People's Democratic Republic of Algeria

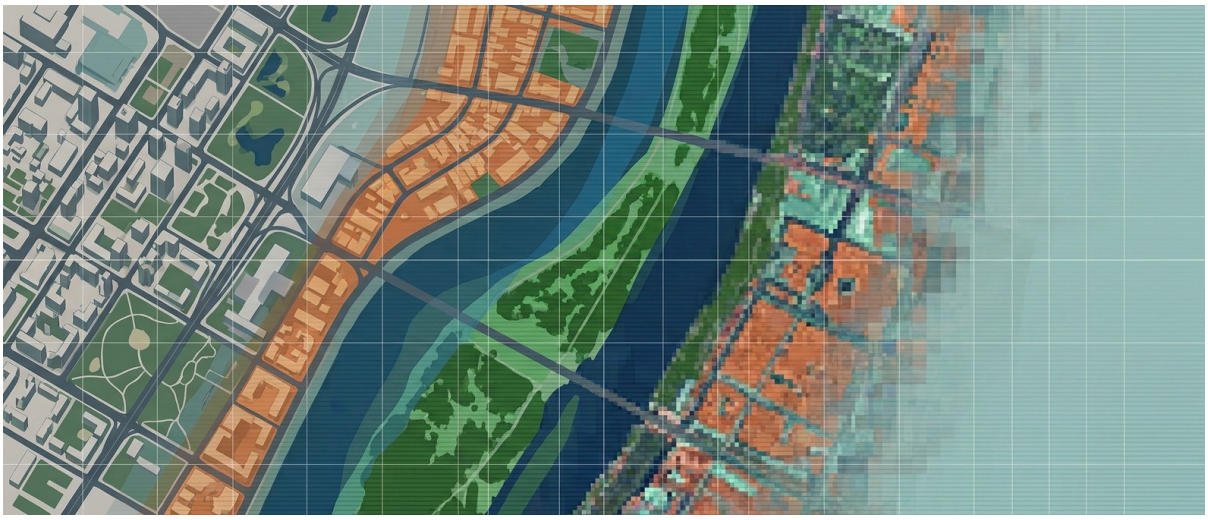
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Institute of Urban Techniques Management



COURSE MATERIAL • EDUCATIONAL HANDBOOK

Remote Sensing

Scientific Foundations and Applications to Urban Techniques Management

2nd Year Bachelor's Degree (Urban Engineering)

Urban Techniques Management

PRESENTED BY

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Foreword — How to Use This Handout

This handout introduces the scientific foundations of **remote sensing** (*télédétection*) and their practical application to **urban techniques management** (*gestion des techniques urbaines*). It is designed for second-year Licence students who have an introductory background in geography, urban planning, physics, and cartography, but little or no prior exposure to Earth observation. The text follows the official *Télédétection* syllabus and develops each theme into a self-contained, exam-ready lesson.

Each chapter follows a consistent pedagogical structure so that students can navigate the material predictably: an **introduction** that situates the topic and states its learning aims; a series of **developed sections** in which every key term is defined, illustrated, and supported by references to the scientific literature; a **conclusion** that synthesises the chapter; a **Key points** box; and a set of **review questions and exercises**. Figures and comparative tables accompany the text to reinforce visual understanding.

Throughout the handout, technical terms are given in English with the French equivalent in parentheses on first use, reflecting the bilingual reality of Algerian higher education. A consolidated bilingual glossary, a full bibliography, and a list of figures are provided at the end.

General Learning Objectives

By the end of this course, the student will be able to:

1. **Explain** the physical principles of remote sensing, including electromagnetic radiation, radiation–matter interactions, and the electromagnetic spectrum (Rees, 2013; Chuvieco, 2016).
2. **Distinguish** between platforms, sensors, and the four types of resolution, and select appropriate data for a given urban problem (Campbell & Wynne, 2011).
3. **Identify** the main satellite systems (Landsat, Sentinel, SPOT, IKONOS, Pléiades, MODIS) and their characteristics (Roy et al., 2014; Drusch et al., 2012).
4. **Apply** basic image-processing operations, including radiometric and geometric corrections, enhancement, and spectral indices such as NDVI, NDBI, and NDWI (Jensen, 2015).
5. **Perform and evaluate** a supervised or unsupervised image classification using standard accuracy measures (Congalton & Green, 2019).
6. **Integrate** remote sensing with GIS (*SIG*) to support urban management decisions concerning land use, urban sprawl, green spaces, heat islands, and change detection (Weng, 2012).

Prerequisites and Course Roadmap

Official course objective: *acquire the physical bases of remote sensing and be able to apply them in various domains of the Earth sciences and related fields.*

Prerequisites (official syllabus): Physics and the basics of cartography. A background in geography, elementary statistics, and introductory GIS is also helpful.

Roadmap: Chapters 1–4 establish the theoretical foundations (definitions, physical principles, platforms, resolutions). Chapters 5–8 address satellite systems, digital image fundamentals, image processing, and classification. Chapters 9–11 focus on urban applications, GIS integration, and a hands-on case study with a practical-works (TP/TD) programme. Chapter 12 offers a synthesis and perspectives, followed by reference material.

General Introduction

Remote sensing has, in the space of a few decades, moved from a specialised military and scientific activity to an everyday instrument of territorial management, and nowhere is its value more evident than in the study and administration of cities. This handout has been written to give second-year Licence students in *Gestion des Techniques Urbaines* a rigorous yet accessible foundation in that discipline, combining the physical theory that explains how the Earth is observed from a distance with the practical skills needed to turn satellite imagery into decisions about real urban territories (Campbell & Wynne, 2011; Weng, 2012).

The motivation for the course is the rapid transformation of Algerian cities. Urban growth, the spread of new poles such as Ali Mendjeli around Constantine, pressure on green space, and rising urban temperatures all demand timely, objective, and repeatable spatial information that traditional field surveys cannot supply economically (Patino & Duque, 2013). Remote sensing, especially now that major archives such as Landsat and the Copernicus/Sentinel missions are freely available, places exactly this capability within reach of universities and planning agencies working with modest budgets (Wulder et al., 2019; Drusch et al., 2012).

The handout is built on three convictions. First, that understanding must precede technique: a student who grasps *why* vegetation is bright in the near-infrared will use an index such as NDVI far more wisely than one who merely memorises a formula (Chuvieco, 2016). Second, that every concept should be anchored in the scientific literature, so that the reader learns not only the material but where to deepen it; in-text citations throughout point to the canonical textbooks and journal articles of the field. Third, that learning is consolidated by doing, which is why the text culminates in a worked case study of Constantine and a full programme of practical exercises reproducible with free data and open-source software (Congalton & Green, 2019; Congedo, 2021).

Structurally, the document proceeds from the general to the applied. It opens with the nature and physical principles of remote sensing (Chapters 1–2), turns to the instruments, resolutions, and satellite systems that acquire data (Chapters 3–5), develops the digital core of image structure, processing, and classification (Chapters 6–8), and finally applies these tools to concrete urban problems and to their integration within a Geographic Information System (Chapters 9–11), before offering a synthesis and outlook (Chapter 12). Annexes provide worked numerical examples, a formula and acronym sheet, a bilingual glossary, a complete bibliography, and a list of figures. Read in sequence, the chapters form a single chain of reasoning that leads from the photon leaving the Sun to the map that informs a planning decision.

