image. Generally, as the spatial resolution of the data becomes coarser, the interpretability of the data decreases, particularly in heterogeneous urban areas.

Digital change detection is the process of determining and/or describing changes in land-cover and land-use properties based on co-registered multitemporal remote sensing data. The basic premise in using remote sensing data for change detection is that the process can identify change between two (or more) dates that is uncharacteristic of normal variation. To be effective, change detection approaches must maximize inter-date variance in both spectral and spatial domains (i.e. using vegetation indices and texture variables). Numerous researchers have addressed the problem of accurately monitoring land-cover and land-use change in a wide variety of environments with a high degree of success (Muchoney and Haack, 1994; Singh, 1989; Chan *et al*., 2001).

The simplest taxonomy separates land-cover and land-use changes that are *categorical* versus those that are *continuous* (Abuelgasim *et al*., 1999). Categorical changes in time, also known as post-classification comparison, occur between a suite of thematic land-cover and land-use categories (e.g. urban, developed, grassland, forest). Post-classification change detection techniques, however, have significant limitations because the comparison of land-cover classifications for different dates does not allow the detection of subtle changes within land-cover categories (Macleod and Congalton, 1998). Further, the change-map product of two classifications often exhibits accuracies similar to the product of multiplying the accuracies of each individual classification (Stow *et al*., 1980; Mas, 1999).

The second taxon of change is continuous, known also as pre-classification enhancement, where changes occur in the amount or concentration of some attribute of the urban/suburban or natural landscape that can be continuously measured (Coppin and Bauer, 1996). The goal of change detection in a continuous context, therefore, is to measure the degree of change in an amount or concentration of a variable such as vegetative, or urban cover, through time. The choice of change detection taxon is germane to the needs of the user, and should be guided using the scene model approach described in Chapter 2.

Once the choice of change detection taxonomy is determined, decisions on the data processing requirements can be made. Requirements include geometric/radiometric

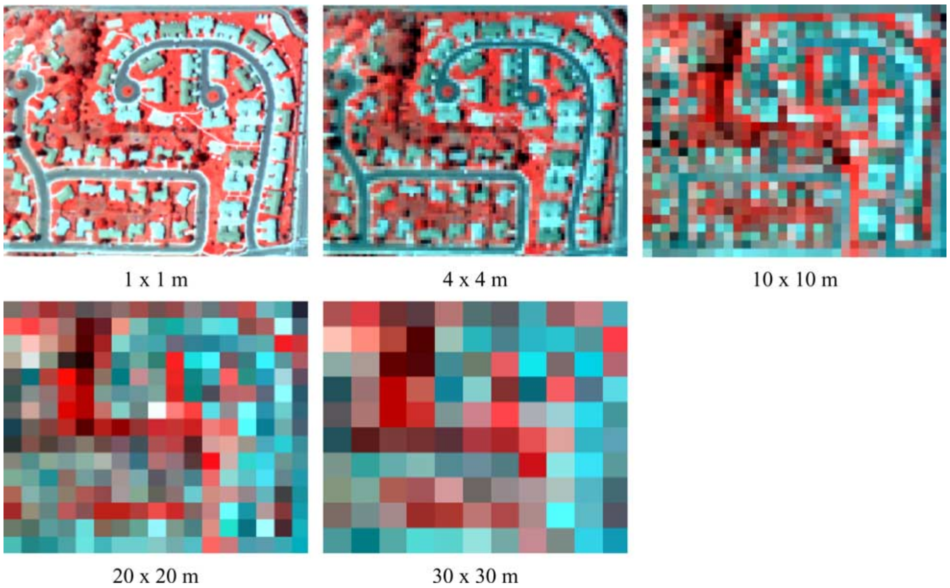

Fig. 2. Images of suburban housing in San Diego, CA. The data were acquired at a nominal spatial resolution of 1 m by an airborne ADAR system. The orginal data were resampled to coarser resolutions, shown here. Imagery is displayed as false-colour infrared, where ADAR band 4 (near-infrared) is coloured in red, band 3 (red) is coloured in green, and band 2 (green) is coloured in blue.

corrections, data normalization, change enhancement, image classification and accuracy assessment (Lunetta and Elvidge, 1998). In Chapter 4.2 we discuss the major issues involved in change detection using remote sensing data including geometric correction, radiometric correction or normalization, change enhancement and detection, and classification for land-cover and land-use monitoring.

