# Chapter 8
# Optical Remote Sensing

*"It is not knowledge, but the act of learning, not possession but the act of getting there, which grants the greatest enjoyment."*
Carl Friedrich Gauss (1777–1855)

## 8.1 Data Acquisition—Sensors and Systems

There are a large variety of systems for collecting remotely sensed data in operation today. Ramapriyan (2002) asserts these can be categorized in several ways according to the:

- type of instrument (imager, sounder, altimeter, radiometer, spectrometer, etc.);
- mechanics of the instrument (push broom, whisk broom, serial cross-track, parallel cross-track, conical scan, step-staring, etc.);
- sensing mechanism (passive or active);
- viewing characteristics (point-able or fixed, nadir- or off-nadir-looking, single- or multi angle (mono or stereo));
- spectral characteristics measured (panchromatic, multi-spectral, hyper-spectral);
- spatial resolution (high, moderate, low);
- observed wavelength range (UV, visible, near infrared, thermal, microwave, etc.);
- platform (aircraft, spacecraft); and
- altitude (in case of airborne sensors) or orbits (in the case of space-borne sensors (e.g., sun-synchronous, geosynchronous, geostationary, low inclination etc.).

Against the above background, the design of remote sensing systems principally revolves around the identification of the most appropriate *sensor-platform* combination. As a matter of fact, this arrangement represents a basic and common denominator in virtually all remote sensing systems. Following a user needs assessment the most pragmatic sensor-platform combination is identified in order to deliver the

J. L. Awange and J. B. Kyalo Kiema, *Environmental Geoinformatics*,
Environmental Science and Engineering, DOI: 10.1007/978-3-642-34085-7_8,

desired remote sensing data solution to suit specific or generic application(s). In view of the often huge financial and human resources required, as well as the diversity and scope of applications, the design of remote sensing systems is definitely not a trivial exercise.

As discussed in Sect. 7.2, and with regard to the type of sensing mechanism applied, mapping sensors may be classified as either passive or active. Furthermore, they may vary in design from classical frame-based to digital aerial cameras employing either frame or line scanning techniques, and from opto-mechanical to push-broom scanners with stereo and even triplet imaging capability. In defining the most appropriate orbit for a sensor, as mentioned above, several attendant factors need to be considered such as altitude, attitude, orbit or flight course, payload etc. By using Kepler's laws of planetary motion, the characteristics of satellite orbits are defined through several parameters including orbit figure (circular, ellipsoidal etc.), inclination (oblique, polar etc.), period (geosynchronous or sun synchronous), recurrence (recurrent or semi-recurrent) etc.

In retrospect, various factors have continued to drive and impact on the development of remote sensing and GIS in general as illustrated in Fig. 2.2. For instance, developments in space technology have strongly influenced the design of mapping sensors. Furthermore, increased size of charged-couple devices (CCD) sensors and high data transmission rates have all given an impetus to this. The increase in the application of space-derived data into new and often diverse fields has also significantly contributed to the development of mapping sensors.

Usually, most of these new applications have brought with them new demands and challenges. Attempts to address these new use requirements have contributed significantly to the development of remote sensing imaging systems as articulated in Kiema (2001). From a purely political perspective, the easing of prior military restrictions on the availability and use of high spatial resolution imagery (HSRI) to civilians has opened up new business opportunities in mapping.

The vehicle or carrier on which remote sensors are borne is called the *platform*. Pigeons were some of the earlier remote sensing platforms employed in remote sensing. Basically, platforms used in remote sensing may be classified as space-borne, airborne or ground-based. Satellites constitute the principal space-borne platforms employed today. Aircrafts are the most common type of airborne platform used in remote sensing, although helicopters, radio controlled planes and balloons are also employed, especially at lower orbits of up to about 500 m.

Ground-based platforms are used in terrestrial and close range imaging applications. Space-borne platforms are predominant at higher altitude orbits stretching from between 240 and 350 km for space shuttle, to between 500 and 1,000 km for Low Earth Orbiting Satellites (LEOS) usually with sun synchronous orbit and 36,000 km for Geostationary Earth Orbiting Satellites (GEOS). On the other hand, airborne sensors are usually employed at lower altitudes from 10 to 12 km. One can compare remote sensing satellites with the Global Navigation Satellite Systems (GNSS) like the Global Positioning Satellite (GPS), which are essentially Medium Earth Orbiting Satellites (MEOS) and orbit at an altitude of about 20,200 km.