Chapter 1 — General Introduction to Remote Sensing

Introduction

Remote sensing has become one of the most powerful tools available to geographers, planners, and environmental scientists for observing the Earth's surface. From the first balloon photographs of the nineteenth century to today's fleets of free-data satellites, the discipline has matured into an operational technology that underpins mapping, environmental monitoring, and urban management worldwide (Campbell & Wynne, 2011; Lillesand et al., 2015). This opening chapter defines remote sensing, situates it historically, describes the physical chain through which information is acquired, and explains why it is indispensable for the management of urban techniques. The aim is to give the student a clear conceptual map of the field before the physical principles are examined in detail in Chapter 2.

Because the discipline sits at the intersection of physics, computing, and geography, it is best approached first through its guiding ideas rather than its equations. The sections below therefore emphasise concepts, vocabulary, and the logic of the acquisition process, all of which will be revisited and formalised in later chapters.

1.1 Definition and Scope

Remote sensing (*télédétection*) is the science and technology of obtaining information about an object, area, or phenomenon **without being in physical contact** with it (Lillesand et al., 2015). In practice, information is derived by measuring the electromagnetic energy that surfaces reflect or emit, using sensors mounted on aircraft, drones, or satellites. A widely cited formulation describes remote sensing as *the acquisition, processing, and interpretation of measurements of electromagnetic radiation to derive information about the Earth's surface and atmosphere* (Campbell & Wynne, 2011).

The scope of the discipline is broad. It encompasses the physics of radiation, the engineering of sensors and platforms, the mathematics of image processing, and the thematic interpretation of results for a particular application domain (Jensen, 2007). For urban studies, remote sensing provides a **synoptic** (large-area), **repeatable**, and increasingly **low-cost** view of the city and its surroundings — an observational capability that field surveys alone cannot achieve efficiently

(Weng, 2012). It is important to distinguish remote sensing, which measures radiation, from Geographic Information Systems (GIS), which store and analyse spatial data; the two are complementary and are integrated in Chapter 10 (Longley et al., 2015).

1.2 A Brief History

The history of remote sensing mirrors advances in photography, aeronautics, and space technology (Colwell, 1983). Key milestones include:

- **19th century:** the first aerial photographs are taken from balloons, establishing the principle of overhead observation.
- **Early–mid 20th century:** aerial photography develops rapidly, particularly for military reconnaissance and topographic mapping during the two World Wars (Campbell & Wynne, 2011).
- **1957–1960s:** the space era begins with Sputnik and the first meteorological satellites (the TIROS series), demonstrating the value of orbital observation.
- **1972:** launch of **Landsat-1** (originally ERTS-1), the first civilian Earth-observation satellite dedicated to land resources — a decisive milestone that inaugurated systematic, repetitive land observation (Wulder et al., 2019).
- **1980s–1990s:** high-resolution commercial systems appear, notably **SPOT-1** in 1986, introducing pointable sensors and stereoscopic capability.
- **2000s–present:** very-high-resolution satellites (IKONOS in 1999, Pléiades in 2011), the free and open **Copernicus/Sentinel** programme, the rise of **drones (UAV)**, and cloud-based processing platforms such as Google Earth Engine (Gorelick et al., 2017).

This trajectory shows a consistent trend toward finer resolution, more frequent revisits, and easier access to data — developments that have progressively democratised the use of Earth observation in planning agencies and universities.

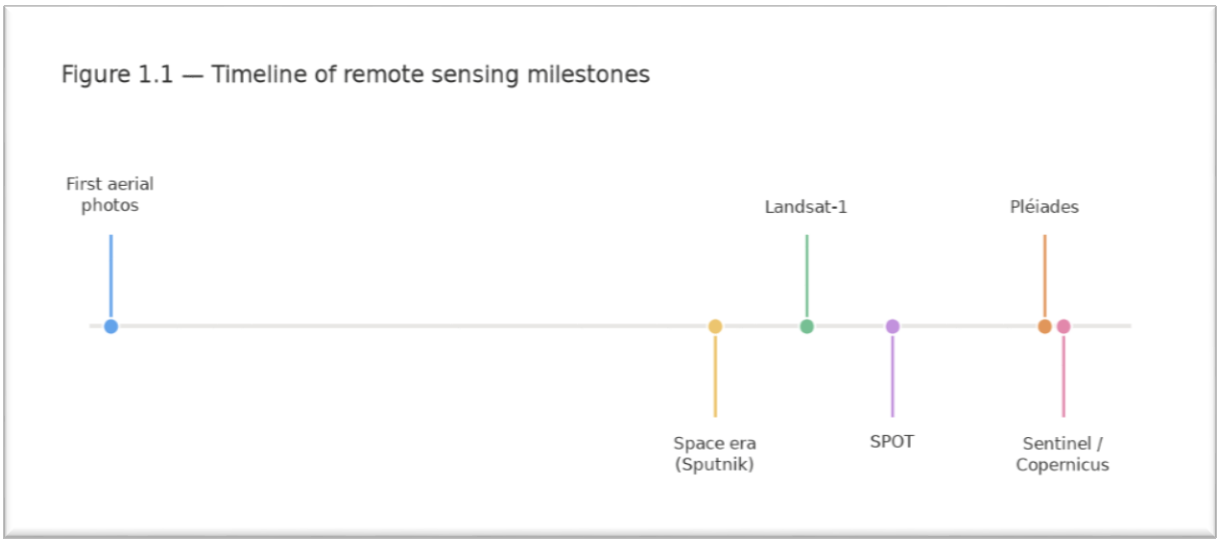


Figure 1.1 — Timeline of remote sensing milestones

1.3 The Remote Sensing Acquisition Chain

Remote sensing can be understood as a chain of seven linked elements, each of which can introduce information or error (Chuvieco, 2016):

1. **Energy source** — usually the Sun for passive systems, or the sensor itself for active systems such as radar and LiDAR.
2. **Atmosphere** — the medium the energy travels through (twice, in passive systems), where scattering and absorption modify the signal.
3. **Target** — the surface being observed (buildings, vegetation, water, soil), whose properties determine how energy is reflected or emitted.
4. **Sensor** — the instrument that records the incoming energy in defined spectral bands.
5. **Transmission and reception** — the downlink of raw data to ground receiving stations.
6. **Processing** — the correction and transformation of raw data into usable images and products.
7. **Interpretation and application** — the extraction of thematic information for the end user (e.g., a land-use map for a planning department).

Understanding this chain is essential because the quality of a final product depends on every link: a well-chosen sensor cannot compensate for uncorrected atmospheric effects, and accurate processing cannot rescue data acquired at an inappropriate resolution (Jensen, 2007).