Geometric correction

Accurate per-pixel registration of multi-temporal remote sensing data is essential for change detection since the potential exists for registration errors to be interpreted as land-cover and land-use change, leading to an overestimation of actual change (Stow, 1999). It can also ensure the user that the change that is identified is accurate and not an artefact of an image processing procedure. Geometric registration is required to remove or reduce the effects of non-systematic or random distortions present in remote sensing data. These distortions include variations in sensor system attitude and altitude, and can only be accurately corrected by developing a model to tie per-pixel image features to specific per-pixel ground features (i.e. ground control points (GCPs)) where geographic coordinates are known (i.e. from an accurate reference map/image or GPS data, Kardoulas *et al.*, 1996).

Geometric registration error between two images is expressed in terms of an acceptable total root mean square error (RMSE), which represents a measure of deviation of corrected GCP coordinate values from the original reference GCPs used to develop the correction model. Robust and unbiased estimates of RMSE should be calculated using independent GCPs not used in model formation (Kardoulas *et al*., 1996). Several authors recommend a maximum tolerable RMSE value of <0.5 pixels (Jensen, 1996), but others have identified acceptable RMSE values ranging from >0.2 pixels to <0.1 pixels, depending on the type of change being investigated (Townshend *et al*., 1992).

Several methods have been developed to compensate for the effects of mis-registration on image change detection. Justice *et al*. (1989) suggested pixel aggregation to a larger spatial resolution to assess change, thus changing the analysis to a larger minimum mapping unit (MMU), and reducing mis-registration effects. Gong *et al*. (1992) used two image-filtering algorithms with some success in reducing mis-registration effects. Finally, Stow (1999) and Stow and Chen (2002) presented and tested a new model on TM and AVHRR data that used estimates of mis-registration across a scene (known as mis-registration fields) combined with calculation of spatial brightness gradients to adjust the magnitude of multitemporal image differences. Their study demonstrated the effects of image resolution on the potential to compensate for mis-registration error, as this error may be more significant in coarse resolution data. Improvements are needed in reporting the characteristics of geometric registration, including improved error analysis in both geometric accuracy and geometric uncertainty (Franklin, 2001).

Radiometric correction and normalization

Variations in solar illumination conditions, atmospheric scattering, atmospheric absorption and detector performance result in differences in radiance values unrelated to the reflectance of land cover. Absolute radiometric quantification is an expensive, time-consuming and likely untenable goal for land-cover and land-use monitoring (Song *et al*., 2001). Therefore, the primary goal of most change detection studies is to achieve image-to-image normalization, so that spatial–temporal differences in image brightness or derivative values primarily convey information about changes in land cover and land use (Roberts *et al*., 1998).

The two most commonly used radiometric normalization techniques are: (1) dark object subtraction (DOS, Chavez, 1996); and (2) relative radiometric normalization using pseudo-invariant features (PIFs) (Schott *et al*., 1988). Both approaches are based on the assumption that the atmospheric scattering component is consistent (i.e. non-spatially varying) throughout the imagery (Carlotto, 1999). Song *et al*. (2001) compared seven DOS algorithms and one PIF method with uncorrected 'raw' multitemporal Landsat TM data and found that all corrections provided an improvement over the raw data. However, these atmospheric normalization algorithms are often unsuitable for removing spatially varying haze resulting from smoke plumes or smog in remote sensing data acquired over both natural and urban areas (Rogan *et al*., 2001). Carlotto (1999) presented a new method for reducing the effects of wavelength-dependent scattering in multispectral imagery, which is intended for use in situations, where atmospheric scattering affects visible wavelengths and varies across space. This method results in an image in which space-varying scattering has been equalized over the entire image so that previously developed techniques (i.e. DOS) for removing constant scattering effects can be used.

Even when great care is taken to normalize satellite data for exogenous effects to allow image analysts to focus on change-related events revealed in the remote sensing data, intra-annual differences in climate, particularly precipitation, can cause significant differences in pixel brightness (Rogan *et al*., 2002). These seasonal effects often lead to errors in change detection products where estimates of land-cover abundance, composition and condition are required (Cihlar, 2000). Recently, Jakubauskas *et al*. (2002) found Fourier harmonic analysis of a NOAA AVHRR NDVI biweekly composite time series data, useful for examining the interactions between landscape environmental factors and inter-annual variability of land-cover types in the southern Great Plains region of the United States.