The key factor in the selection of a platform is the altitude which determines the ground resolution if the instantaneous field of view (IFOV) of the sensor is constant. The selection of the appropriate platform also depends on the purpose—which is sometime requested for *a priori*. For example, a constant altitude is required for aerial surveys, while various altitudes are needed to survey vertical atmospheric distribution. Moreover, for aerial photogrammetry, the flight path is strictly controlled to meet the requirement of geometric accuracy. However, helicopter or radio controlled planes are used for a free path approach, for example in disaster monitoring.

There are probably several hundreds of *space utility vehicles* (SUVs) employing different sensor-platform arrangements in operation today. Undoubtedly, the number of such systems is bound to continue growing even further. This prediction is true, especially as more enterprise or domain specific sensors continue to be launched into orbit and as many more countries, including even those in the developing world, begin to recognize the strategic importance and value of investing in space technology.

## 8.2 Characteristics of Optical Remote Sensing Data

As highlighted in Sect. 7.1, electromagnetic radiation which is either reflected or emitted from objects is what is referred to as remote sensing data. This data can be in either analogue format (e.g., hard-copy aerial photography or video data) or digital format (e.g., a matrix of brightness values corresponding to the average radiance measured within an image pixel). The success of data collection from remotely sensed imagery requires an understanding of four basic image resolution characteristics, namely; spatial, spectral, radiometric, and temporal resolution (Jensen 2005). From the very outset, however, it is important to acknowledge the fact that the interpretation of different sensor performance characteristics is anything but trivia (Joseph 2000).

*Spatial resolution* is a measurement of the minimum distance between two objects that will allow them to be differentiated from one another in an image and is a function of sensor altitude, detector size, focal size, and system configuration (Jensen 2005). As much as the spatial resolution determines the smallest object that can be perceived in an image, the contrast of an object with respect to the surrounding object also influences its interpretation. The impact of spatial resolution on the pointing accuracy and overall interpretation has been investigated in several works (e.g., Forshaw et al. (1983), Bähr and Vögtle (1998)).

These studies have demonstrated the importance of specifying the *Modulation Transfer Function* (MTF) of an imaging system in order to adequately describe its geometric capability. For aerial photography, spatial resolution is measured in resolvable line pairs per millimeter, whereas for other sensors, it refers to the dimensions (in meters) of the ground area that falls within the instantaneous field of view (IFOV) of a single detector within an array or pixel size (Jensen 2005). Spatial resolution, which defines a sensor's footprint on the ground, determines the level of spatial details that can be observed on the earth's surface from a particular sensor.

**Table 8.1** Typical costs of different types of remote sensing imagery. *Source* Kumi-Boateng (2012)

| Sensor category | Sensor type | Spatial resolution (m) | Scene coverage ($Km^2$) | Estimated acquisition cost per $Km^2$ (US$) | Estimated pre-processing cost per $Km^2$ (US$) |
|---|---|---|---|---|---|
| Coarse resolution (>250 m) | NOAA AVHRR | 1090 | 5,760,000 | 0.00015 | 0.00008 |
| | Terra MODIS | 250 | 5,428,900 | 0.00000 | 0.00005 |
| | Orbview-1 | 1000 | 3,750,000 | 0.00013 | 0.00006 |
| Medium resolution (10–250) | Landsat MSS | 80 | 34,000 | 0.00880 | 0.00440 |
| | Landsat TM 4-5 | 30 | 34,000 | 0.01620 | 0.00810 |
| | Landsat ETM 7 | 30 | 34,000 | 0.02130 | 0.01065 |
| | IRS (XS) | 23 | 21,900 | 0.11400 | 0.02800 |
| | SPOT 1-3 | 10 | 3,600 | 0.41600 | 0.15000 |
| | ASTER | 15 | 3,600 | 0.01520 | 0.00760 |
| | RADARSAT | 10–100 | 1,000 | 2.53000 | 1.20000 |
| High resolution (<10 m) | IKONOS | 1 (Pan) | 121 | 29.00000 | 14.50000 |
| | SPOT 5 | 2.5 | 3,600 | 0.73000 | 0.27000 |
| | IRS | 6 (Pan) | 4,900 | 0.33000 | 0.08000 |
| | Quickbird | 0.6 (Pan) | 400–1,600 | 39.00000 | 19.50000 |
| | Color-IR Photography | 10 | 83 | 5.50000 | 2.75000 |
| | Aircraft digital imagery | 1 | variable | 50.00000 | 25.00000 |
| | AVIRIS | 20 | 99 | 5.00000 | 2.50000 |
| | LiDAR | 0.1 | variable | 74.00000 | 37.00000 |