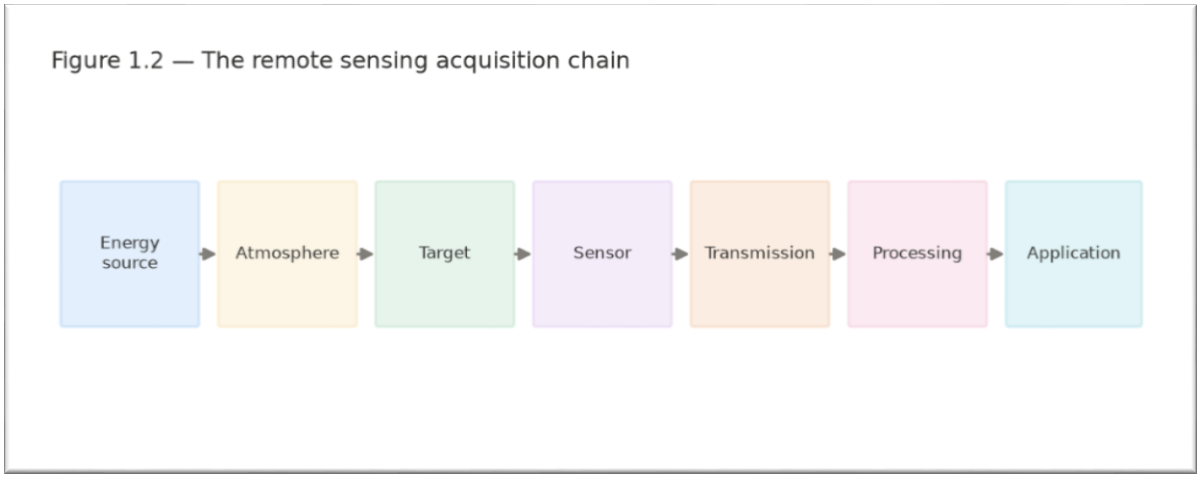


Figure 1.2 — The remote sensing acquisition chain

1.4 Why Remote Sensing Matters for Urban Techniques Management

Urban techniques management deals with the planning, monitoring, and maintenance of the physical city: land use, technical networks, green spaces, and public services. Remote sensing supports these tasks by supplying spatially exhaustive, regularly updated information (Weng, 2012). Its principal contributions include:

- **Up-to-date land-use / land-cover maps** that provide the spatial baseline for master plans and zoning.
- **Monitoring of urban growth** and informal expansion over time, enabling proactive infrastructure planning (Weng, 2012).
- **Inventory of green spaces** and assessment of vegetation health through spectral indices (Tucker, 1979).
- **Detection of urban heat islands** using thermal imagery, informing climate-sensitive design (Voogt & Oke, 2003).
- **Rapid assessment** after disasters such as floods or earthquakes, when field access is limited.

Compared with ground surveys, remote sensing is faster over large areas, repeatable at regular intervals, and increasingly affordable owing to free archives such as Landsat and Sentinel (Wulder et al., 2019; Drusch et al., 2012). For a rapidly urbanising country such as Algeria, these characteristics make it a strategic tool for evidence-based urban governance.

1.5 The Breadth of Application Domains

Although this handout concentrates on the city, the same principles serve many fields, which helps students see remote sensing as a general-purpose observational science (Campbell & Wynne, 2011). In **agriculture**, vegetation indices support crop monitoring and yield estimation (Tucker, 1979); in **forestry**, imagery maps deforestation and biomass; in **hydrology**, it delineates water bodies and flooded areas (McFeeters, 1996); in **geology**, spectral response reveals lithology and mineral alteration; and in **disaster management**, rapid imaging supports the response to floods and earthquakes (Jensen, 2007). Urban techniques management draws on all of these, because the city is simultaneously an agricultural fringe, a watershed, a geological setting, and a zone of risk. Recognising this breadth also clarifies why the physical and methodological foundations of the course are transferable well beyond the urban examples given here.

Conclusion

This chapter has defined remote sensing as the contactless acquisition of information through electromagnetic radiation, traced its evolution from balloon photography to free-data satellite constellations, and set out the seven-element acquisition chain that structures the whole discipline. It has also argued that remote sensing is uniquely suited to urban techniques management because it is synoptic, repeatable, and increasingly inexpensive. The conceptual vocabulary introduced here — source, atmosphere, target, sensor, resolution — provides the scaffolding for the physical principles developed in Chapter 2 and for the applied methods that follow.

✓ Key points

- Remote sensing = acquiring information about a surface without direct physical contact.
- It relies on measuring reflected or emitted electromagnetic energy.
- The acquisition chain runs through seven elements, from energy source to end-user application.
- For cities, it offers synoptic, repeatable, and cost-effective observation.

Review questions

8. Define remote sensing in your own words and contrast it with GIS.
9. List the seven elements of the acquisition chain and give one source of error for each.
10. Why was 1972 an important year for civilian remote sensing?
11. Give three advantages of remote sensing over field surveys for urban management.
12. Explain why every link in the acquisition chain matters for final product quality.

Chapter 2 — Physical Principles

Introduction

All remote sensing rests on a single physical fact: matter interacts with electromagnetic energy in ways that depend on wavelength and on the properties of the matter itself (Rees, 2013). To interpret an image correctly, the analyst must therefore understand what electromagnetic radiation is, how it is organised into a spectrum, how it interacts with surfaces and with the atmosphere, and why each material produces a characteristic response. This chapter builds that physical foundation. It corresponds directly to the "physical bases" component of the official syllabus, covering the electromagnetic spectrum, wave–matter interactions, scattering and absorption, the black-body concept, specular and diffuse reflection, and the spectral signature. Mastery of these principles is what separates the mechanical production of maps from their reasoned interpretation.

2.1 Electromagnetic Radiation and the Electromagnetic Spectrum

Remote sensing is based on **electromagnetic radiation (EMR)** — energy that propagates through space as coupled electric and magnetic waves at the speed of light (Rees, 2013). Each wave is described by its **wavelength** (*longueur d'onde*, symbol λ, commonly expressed in micrometres, μm) and its **frequency**; the two are inversely related through the speed of light. Radiation can also be treated as discrete packets of energy called photons, whose energy increases as wavelength decreases (Chuvieco, 2016).

The **electromagnetic spectrum** (*spectre électromagnétique*) is the ordered continuum of all wavelengths, from extremely short gamma rays to very long radio waves. Remote sensing exploits only certain regions of this continuum, chosen because surfaces respond diagnostically in them and because the atmosphere allows the energy to pass (Lillesand et al., 2015). The most useful regions are summarised below.

Region	Approx. wavelength	Typical use
Visible (blue, green, red)	0.4–0.7 µm	Natural-colour imaging, general mapping
Near-infrared (NIR)	0.7–1.3 µm	Vegetation analysis, biomass
Shortwave infrared (SWIR)	1.3–3 µm	Moisture, minerals, built-up areas
Thermal infrared (TIR)	3–14 µm	Surface temperature, heat islands
Microwave	1 mm–1 m	Radar, all-weather and night imaging

Figure 2.1 — The electromagnetic spectrum and the main remote sensing regions

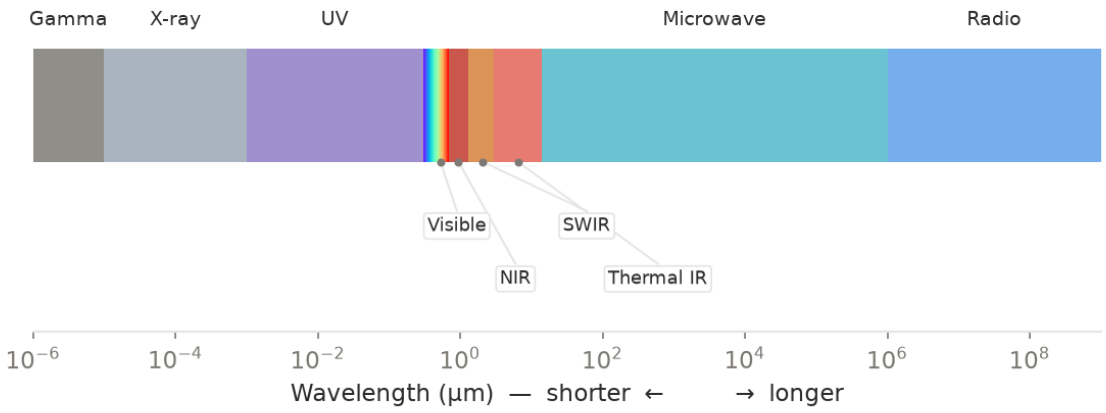


Figure 2.1 — The electromagnetic spectrum and the main remote sensing regions

2.2 Spectral Bands

Sensors do not record the whole spectrum continuously; they measure energy in discrete **spectral bands** (*bandes spectrales*) — defined wavelength intervals over which the incoming energy is integrated (Jensen, 2007). A **multispectral** sensor records a modest number of relatively broad bands (for example blue, green, red, and NIR), whereas a **hyperspectral** sensor records hundreds

of very narrow, contiguous bands, approximating a continuous spectrum for each pixel (Chuvieco, 2016).