Change enhancement

Change enhancement applies to pre-classification enhancement only, as it is not required in post-classification approaches. One of the most commonly applied change enhancements is 'image subtraction'. This involves calculating a change image based on the difference between corresponding image-channels from two dates. Change images are easily interpreted because their histograms are normally distributed (i.e. unchanged pixels fall along the center of the histogram, with change pixels falling to the left and right of the histogram, depending on the darkness and brightness of these areas, Jensen, 2000). The same procedure is often performed on enhanced imagery, such as vegetation indices (Singh, 1989). This approach can also be performed on a ratio-based or perpendicular index.

Principal components analysis (PCA) involves the orthogonalization of a multispectral and multi-date dataset based on components generated from an eigenvector-derived factor-loading matrix (Schowengerdt, 1997). The factor-loading matrix is based on a correlation matrix approach (standardized), or based on the variance-covariance matrix (non-standardized). Studies have shown that the choice of matrix can affect the statistical nature of the final components (Patterson and Yool, 1998). In general, when PCA is performed on a multi-date layer stack, the first component will be representative of the overall multi-date image variance (similar to an albedo image, Rogan and Yool, 2001). Higher components (i.e. PC2, PC3, etc.) will be representative of changes in image variance between the dates. These high-order components, therefore, are responsive to inter-date change and can be used to classify changes in a study area. PCA works well, and is widely used for this purpose (Lunetta and Elvidge, 1998). In addition, the process results in data reduction (i.e. a large data set is compressed into a limited number of components). A drawback of PCA, however, is that the technique is based only on the statistical properties of the data, and is therefore limited in its application to different times and different areas. In addition, the statistical nature of PCA determines that areas of high inter-date variance in the imagery tend to 'drive' the eigenvector process, which can prove frustrating if those areas are not the change features of interest to the interpreter.

Some of the drawbacks associated with PCA are easily overcome using the Multitemporal Kauth Thomas transformation (MKT). This index is based on the orthogonalization of a multiband, and multi-date dataset (Collins and Woodcock, 1996). For example, the MKT can produce six output features based on the transformation of a 12-band multi-temporal Landsat TM dataset. These output features represent: (1) stable brightness; (2) stable greenness; (3) stable wetness; (4) change in brightness; (5) change in greenness; and (6) change in wetness. The MKT has been used in several studies to date (Levien *et al*., 1999; Rogan *et al*., 2002), and appears to be a robust indicator of land-cover change. Unlike the PCA, MKT is not scene-dependent, and its use of stable and calibrated transformation coefficients ensures that its application is suitable between regions and across time. The fact that the MKT produces several sets of change features, rather than a single feature (e.g. Normalized Difference Vegetation Index (NDVI)) is another attractive quality. Further, the MKT produces stable spectral components, which could be used in developing baseline spectral information for long-term studies (Rogan *et al*., 2003).

Change vector analysis (CVA, Malila, 1980) involves the calculation of two change features (magnitude of change, and direction of change) based on a multitemporal dataset. Magnitude (i.e. quantity of inter-date change) is calculated based on the Euclidean distance of a bi-temporal (or multi-temporal) spectral vector. The direction image is calculated based on the angularity of the vector (Cohen and Fiorella, 1998). Several methods exist for calculating the vector angle. Lambin and Strahler (1994) used PCA of a 12-date AVHRR dataset to calculate the angular distance of the multispectral vectors. Further, Cohen and Fiorella (1998) based their calculation on the Gramm-Schmidt orthogonal distance from a baseline (i.e. a stable image date). Both approaches produced physically meaningful magnitude and direction images and their subsequent analyses were also successful. In light of these facts, it is odd that explicit application of CVA is not seen more often in the remote sensing literature. Strahler *et al*. (1996) stated that this was to be the 'algorithm of choice' for the MODIS quarter-annual land-cover change product (at 1 km spatial resolution). Better use will be made of CVA when algorithms become automated, and a steadfast and reliable method is developed for measuring the change direction angle.

Composite analysis (CA) has been used often in change detection applications (Yuan and Elvidge, 1998). This approach involves compositing all desired bands into a multi-date layer stack (the layer stack may contain raw or enhanced image data). Following this, supervised classification (using calibration data), or unsupervised classification is then performed on the data set to obtain the desired number of output classes. This approach is straightforward and intuitive. The premise of CA is that 'change' classes will be located in the entire set of available classes (Cohen and Fiorella, 1998). A drawback of this approach, however, is that non-change classes may mask the statistical variance of the change classes.