Generally speaking, the finer the spatial resolution, the higher the level of detail it records and certainly the more expensive the satellite imagery as shown in Table 8.1.[1] From a practical standpoint, cost is often the most important factor in a remote sensing application as reiterated by Phinn (1998). Coarse spatial resolution data may include a large number of mixed pixels, where more than one land-cover type can be found within a pixel. Whereas fine spatial resolution data considerably reduce the mixed-pixel problem, they may increase internal variation within the land-cover types. Higher spatial resolution also implies need for greater data storage and higher cost and may even introduce difficulties in image processing for a large study area as pointed out by Weng (2010).

The relationship between geographic scale and spatial resolution has been investigated in Quattrochi and Goodchild (1997). From such studies and experience gained over the years, it has been confirmed that high spatial-resolution imagery, such as that employing IKONOS and QuickBird data, is more effective on the local scale. On the regional scale, medium-spatial-resolution imagery, such as that employing Landsat Thematic Mapper/Enhanced Thematic Mapping Plus (TM/ETM+) and Terra Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) data, is more common. At the continental or global scale, coarse-spatial-resolution

[1] All the tabulated sensors are passive, except RADARSAT and LiDAR that are active sensors.

imagery, such as that employing Advanced Very High Resolution Radiometer (AHVRR) and Moderate Resolution Imaging Spectrometer (MODIS) data is mundane as shown in Table 8.1.

Each remote sensor is unique with regard to what portion(s) of the electromagnetic spectrum's energy it is able to detect. Different remote sensing instruments record different segments, or bands, of the electromagnetic spectrum. *Spectral resolution* of a sensor refers to the number and size of the bands it is able to record (Jensen 2005). In general, the finer the spectral resolution, the narrower the wavelength range for a particular band. To describe the spectral resolution more precisely, however, it is necessary to define a number of related parameters including the central wavelength, bandwidth size, jointly with the percentage of out-of-band response as noted by Joseph (2000).

The spectral resolution may vary from panchromatic to multi-spectral and even hyper-spectral sensors. Panchromatic sensors record images in either black or white, while multi-spectral sensors detect images in a few bands e.g., visible and reflected infrared. For most high spatial resolution sensors the panchromatic (Pan) and multi-spectral (MSS) channels are usually separated, with the panchromatic channel often having a finer spatial resolution than the multi-spectral channels. Hyper-spectral sensors (imaging spectrometers) are instruments that acquire images in many very narrow contiguous spectral bands. An example of a hyperspectral sensor is MODIS on-board National Aeronautics and Space Administration (NASA)'s Terra and Aqua missions that has a spectral resolution in 36 spectral bands designed to capture data about land, ocean, and atmospheric processes simultaneously.

*Radiometric resolution* refers to the sensitivity of a sensor to incoming radiance, that is, how much change in radiance there must be on the sensor before a change in recorded brightness value takes place Jensen (2005). Coarse radiometric resolution would record a scene using only a few brightness levels, that is, at very high contrast, whereas fine radiometric resolution would record the same scene using many brightness levels. For example, remote sensors with a radiometric resolution of 8 bits can record data in 256 brightness or gray levels ranging from 0 to 255. The finer the radiometric resolution of a sensor, the more sensitive it is in detecting small differences in reflected or emitted energy.

*Temporal resolution* defines the duration it takes a sensor to return to a previously imaged location. It is important to note that because of some degree of overlap in the imaging swath of adjacent orbits for most remote sensing satellites, coupled with the increase of this overlap with increasing latitude, some parts of the earth tend to be re-imaged more frequently than others. This is besides the fact that some satellite systems are also able to "point their sensors".

Temporal resolution has an important and critical implication in change detection and environmental monitoring. For instance, many environmental phenomena such as vegetation, weather, forest fires, volcanoes etc. periodically change over time. To monitor the development of crops and vegetation, temporal resolution is an important consideration to be able to detect and explain changes and anomalies. In view of the often sporadic changes in weather patterns worldwide, most weather sensors have a high temporal resolution such as, Geostationary Operational Environmental Satellite

(GOES), 0.5/h; NOAA-9 AVHRR local-area coverage, 14.5/day; and METEOSAT first generation, every 30 min (Weng 2010).