The choice of bands is not arbitrary: it is engineered around the phenomena the mission is designed to observe. The pairing of a red band with a near-infrared band, for instance, is fundamental to vegetation studies because of the sharp increase in leaf reflectance across that boundary, a property exploited by the NDVI (Rouse et al., 1974; Tucker, 1979). Band placement therefore encodes the scientific priorities of a mission.

2.3 Radiation–Matter Interactions

When incoming energy reaches a surface, the total incident energy is partitioned among three processes, in proportions that depend on the material and the wavelength (Rees, 2013):

- **Reflection** (*réflexion*) — energy redirected away from the surface; this is the dominant signal in optical remote sensing.
- **Absorption** (*absorption*) — energy retained by the material and commonly re-emitted at longer (thermal) wavelengths.
- **Transmission** (*transmission*) — energy that passes through the body, as occurs partly in clear water.

Conservation of energy requires that the reflected, absorbed, and transmitted fractions sum to the incident energy (Chuvieco, 2016). Because these fractions vary with wavelength, every material reflects, absorbs, and transmits in a distinctive pattern — the physical origin of the **spectral signature** discussed in Chapter 6. The analyst's task is, in effect, to invert these interactions: to infer surface properties from the reflected and emitted energy the sensor records.

2.4 Atmospheric Effects

Between the Sun, the surface, and the sensor lies the atmosphere, which modifies the radiation and must be accounted for (Jensen, 2015). Two processes dominate:

- **Scattering** (*diffusion*) — the redirection of radiation by gases and aerosols. **Rayleigh scattering** by molecules is strongest at short wavelengths and explains the blue sky; **Mie scattering** by larger particles such as dust and smoke affects longer wavelengths; **non-**

selective scattering by cloud droplets affects all visible wavelengths equally, producing white clouds (Lillesand et al., 2015).

- **Absorption** (*absorption*) — the removal of energy at specific wavelengths by gases such as water vapour, carbon dioxide, and ozone.

Wavelength ranges in which the atmosphere is relatively transparent are called **atmospheric windows** (*fenêtres atmosphériques*), and sensors are deliberately designed to operate within them (Chuvieco, 2016). Because scattering and absorption alter the measured signal, **atmospheric correction** (Chapter 7) is required before images from different dates can be compared quantitatively.

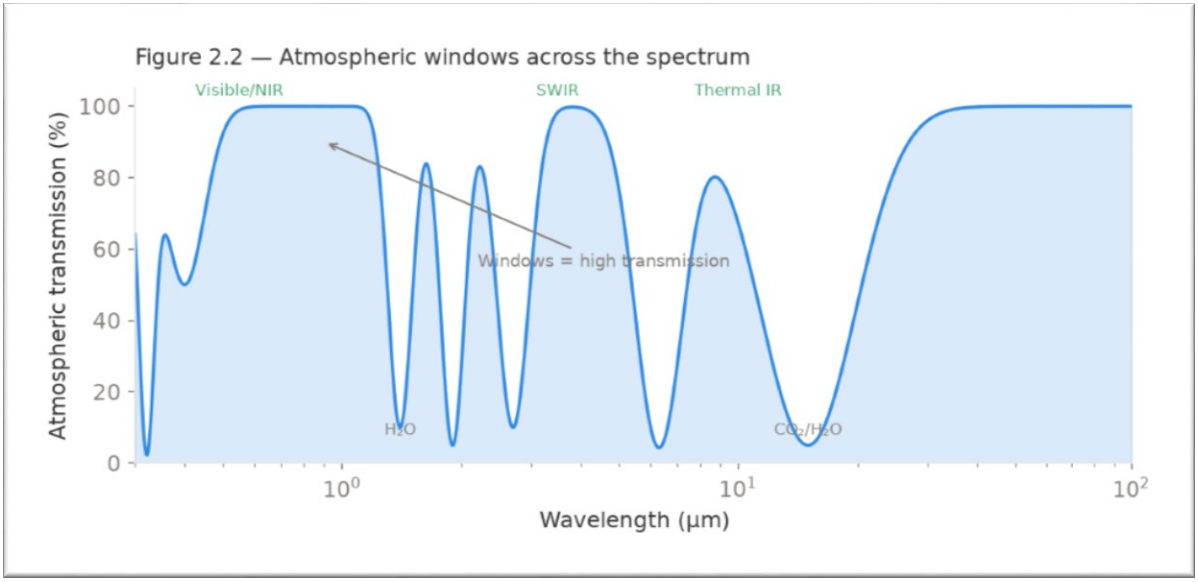


Figure 2.2 — Atmospheric windows across the spectrum

2.5 Black Body, Specular and Diffuse Reflection

Several idealised concepts allow surface behaviour to be modelled and compared (Rees, 2013):

- **Black body** (*corps noir*): an idealised object that absorbs all incident radiation and re-emits energy as a function of its temperature alone, following Planck's law; the total emitted energy rises steeply with temperature (Stefan–Boltzmann law) and the wavelength of peak emission shifts to shorter values as temperature increases (Wien's displacement law). Real surfaces emit less than a black body at the same temperature, a ratio expressed by their **emissivity** (*émissivité*), which is central to estimating land-surface temperature (Voogt & Oke, 2003).

- **Specular reflection** (*réflexion spéculaire*): mirror-like reflection from a surface that is smooth relative to the wavelength, such as calm water, where the angle of reflection equals the angle of incidence.
- **Diffuse reflection** (*réflexion diffuse*): reflection scattered in all directions by a rough surface, such as soil or vegetation; an ideal diffuse (Lambertian) reflector appears equally bright from all viewing angles.

Whether a given surface behaves specularly or diffusely depends on its roughness relative to the observing wavelength, which is why a surface may act as a mirror in the microwave region yet as a diffuse reflector in the visible (Chuvieco, 2016).