It is generally recommended that a thresholding procedure be performed on the data, so that change and no-change pixels can be readily located in the change imagery. Thresholds are usually based on the number of standard deviations from the mean of the change image, typically an iterative and subjective procedure (Lunetta *et al*., 2002). Therefore, recent research has examined the selection of thresholds based on a sound statistical basis (Rogerson, 2002).

Image classification

Image classification applies to both post-classification and pre-classification change detection approaches and can be performed using either supervised or unsupervised approaches. Prior to supervised classification, calibration data must be sufficiently sampled from appropriate areas to account for the spectral variability of each class in question. In unsupervised classification, an algorithm is chosen that will take a remotely sensed image data set and find a pre-specified number of statistical clusters in measurement space (Schowengerdt, 1997). Although these clusters must then be assigned to classes of land cover and land use, this method can be used without having prior knowledge of the ground cover in the study site.

Supervised classification, however, does require prior knowledge of the ground cover in the study area and is, therefore, a more intuitive method for land-cover change mapping. With the supervised approach, calibration pixels are selected and associated statistics are generated for the classes of interest. Recent work by Chen and Stow (2002) compared the performance of three different calibration strategies for supervised classification (single pixel, seed, and polygon). The calibration set size, the image resolution, and the degree of autocorrelation inherent within each class influenced the performance of these strategies, and polygon-based calibration performed best in areas of heterogeneous land-cover type.

The vast majority of land-cover and land-use monitoring approaches have used traditional image classification algorithms (e.g. maximum likelihood), which assume: (i) image data are normally distributed, (ii) the images are H-resolution[2]; and (iii) pixels are composed entirely of a single land-cover or land-use type (Franklin *et al*., 2003). Conversely, L-resolution[3] approaches have employed empirical models to estimate biophysical, demographic and socio-economic information (Rashed *et al*., 2001). Recently, researchers have investigated scenes using a combination of L- and H-resolution approaches (Roberts *et al*., 1998; Rogan *et al*., 2002). For example, spectral mixture analysis (SMA) can be used to estimate sub-pixel information about both natural and urban/suburban scenes (Phinn *et al*., 2002). Fuzzy sets approaches, where an observation can have degrees of membership in more than one class, have also shown promise (Foody, 1999).

Machine learning classifiers (e.g., decision trees and artificial neural networks) have been used effectively in a variety of single-date land-cover mapping studies (Huang and Jensen, 1997; DeFries and Chan, 2000). In almost all cases, these classifiers have proven superior to conventional classifiers (e.g. maximum likelihood), often recording overall accuracy improvements of 10–20%. The success of machine learning classifiers in resolving land cover and changes in land cover and land use for complex measurement spaces can be attributed to several factors. Machine learning

[2] H-resolution indicates that the objects of interest on the surface are larger than the pixel size (Strahler *et al*., 1986). Hence, the reflectance measured for a given location is likely to be closely related to the object itself.

[3] L-resolution indicates that the objects of interest on the surface are smaller than the pixel size (Strahler *et al*., 1986). Hence the reflectance measured for a given location is a combination of the objects within the instantaneous field of view.

classifiers are not constrained by parametric statistical assumptions. Hence, they are better suited for analyzing: (i) multi-modal, noisy, and/or missing data; and (ii) a combination of categorical and continuous ancillary data. However, few studies, to date, have examined the potential of this approach in a change detection context (Gopal and Woodcock, 1996; Abuelgasim *et al*., 1999; Rogan *et al*., 2002; Langevin and Stow, this issue).

Summary and future developments

Remote sensing data and analysis techniques are now providing detailed information for detecting and monitoring changes in land cover and land use. This has become increasingly apparent over the last decade. In the first decade of data availability, change detection methods were not used widely (Franklin, 2001). This can be attributed to a general lack of familiarity and experience with the data (in both analog and digital formats), a lack of understanding among researchers about the spatial and temporal dynamics of the landscapes under investigation, and the fact that the data originally were too coarse (spectrally and spatially) to be of any use beyond Anderson Level I classification (Table 2). These drawbacks have steadily diminished over time, due to advances in sensor performance, image processing techniques, and informative research applications. Further, quality in sensor design and data flow will continue to improve, which will no doubt lead to an expansion of our understanding of the types and rates of land-cover and land-use changes and their causes, distributions, rates and consequences.

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