Fine spatial resolution remote sensing image data can be very expensive, with the cost often spiraling to several hundred dollars per square kilometer (see Table 8.1) depending on the type of sensor and the timeliness of the desired data. Given the availability of a wide array of different types of remote sensing data with different characteristics, the selection of the most appropriate data for a particular exercise is not trivial at all. This is further compounded by the fact that in many remote sensors, clear trade-offs exist between different forms of resolution as described in Campbell (2007). In the final analysis, therefore, the selection of the most appropriate remote sensing data in a particular application will be influenced by several factors including: the nature of the specific application, the information or classes of interest that need to be extracted, the sensor characteristics assessed and the available budget.

## 8.3 High Spatial Resolution Imagery

### *8.3.1 Development and Characteristics of HSRI*

With the onset of space-based mapping, which was incidentally triggered off way back in 1972 with the launch of *Landsat-1*, most of the space-borne sensors that were employed belonged to national mapping and other federal agencies. Despite the fact that mapping applications involving the use of satellite imagery have continued to grow impressively since then, these have, nevertheless, been rather constrained and have never realized the full potential of satellite remote sensing *per se*. This is basically due to the relatively low spatial resolution of most of the earlier satellite imagery. Consequently, photogrammetry (discussed in Chap. 11) continued to be used in applications, like in medium to large scale topographic mapping, where the accuracy offered by satellite imagery was deemed to be inadequate.

The inauguration of high spatial resolution mapping sensors, which was pioneered in 1999 with the successful launch of *IKONOS*, has significantly changed the above scenario (see Table 8.1). The introduction of high spatial resolution imagery (HSRI) addressed the inherent weakness of the earlier generation of satellite imagery and ideally marked the beginning of a new era in space imaging for earth observation as articulated in Fritz (1996), Aplin et al. (1997) etc. With the use of sensors characterized by high geometric fidelity, HSRIs have demonstrated remarkable mapping capability as explained in Sect. 8.3.2.

In addition, high spatial resolution mapping sensors have exhibited very rapid cycle of image collection that is flexible enough to satisfy varied customer delivery needs. A distinctive feature of most high spatial resolution commercially-based earth observation satellites is that, unlike the earlier mapping sensors, they are largely owned by different private consortia, often with an international dimension. Fig. 8.1 highlights examples of some typical HSRI.


**Fig. 8.1** Examples of HSRI. *Source* Murai (2004)

Some of the typical products associated with HSRI include: (i) Geo-coded image: Panchromatic (Pan), Multi-spectral (MS), Pan sharpened etc; (ii) Orthoimage corrected for topography; (iii) Digital Surface Models (DSMs)/Digital Elevation Models (DEMs) from stereo imagery; (iv) Contour line map generated from DEM; (v) Land cover map: auto/semi-automatically produced; (vi) Overlay on GIS; and (vii) 3D landscape animations.

### *8.3.2 Potential of HSRI*

HSRI contain rich spatial information, providing a greater potential to extract much more detailed thematic information (e.g., land use and land cover, impervious surface, and vegetation), cartographic features (e.g., buildings and roads), and metric information with stereoimages (e.g., height and area) that are ready to be used in GIS (Weng 2010). Murai (2004) deduces the potential of HSRI from the typical products provided to include the following:

(1) Mapping capability: A ground resolution of 1 m coupled with a pointing accuracy of 0.3 pixel will provide 1:10,000 line drawing map with contour interval of between 2.5 and 5 m. Background image map will also be possible at the scale of 1:5,000 including orthoimage.
(2) GIS: HSRI can be overlaid as background image on GIS vector data.
(3) Provision of DEM from stereo imagery.
(4) Automated feature extraction.
(5) Fused data products.
(6) 3D Modeling: This requires stereo imagery to succeed. Moreover, the central perspective projection (see Sect. 11.2), upon which the basic photogrammetric theory is anchored, is not applicable here due to the very narrow field of

view (less than 2°). Instead, *generic* or *replacement* sensor models described in Sect. 12.2 are used. Specifically, two methods have been developed for 3D modeling namely; (a) affine transformation with 6 parameters as shown in Eq. 8.1

$$\begin{aligned} x &= a_1 + a_2 X + a_3 Y \\ y &= b_1 + b_2 X + b_3 Y \end{aligned} \tag{8.1}$$

where; $x$, $y$ are the image coordinates; $X$, $Y$ are the object point coordinates; $a_1, a_2, a_3, \ldots$ etc. are the transformation coefficients.
(b) rational function with up to 80 parameters that are provided by the HSRI distributor as exemplified in Eq. 8.2.