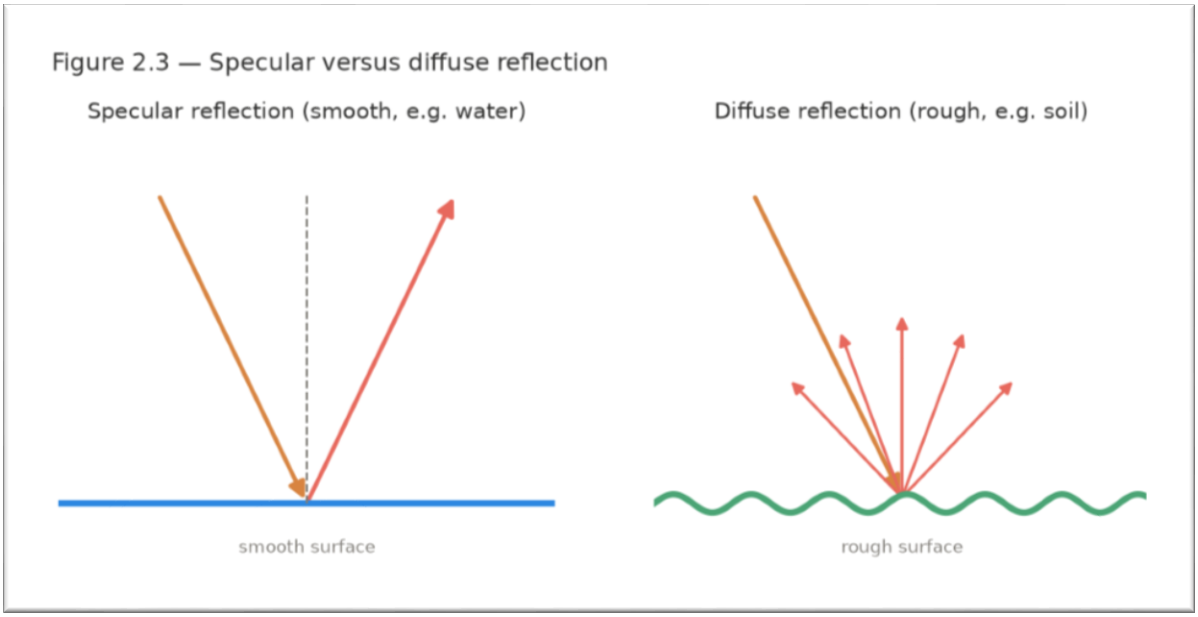


Figure 2.3 — Specular versus diffuse reflection

2.6 The Spectral Signature

The cumulative result of these interactions is that each surface reflects energy in a characteristic way across wavelengths — its **spectral signature** (*signature spectrale*). Healthy vegetation, for example, absorbs strongly in the red (chlorophyll absorption) and reflects strongly in the near-infrared (leaf cell structure), producing the steep "red edge" that vegetation indices exploit (Tucker, 1979). Water absorbs progressively toward the infrared and therefore appears dark there, while dry soils show a gradual rise in reflectance with wavelength (Lillesand et al., 2015). Spectral

signatures are the physical basis of image classification (Chapter 8) and are examined in detail in Chapter 6.

2.7 Quantifying Thermal Emission

The black-body concept becomes operational through three classical laws that the student should be able to state qualitatively (Rees, 2013). **Planck's law** describes how the energy a black body emits is distributed across wavelengths for a given temperature, producing a characteristic curve. **Wien's displacement law** states that the wavelength of peak emission is inversely proportional to temperature, which is why the very hot Sun peaks in the visible while terrestrial surfaces near 300 K peak in the thermal infrared around 9.7 μm (Chuvieco, 2016). **The Stefan–Boltzmann law** states that the total energy emitted rises with the fourth power of temperature, so small temperature increases produce large increases in emitted energy. Together these laws explain why thermal sensors are designed for the 8–14 μm window and why land-surface-temperature retrieval must account for emissivity, providing the physical justification for the urban-heat-island studies of Chapter 9 (Voogt & Oke, 2003).

Conclusion

This chapter has established the physics on which the whole discipline depends. It has shown that electromagnetic radiation, organised into a spectrum, interacts with matter through reflection, absorption, and transmission, and with the atmosphere through scattering and absorption. It has introduced the black-body model that underpins thermal remote sensing, distinguished specular from diffuse reflection, and defined the spectral signature that makes surfaces identifiable. These principles explain why particular bands are chosen, why atmospheric correction is necessary, and why classification is possible at all. With this foundation in place, Chapter 3 turns to the instruments and vehicles — sensors and platforms — that put these principles to work.

✓ Key points

- Remote sensing measures electromagnetic radiation, described by wavelength and frequency.
- The visible, infrared, thermal, and microwave regions are the most exploited.
- Energy interacts with surfaces (reflection, absorption, transmission) and the atmosphere (scattering, absorption).
- A black body is the ideal thermal emitter; real surfaces reflect specularly or diffusely and emit according to their emissivity.
- Sensors operate within atmospheric windows; each surface has a diagnostic spectral signature.

Review questions

13. Define wavelength and spectral band, and state how wavelength relates to photon energy.
14. Distinguish multispectral from hyperspectral sensors and give one use of each.
15. Name the three radiation–matter interactions and state the conservation principle linking them.
16. Explain Rayleigh scattering and why the sky appears blue.
17. State Planck's, Wien's, and Stefan–Boltzmann's roles in the black-body concept.
18. Distinguish specular from diffuse reflection and relate the distinction to surface roughness.

Chapter 3 — Platforms and Sensors

Introduction

The physical principles of Chapter 2 become useful only when they are embodied in real instruments carried on real vehicles. This chapter introduces the **platforms** that carry sensors and the **sensors** themselves, together with the orbits that govern when and where a satellite observes. It distinguishes passive from active systems and introduces radar and LiDAR, the two active technologies of greatest relevance to urban work. Understanding this hardware layer is a prerequisite for the informed selection of data discussed in Chapters 4 and 5, and it directly addresses the syllabus components on platforms, sensor characteristics, and active/passive sensing (Campbell & Wynne, 2011).

3.1 Platforms

A **platform** (*plateforme*) is the vehicle that carries the sensor, and its altitude and stability determine the scale, detail, and cost of the resulting imagery (Lillesand et al., 2015). The main categories are:

- **Ground-based platforms** — masts, towers, and field spectrometers used mainly for calibration and for building spectral libraries against which airborne and spaceborne data are validated (Chuvieco, 2016).
- **Aerial platforms** — crewed aircraft carrying metric cameras or digital sensors; they offer very high detail and flexible scheduling but at a high cost per unit area, which limits their use to targeted campaigns.
- **Drones / UAVs** (*drones*) — Unmanned Aerial Vehicles that deliver centimetre-scale detail over small areas and can be flown on demand, making them increasingly valuable for local urban inspection, construction monitoring, and heritage documentation (Colomina & Molina, 2014).
- **Satellites** (*satellites*) — orbital platforms that provide regular, large-area, and often global coverage, and which constitute the backbone of operational Earth observation (Wulder et al., 2019).

Each platform occupies a niche defined by the trade-off between spatial detail, areal coverage, revisit frequency, and cost; no single platform is optimal for every task.

3.2 Orbits

A satellite's usefulness is largely determined by its **orbit** (Rees, 2013). Two types dominate Earth observation:

- **Geostationary orbit** — at roughly 36,000 km altitude, the satellite completes one revolution per day and therefore appears fixed above a point on the equator. This geometry gives constant coverage of a fixed hemisphere and is ideal for meteorology and communications, but the great altitude yields coarse spatial detail (Campbell & Wynne, 2011).
- **Sun-synchronous (polar) orbit** — a near-polar, low-Earth orbit (typically 500–900 km) whose plane precesses so that the satellite crosses the equator at the same local solar time on every pass. This ensures consistent illumination conditions from date to date, which is essential for multi-temporal analysis, and it is used by most land-observation satellites, including Landsat and Sentinel-2 (Roy et al., 2014; Drusch et al., 2012).

Consistent illumination is not a technicality: comparing images acquired at different sun angles would confound genuine surface change with variation in shadowing, so the sun-synchronous design is what makes reliable change detection possible.

3.3 Passive vs. Active Sensors

Sensors are classified by their energy source (Chuvieco, 2016):

- **Passive sensors** (*capteurs passifs*) measure naturally available energy, chiefly reflected sunlight or the Earth's own thermal emission. They depend on solar illumination in the optical range and therefore cannot image at night (except in the thermal region) or through cloud. Optical and multispectral cameras are typical examples.
- **Active sensors** (*capteurs actifs*) generate their own energy, illuminate the target, and measure the returned signal. Because they carry their own "flashlight," they can operate day or night, and radar can penetrate cloud and rain. Radar and LiDAR are the principal examples (Lillesand et al., 2015).

The distinction has direct operational consequences: for monitoring a monsoon-season flood under persistent cloud, an active radar system is indispensable, whereas a passive optical sensor would be blind.

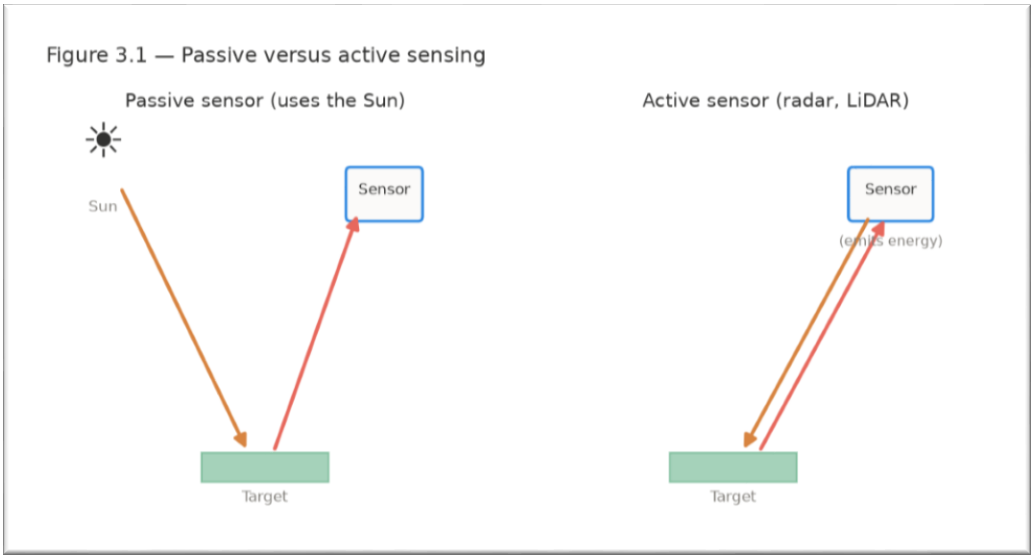


Figure 3.1 — Passive versus active sensing

3.4 Radar and LiDAR

Two active technologies deserve special mention because of their growing role in urban studies:

- **Radar** (RAdio Detection And Ranging), and in particular **Synthetic Aperture Radar (SAR)**, uses microwaves and so is largely unaffected by cloud and darkness. SAR is valuable for flood mapping, for detecting built structures through their strong backscatter, and, through interferometry (InSAR), for measuring ground and building deformation to millimetric precision (Ferretti et al., 2001).
- **LiDAR** (Light Detection And Ranging) uses laser pulses to measure distance with high accuracy, producing dense three-dimensional point clouds. It is the method of choice for deriving building heights, digital elevation and surface models, and detailed urban 3-D reconstructions (Colomina & Molina, 2014).

Together, radar and LiDAR complement optical imagery by adding all-weather capability and the third (vertical) dimension, both of which are increasingly demanded in modern urban management.

3.6 Matching Platform and Sensor to the Mission

Selecting a platform–sensor combination is an engineering compromise as much as a scientific choice (Joseph, 2005). A drone carrying a compact multispectral camera can deliver centimetre detail over a neighbourhood but cannot cover a metropolitan region; a sun-synchronous satellite covers the region repeatedly but at coarser detail. Likewise, an active radar system guarantees imagery through cloud yet requires specialised processing, whereas a passive optical sensor is intuitive to interpret but weather-dependent (Lillesand et al., 2015). The competent analyst therefore begins not with the instrument but with the question: the required detail, extent, frequency, and budget together determine which platform and sensor are appropriate. This mission-first logic recurs throughout the course and is formalised through the language of resolution in Chapter 4.

Conclusion

This chapter has surveyed the instruments of remote sensing: the platforms that carry sensors, from towers to satellites; the geostationary and sun-synchronous orbits that determine coverage and illumination; and the fundamental division between passive sensors, which rely on the Sun, and active sensors, which supply their own energy. It has shown why sun-synchronous orbits enable reliable change detection and why active systems such as SAR and LiDAR are indispensable when cloud, darkness, or the vertical dimension are at stake. The characteristics introduced here — altitude, orbit, and energy source — lead naturally to the quantitative language of resolution, which Chapter 4 develops.

✓ Key points

- A platform carries the sensor: ground, aerial, drone, or satellite, each with a distinct cost–detail–coverage niche.
- Geostationary orbits suit meteorology; sun-synchronous orbits give constant illumination for land observation.
- Passive sensors depend on the Sun; active sensors supply their own energy.
- Radar (SAR) works in all weather; LiDAR delivers precise 3-D data.

Review questions

19. List four platform types and give one advantage and one limitation of each.
20. Contrast geostationary and sun-synchronous orbits, and explain why illumination consistency matters.
21. Give two operational differences between passive and active sensors.
22. For mapping building heights across a city, would you choose radar or LiDAR? Justify your answer.
23. Explain how InSAR can contribute to urban risk management.

Chapter 4 — The Four Resolutions

Introduction

When planners ask whether a particular satellite is "good enough" for a task, they are really asking about its resolutions. Resolution is the vocabulary with which the capabilities and limits of a sensor are described, and it has four distinct dimensions — spatial, spectral, temporal, and radiometric (Jensen, 2007). This chapter defines each in turn, explains the inevitable trade-offs among them, and shows how to match a sensor's resolutions to an urban question. It corresponds to the syllabus component on spatial, spectral, and radiometric resolution and prepares the comparative survey of satellite systems in Chapter 5.

4.1 Spatial Resolution

Spatial resolution (*résolution spatiale*) is the size of the smallest feature that a sensor can distinguish, usually expressed as the ground dimension of a single **pixel** — for example 10 m for Sentinel-2 or 30 m for Landsat (Lillesand et al., 2015). High spatial resolution (small pixels) reveals fine urban detail such as individual buildings and roads, whereas low resolution covers large areas efficiently but blurs small objects. The appropriate resolution depends on the smallest object of interest: cadastral mapping demands sub-metre data, whereas regional land-cover monitoring is well served by tens of metres (Weng, 2012).

4.2 Spectral Resolution

Spectral resolution (*résolution spectrale*) refers to the number and narrowness of the bands a sensor records (Chuvieco, 2016). Finer spectral resolution — many narrow bands — allows subtler discrimination between materials that look similar to the eye, such as different roofing materials or vegetation species. Hyperspectral sensors carry this to its limit, recording hundreds of contiguous bands, but at the cost of data volume and processing complexity (Jensen, 2015).

4.3 Temporal Resolution

Temporal resolution (*résolution temporelle*), or **revisit time**, is how frequently a sensor images the same location — for example roughly five days for the Sentinel-2 constellation and sixteen days for a single Landsat satellite (Drusch et al., 2012; Roy et al., 2014). It is decisive for monitoring dynamic processes such as seasonal vegetation cycles, construction progress, and rapid urban expansion, and it is the resolution most directly linked to **change detection** (Singh, 1989).