$$\begin{aligned} x_{ij} &= \frac{P_{i1}(X, Y, Z)_j}{P_{i2}(X, Y, Z)_j} \\ y_{ij} &= \frac{P_{i3}(X, Y, Z)_j}{P_{i4}(X, Y, Z)_j} \end{aligned} \tag{8.2}$$

where; $x_{ij}$, $y_{ij}$ are normalized image coordinates; $X$, $Y$, $Z$ are the object point coordinates (normalized latitude, longitude & height); and $P_{i1}(X, Y, Z)_j = a_1 + a_2 Y + a_3 X + a_4 Z + \cdots + a_{19} X^2 Z + a_{20} Z^3$
$P_{i2}(X, Y, Z)_j = b_1 + b_2 Y + b_3 X + b_4 Z + \cdots + b_{19} X^2 Z + b_{20} Z^3$
$P_{i3}(X, Y, Z)_j = c_1 + c_2 Y + c_3 X + c_4 Z + \cdots + c_{19} X^2 Z + c_{20} Z^3$
$P_{i4}(X, Y, Z)_j = d_1 + d_2 Y + d_3 X + d_4 Z + \cdots + d_{19} X^2 Z + d_{20} Z^3$ and $a_1, a_2, a_3, \ldots$ etc. are the polynomial coefficients.

(7) Visualization and 3D fly throughs.

Subsequently, the advantages of HSRI include:

(a) Frequent data acquisition from high temporal resolution;
(b) Good image quality;
(c) Simple 3D modeling;
(d) Access possibility (high mountain, boundary etc.);
(e) Less number of ground control points (GCPs) are required; and
(f) No special skill is required.

On the contrary, the disadvantages of HSRI include:

(a) High cost;
(b) Cloud coverage;
(c) Shadows caused by topography, tall buildings, or trees;
(d) High spectral variation within the same land-cover class, especially in complex landscape, e.g., urban areas;
(e) Fixed frequency and acquisition time;
(f) Huge amount of data storage and computer display, which can adversely affect image processing; and
(g) Less development history.

## 8.4 Light Detection and Ranging

Although growing in popularity only in recent years, Light Detection And Ranging (LiDAR), otherwise referred to as laser scanning technology, has been in use from around 1972 when the *Airborne Profile Recorder* (APR) was first employed and effectively combined in photogrammetric block adjustment Ackermann (1999). Throughout the 1980s different feasibility studies were conducted with the viability of LiDAR only confirmed following the steady growth of Global Positioning System (GPS) and development of rotational sensors. This then saw the first laser profiling research conducted at the University of Stuttgart, Federal Republic of Germany between 1989–1990 under the direction of Prof. Ackermann in the special research project titled "High Precision Navigation". Commercial applications of LiDAR commenced later in the early 1990s spearheaded by firms like TopScan,[2] Toposys[3] etc.

As mentioned in Sect. 7.3, LiDAR is essentially an active remote sensing technology that employs Light Amplification by Stimulated Emission of Radiation (LASER). In principle, it operates by firing laser pulses towards the object/target and measuring the range between the sensor and the object based on either the return time for pulse ranging systems or the phase difference for side tone (continuous wave) ranging systems. From a knowledge of the instantaneous position and attitude of the LiDAR sensor, derived from real-time kinematic (RTK) GPS positioning (discussed in Sect. 6.11) and inertial measuring units (IMU) respectively, through simple polar determination, it is possible to compute the three-dimensional coordinates of the object/target. These initial estimates, however, still need to be filtered to correct for noise after which LiDAR data in the form of discrete x, y, and z coordinates are generated and transformed into the desired local coordinate system. Intensity data (images) may also be delivered together with other elevation derived surfaces such as digital elevation model (DEM), digital surface model (DSM) etc. LiDAR data provide fairly good vertical and horizontal resolutions with accuracies of $\pm 0.3$ m reported (Webster et al. 2004).

Unlike other remotely sensed data, LiDAR data focus solely on geometry rather than radiometry (Weng 2010). With the ability to detect and record more than one return for each height point measured (Alharthy and Bethel 2002), LiDAR possesses distinct advantages over most other remote sensing systems. Specifically, most LiDAR allow the recording of the first- and last-pulse returns as shown in Fig. 8.2. The first-pulse returns are registered by surfaces of all ground objects, including both solid and transparent objects, and is extremely useful for detecting penetrable objects such as trees. Starting from individual tree analysis, forest volume and biomass can be estimated subsequently, see e.g., Renslow (2000), Popescue et al. (1998), Secord and Zakhor (2007), Voss and Sugumaran (2008) etc. In contrast, the last-pulse returns are recorded by laser that penetrates through and is finally reflected from non-penetrable objects such as the ground and buildings. While the first pulse LiDAR data is useful for generation of DSMs, the last pulse data is important for producing

[2] http://www.toposcan.de

[3] http://www.toposys.de

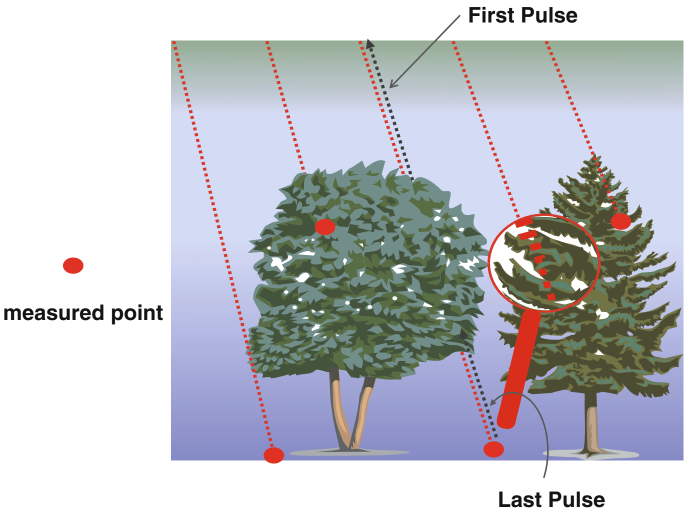


**Fig. 8.2** First- and last-pulse measurements

DEMs. The normalized DSM (nDSM), otherwise known as the *normalized height model*, derived from Eq. 8.3, is important in the extraction of urban objects such as buildings and trees.

$$nDSM = DSM - DEM \tag{8.3}$$

Over the years, LiDAR technology has distinguished itself in many applications largely due to its ability to deliver high resolution data, within a short acquisition time and at a lower cost compared with classical methods like photogrammetry, irrespective of weather conditions. LiDAR is today a critical data source in urban studies, especially for extraction of buildings and trees, see e.g., Haala and Brenner (1999), Brunn and Weidner (1997), Clode et al. (2007), Forlani et al. (2006), Miliaresis and Kokkas (2007) etc. LiDAR data have also been used in urban planning, telecommunications network planning, and vehicle navigation (Kokkas 2005). To demonstrate its versatility, many urban studies have also examined the extraction of urban objects by fusing LiDAR with high spatial resolution imagery (HSRI), see e.g., Lee et al. (2008), Secord and Zakhor (2007), Voss and Sugumaran (2008), Sohn and Dowman (2005) etc.

Given the diversity and quality of products offered by LiDAR technology, there has been discussion in the literature whether this technology is in competition with or complimentary to older technologies, such as photogrammetry, that leverage on similar outputs, see e.g., Baltsavias (1999), Liu (2008), Schenk and Csatho (2002), Ma (2005) etc. Some of the advantages that LiDAR possesses over photogrammetry include the fact that; (i) it is virtually independent from environmental conditions; (ii) it can operate both during day or night; (iii) it does not need control points and signals; (iv) it does not need expensive mapping equipment; (v) it has a high point density

(1–5 m); and (vi) although it has a higher cost per square kilometer (see Table 8.1), it is still more competitive in terms of both cost and time by between 25–50 % Konecny (2003). Evidently, LiDAR together with HSRI (discussed in Sect. 8.3) provide high impact data sets that will continue to influence many future developments in remote sensing.

## 8.5 Concluding Remarks

That space technology is expensive business is a matter of fact. This partly explains why for slightly over half a century since their introduction, the earlier generation of earth observation satellites remained the preserve of only a handful of national mapping and federal agencies. However, the ever growing business opportunities present in the space industry seem to have changed this situation in recent times, with several private consortia and companies already fully engaged in the provision of high-end remote sensing imaging data and associated value-added products. This paradigm shift seems to be emerging even as many first world countries continue to cut down on their budgets for space technology, owing largely to the recurrent global financial crisis.

Conversely, we are increasingly witnessing the deployment of many miniature earth observation satellites, particularly in the emerging economies in Asia like China, Korea, Malaysia etc., thanks to innovation and development in nano technology. Murai (2004) contends that these small satellites cover up to about 95 % of the basic functions of large satellites at only about 5 % of the total cost of the same. Furthermore, they also have a relatively short development time and reasonable reliability, besides requiring smaller and cheaper launch vehicles, see e.g., Xue et al. (2008), Kramer and Cracknell (2008), Guelman and Ortenberg (2009) etc.