4.4 Radiometric Resolution

Radiometric resolution (*résolution radiométrique*) is the sensor's ability to distinguish small differences in energy intensity, expressed as the number of bits used to store each measurement — an 8-bit sensor records 256 levels, a 12-bit sensor 4,096 levels (Lillesand et al., 2015). Higher radiometric resolution captures subtle contrasts, for instance small temperature differences within a city, which coarser quantisation would merge into a single value.

4.5 Trade-offs and Choosing the Right Data

The four resolutions cannot all be maximised at once, because of physical and engineering constraints on how much energy a small detector can collect in a short dwell time (Joseph, 2005). A sensor with very fine spatial resolution typically images a narrow swath and therefore revisits less often, whereas a wide-swath sensor achieving daily coverage must accept coarse pixels. Selecting data is thus an exercise in matching the dominant resolution requirement to the task, subject to budget and area constraints.

Urban task	Priority resolution
Detailed building and cadastral mapping	Spatial (very high)
Vegetation-type or material discrimination	Spectral
Monitoring rapid urban growth	Temporal
Subtle surface-temperature differences	Radiometric + thermal

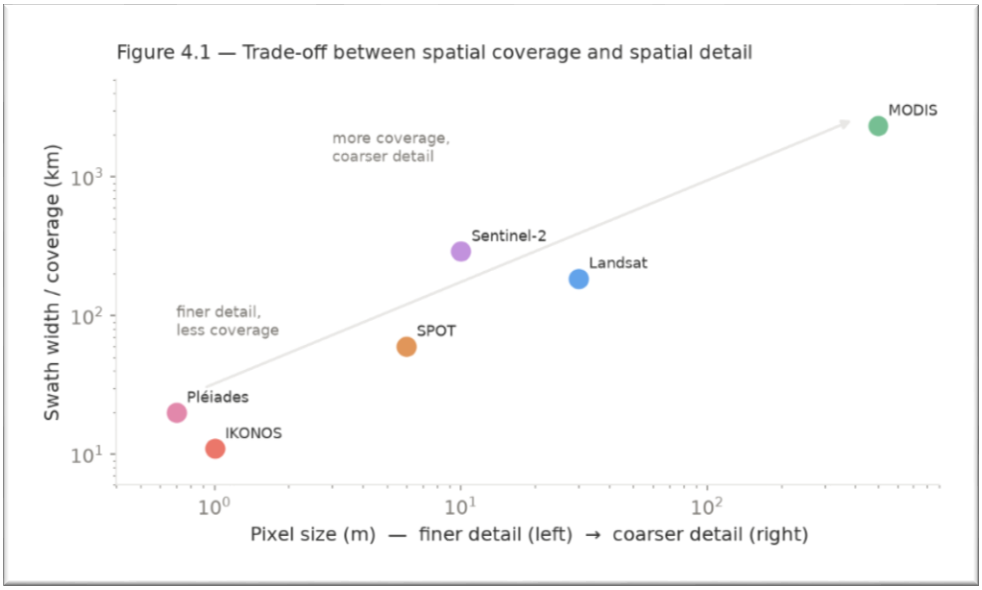


Figure 4.1 — Trade-off between spatial coverage and spatial detail

4.6 Illustrating the Trade-off

Consider a planner who must monitor annual built-up growth across an entire wilaya while also mapping individual new buildings in one district. No single sensor serves both needs. Sentinel-2, free and revisiting every five days at 10 m, is ideal for the regional annual monitoring because its temporal and spatial resolutions suit the scale of the phenomenon (Drusch et al., 2012). For the district-level building inventory, however, sub-metre data from Pléiades or an equivalent very-high-resolution source is required, accepting the higher cost and narrower coverage (Gleyzes et al., 2012). The rational solution is thus a two-tier data strategy — free medium-resolution data for extensive monitoring and targeted very-high-resolution data for detail — which is exactly what the resolution trade-off predicts and what many planning agencies now adopt (Weng, 2012).

Conclusion

This chapter has introduced the four resolutions — spatial, spectral, temporal, and radiometric — that together characterise any imaging sensor, and it has shown that they stand in tension with one another. The practical consequence is that data selection is always a compromise guided by the specific urban question, the available budget, and the size of the study area. Equipped with this framework, the student can now evaluate and compare the real satellite systems presented in Chapter 5 rather than being dazzled by any single specification.

✓ Key points

- Spatial = pixel/ground detail; spectral = number and width of bands.
- Temporal = revisit frequency; radiometric = sensitivity to intensity, in bits.
- The four resolutions trade off against one another; no sensor maximises all four.
- Data selection matches the dominant resolution to the task, budget, and area.

Review questions

24. Define the four types of resolution.
25. A sensor has 30 m pixels and a 16-day revisit; which resolutions are described?
26. Explain, in physical terms, why a sensor cannot maximise spatial and temporal resolution simultaneously.
27. For each task in the table, justify the priority resolution indicated.
28. Why does higher radiometric resolution help in mapping urban heat islands?

Chapter 5 — Main Satellite Systems

Introduction

Having established the language of resolution, this chapter surveys the satellite systems most relevant to urban techniques management and explains how their characteristics suit particular tasks. It covers the long-running Landsat archive, the European Sentinel constellation, the French SPOT and Pléiades series, the pioneering commercial IKONOS mission, and the coarse-resolution MODIS system, before summarising them in a comparative table and indicating where free data may be obtained. The systems named here — LANDSAT, SPOT, and IKONOS in particular — are those specified in the official syllabus (Wulder et al., 2019; Roy et al., 2014).

5.1 Landsat Programme

The **Landsat** programme, operated jointly by NASA and the USGS since 1972, provides the longest continuous record of the Earth's land surface and is a cornerstone of change studies (Wulder et al., 2019). Current sensors (the OLI and TIRS instruments on Landsat 8 and 9) deliver multispectral bands at **30 m** resolution, a 15 m panchromatic band, thermal bands at 100 m, and a **16-day** revisit that halves to eight days when both satellites are combined (Roy et al., 2014). Since 2008 the entire archive has been distributed free of charge, a policy change that transformed the discipline and greatly expanded its use in universities and planning agencies (Wulder et al., 2019).

5.2 Sentinel (Copernicus Programme)

The **Sentinel** satellites form the space component of the European Union's **Copernicus** programme, operated by ESA, and provide free and open data (Drusch et al., 2012). Two missions are especially relevant to urban work:

- **Sentinel-2** (optical/multispectral): a two-satellite constellation carrying thirteen bands at **10–20 m** resolution with a combined revisit of about five days — outstanding for land-cover mapping and vegetation monitoring (Drusch et al., 2012).
- **Sentinel-1** (C-band SAR): an active radar mission providing all-weather, day-and-night imaging, widely used for flood mapping and for measuring ground deformation through interferometry (Torres et al., 2012).

The combination of free access, fine resolution, and frequent revisit has made Sentinel data a default choice for operational monitoring.

5.3 SPOT, IKONOS, and Pléiades

- **SPOT** (*Satellite Pour l'Observation de la Terre*, France, since 1986): a series that introduced pointable, stereo-capable sensors; the current SPOT 6/7 provide resolutions down to about 1.5 m and are widely used for detailed topographic mapping (Lillesand et al., 2015).
- **IKONOS** (USA, launched 1999): one of the first commercial **very-high-resolution** satellites, offering 1 m panchromatic and 4 m multispectral imagery. It pioneered detailed urban and cadastral mapping from space and demonstrated a commercial market for sub-metre data before it was retired in 2015 (Dial et al., 2003).
- **Pléiades** (France, since 2011): a very-high-resolution pair providing 0.5 m panchromatic and 2 m multispectral imagery with daily revisit capability, suited to detailed urban and cadastral studies; the data are largely commercial (Gleyzes et al., 2012).