These attractive propositions will certainly result in many more developing countries leapfrogging into the league of select nations that own earth observation satellites to support assorted human, environmental and other strategic interests and applications. However, like the proverbial two sides of a coin, these new developments will most likely introduce new technical, institutional and legal challenges, such as the need for better measures and procedures to deal with debris mitigation, frequency allocation and satellite registration, among other contemporary space issues.

With the benefit of hindsight, one can postulate that it is unlikely that any one single sensor-platform combination will provide all the data required in remote sensing. What is required today is the development of appropriate sensor networks and webs. Such technologies that are currently being deployed in environmental monitoring, present new opportunities for gathering land surface information that allow the integration of field data collection in remote sensing McCoy (2005), thus amplifying the utility of remotely sensed data (Ho et al. 2005; Porter et al. 2005; Kussul et al. 2009) etc. Additionally, the emergence of a more spatially literate society will no doubt continue to demand for high quality remote sensing data to suit their diverse applications. The quality of the wide array of remote sensing data on offer will be evaluated on the basis of several factors such as *lineage*, *consistency*, *completeness*, *positional accuracy*, *semantic accuracy*, *temporal accuracy* and *attribute accuracy*, see e.g., Groot and McLaughlin (2000), Devillers and Jeansoulin (2006), Congalton and Green (2009) etc.

Furthermore, the future use of earth sensor data, and through this, the future development of mapping sensors will continue to be influenced by algorithmic advances in various fields including automatic image understanding, data fusion, and data compression (Schiewe 1998). Ultimately, however, the final selection of the most suitable remote sensing data in an application will be made based on several factors including; the specific type of the application, the information or classes to be extracted, the sensor characteristics assessed, and perhaps even more importantly, the available budget (Kiema 2001).

## References

Ackermann F (1999) Airborne laser scanning—present status and future expectations. ISPRS J Photogramm Remote Sens 54:64–67

Alharthy A, Bethel J (2002) Heuristic filtering and 3D feature extraction from LIDAR data. In: International Archives of Photogrammetry and Remote Sensing (IAPRS), Graz, Austria, vol XXXIV, Part 3A:29–34

Aplin P, Atkinson PM, Curran PJ (1997) Fine Spatial resolution satellite sensors for the next decade. Int J Remote Sens 18:3873–3881

Bähr H-P, Vögtle T (eds) (1998) Erderkundungssatelliten und ihre Produkte. Digitale Bildverarbeitung, vol 3. Wichmann Verlag, Heidelberg, pp 29–43

Baltsavias E (1999) A comparison between photogrammetry and laser scanning. ISPRS J Photogramm Remote Sens 54:83–94

Brunn A, Weidner U (1997) Extracting buildings from digital surface models. Int Arch Photogramm Remote Sens 32:27–34

Campbell JB (2007) Introduction to remote sensing, 4th edn. Guilford Press, New York

Clode S, Rottensteinerb F, Kootsookosc P, Zelniker E (2007) Detection and vectorization of roads from LiDAR data. Photogramm Eng Remote Sens 73:517–535

Congalton R, Green K (2009) Assessing the accuracy of remotely sensed data: principles and practices. Taylor & Francis Group, Boca Raton

Devillers R, Jeansoulin R (eds) (2006) Fundamentals of spatial data quality. ISTE, London

Forlani G, Nardinocchi C, Scaioni M, Zingaretti P (2006) Complete classification of raw LiDAR data and 3D reconstruction of buildings. Pattern Anal Appl 8:357–374

Forshaw MRB, Haskell A, Miller PF, Stanley DJ, Townshend JRG (1983) Spatial resolution of remotely sensed imagery: a review paper. Int J Remote Sens 4(3):497–520

Fritz LW (1996) The Era of commercial earth observation satellites. Photogramm Eng Remote Sens 1:39–45

Groot R, McLaughlin J (eds) (2000) Geospatial data infrastructure: concepts, cases and good practice. Oxford University Press, New York

Guelman M, Ortenberg F (2009) Small satellite's role in future hyperspectral earth observation missions. Acta Astronaut 64:1252–1263

Haala N, Brenner C (1999) Extraction of buildings and trees in urban environments. ISPRS J Photogramm Remote Sens 54:130–137

Ho C, Robinson A, Millerm D, Davis M (2005) Overview of sensors and needs for environmental monitoring. Sensors 5:4–37

Jensen JR (2005) Introductory digital image processing: a remote sensing perspective, 3rd edn. Prentice-Hall, Upper Saddle River

Joseph G (2000) How well do we understand earth observation electro-optical sensor parameters? ISPRS J Photogramm Remote Sens 55:9–12

Kiema JBK (2001) Multi-source data fusion and image compression in urban remote sensing. Doctor of engineering. Dissertation, University of Karlsruhe. ISBN3-8265-9312-X. Shaker Verlag, pp 130

Kokkas N (2005) City modeling and building reconstruction with Socet Set v.5.2 BAE Systems. Customer presentation at the 2005 GXP regional user conference. Cambridge, England, pp 19–21

Konecny G (2003) Geoinformation: Remote sensing, photogrammetry, Geographic Information Systems. Taylor and Francis, London

Kramer HJ, Cracknell A (2008) An overview of small satellites. Int J Remote Sens 29:4285–4337

Kumi-Boateng B (2012) A spatio-temporal based estimation of vegetation changes in the Tarkwa mining area of Ghana. Doctor of philosophy. Dissertation, University of Mines and Technology, Ghana, pp 165

Kussul N, Shelestov A, Skakun S (2009) Grid and sensor web technologies for environmental monitoring. Earth Sci Inform 2(1–2):37–51

Lee DH, Lee KM, Lee SU (2008) Fusion of LiDAR and imagery for reliable building extraction. Photogramm Eng Remote Sens 74:215–225

Liu X (2008) Airborne LiDAR for DEM generation: some critical issues. Prog Phys Geogr 32(1):31–49. doi:10.1177/0309133308089496

Ma R (2005) DEM generation and building detection from lidar data. Photogramm Eng Remote Sens 71(7):847–854

McCoy R (2005) Field methods in remote sensing. The Guilford Press, New York 158p

Miliaresis G, Kokkas N (2007) Segmentation and object-based classification for the extraction of the building class from LiDAR DEMs. Comput Geosci 33:1076–1087

Murai S (2004) Remote sensing and GIS courses—distance education, Japan International Cooperation Agency (JICA)-Net

Phinn SR (1998) A framework for selecting appropriate remote sensed data dimensions for environmental monitoring and management. Int J Remote Sens 19:3457–3463

Popescue SC, Wynne RH, Nelson RF (2003) Measuring individual tree crown diameter with LiDAR and assessing its influence on estimating forest volume and biomass. Can J Remote Sens 29:564–577

Porter J, Arzberger P, Braun H, Brynat P, Gage S, Hansen T, Lin C, Lin F, Kratz T, Michener W, Shapiro S, Williams T (2005) Wireless sensor networks for ecology. BioScience 55:561–572

Quattrochi DA, Goodchild MF (1997) Scale in remote sensing and GIS. Lewis Publishers, New York

Ramapriyan HK (2002) Satellite imagery in earth science applications. In: Castelli V, Bergman LD (eds) Image databases search and retrieval of digital imagery. Wiley, Chichester

Renslow M, Greenfield P, Guay T (2000) Evaluation of multi-return LiDAR for forestry applications. Project report for the inventory and monitoring steering committee, RSAC-2060/4810-LSP-0001-RPT1

Schenk T, Csatho B (2002) Fusion of lidar data and aerial imagery for a more complete surface description, Archives of photogrammetry

Schiewe J (1998) Experiences from the MOMS-02-Project for future developments. Intl Arch Photogramm Remote Sens 32:533–539

Secord J, Zakhor A (2007) Tree detection in urban regions using aerial lidar and image data. IEEE Geosci Remote Sens Lett 4:196–200

Sohn G, Dowman I (2005) Data fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction. ISPRS J Photogramm Remote Sens 62(1):43–63

Voss M, Sugumaran R (2008) Seasonal effect on tree species classification in an urban environment using hyperspectral data, LiDAR, and an object-oriented approach. Sensors 8:3020–3036

Webster TL, Forbes DL, Dickie S, Shreenan R (2004) Using topographic LiDAR to map flood risk from storm-surge events for Charlottetown, Prince Edward Island, Canada. Can J Remote Sens 30:64–76

Weng Q (2010) Remote sensing and GIS integration: theories, methods, and applications. McGraw-Hill, New York, p 416

Xue Y, Li Y, Guang J, Zhang X, Guo J (2008) Small satellite remote sensing applications—history, current and future. Int J Remote Sens 29:4339–4372