These systems illustrate the very-high-resolution end of the spectrum, where cost is exchanged for the ability to resolve individual buildings and parcels.

5.4 MODIS and Other Systems

- **MODIS** (on NASA's Terra and Aqua satellites): a coarse-resolution sensor (250 m—1 km) with **daily** global coverage, ideal for regional and climate-scale monitoring but unsuitable for detailed urban mapping (Justice et al., 1998).
- Other systems include the commercial very-high-resolution **WorldView/GeoEye** series, the multispectral/thermal **ASTER** instrument, and rapidly growing constellations of small satellites such as PlanetScope, which trade radiometric fidelity for near-daily, metre-scale coverage.

The proliferation of these systems means that, for most urban questions, the analyst now chooses among several suitable data sources rather than being constrained to one.

5.5 Comparative Table and Data Access

System	Spatial resolution	Revisit	Access
Landsat 8/9	30 m (15 m pan)	16 days	Free
Sentinel-2	10–20 m	~5 days	Free
SPOT 6/7	1.5–6 m	1–3 days	Commercial
IKONOS	1–4 m	~3 days	Commercial (retired 2015)
Pléiades	0.5–2 m	~1 day	Commercial
MODIS	250 m–1 km	Daily	Free

Free data (Landsat, Sentinel, MODIS) can be downloaded from portals such as USGS EarthExplorer and the Copernicus Data Space Ecosystem (Wulder et al., 2019).

5.6 Choosing a System in Practice

In practice, the choice of satellite system follows a short decision sequence (Wulder et al., 2019). First, the analyst asks whether the budget permits commercial data; if not, the choice narrows to the free Landsat, Sentinel, and MODIS archives. Second, the required spatial detail is compared with the smallest feature of interest: tens of metres suffice for regional land cover, whereas metres or sub-metre are needed for buildings and parcels. Third, the revisit requirement is checked against the pace of the phenomenon. For the majority of urban monitoring tasks in a resource-conscious setting, **Sentinel-2** offers the best compromise of resolution, revisit, and cost, while **Landsat** supplies the essential historical baseline reaching back to the 1970s and 1980s (Roy et al., 2014; Drusch et al., 2012). This reasoning turns an intimidating catalogue of satellites into a manageable, criteria-driven decision.

Conclusion

This chapter has compared the principal satellite systems used in urban remote sensing, from the fifty-year Landsat archive and the free, frequent Sentinel-2 mission to the very-high-resolution SPOT, IKONOS, and Pléiades series and the coarse but daily MODIS sensor. The recurring theme is the resolution trade-off of Chapter 4: free medium-resolution missions excel at monitoring and change detection, whereas commercial very-high-resolution systems are reserved for detailed

mapping where budgets allow. With a clear view of available data, the student is ready to consider how that data is structured digitally, the subject of Chapter 6.

✓ Key points

- Landsat offers a fifty-year free archive at 30 m; Sentinel-2 gives free 10 m data every ~5 days.
- SPOT, IKONOS, and Pléiades provide very high resolution but are commercial.
- MODIS trades resolution for daily global coverage.
- Free imagery is available from USGS EarthExplorer and the Copernicus Data Space.

Review questions

29. Which free satellite would you choose for 10 m land-cover mapping, and why?
30. Compare Landsat and Pléiades in terms of resolution, revisit, and cost.
31. Why is MODIS unsuitable for detailed urban mapping but valuable for regional monitoring?
32. What was the historical significance of IKONOS?
33. Name two portals from which free imagery can be downloaded.

Chapter 6 — Digital Image Fundamentals

Introduction

A satellite image is, before anything else, a structured array of numbers. To process and interpret imagery competently, the student must understand how that array is organised, what its values mean, and how the multiple spectral bands relate to one another. This chapter explains pixels and digital numbers, the raster band structure, the spectral signature as it appears in real data, and the colour composites through which multispectral information is made visible. It provides the conceptual bridge between the physics of Chapter 2 and the processing operations of Chapter 7 (Jensen, 2015).

6.1 Pixels and Digital Numbers

A digital remote sensing image is a **raster** — a regular grid of cells called **pixels** (*pixels*) — in which each cell stores a **digital number (DN)**, an integer proportional to the radiant energy the sensor recorded within a given band (Lillesand et al., 2015). The DN is not itself a physical quantity; it is a quantised, sensor-specific value that must be converted, through radiometric calibration, into radiance and then into reflectance before it can be compared across sensors or dates (Jensen, 2015). The number of distinct DN values a pixel can take is set by the sensor's radiometric resolution (Chapter 4).

6.2 Raster Structure and Image Bands

A multispectral image is not a single grid but a **stack of co-registered bands**, one grid per spectral interval, so that every pixel is associated with a vector of values — one per band (Richards, 2013). This layered structure is what enables band arithmetic and the computation of spectral indices, because operations can be performed pixel-by-pixel across bands. It also underlies classification, in which the multi-band vector of each pixel is treated as a point in a feature space and assigned to the class whose training statistics it most closely matches (Chapter 8).

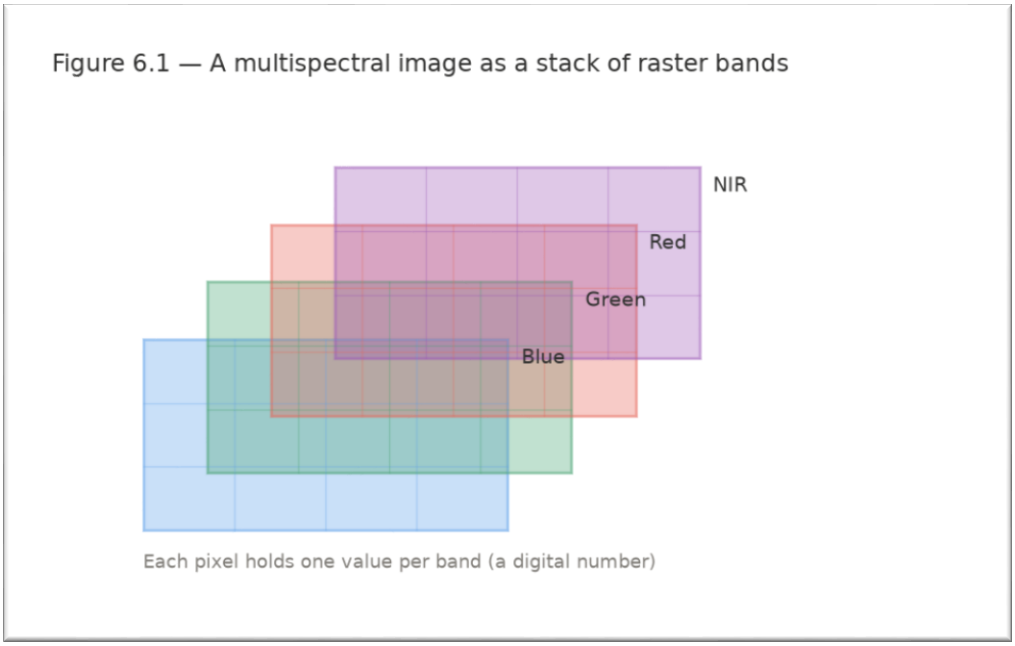


Figure 6.1 — A multispectral image as a stack of raster bands

6.3 Spectral Signatures

The **spectral signature** (*signature spectrale*) of a surface is the pattern of its reflectance across wavelengths, and it is the practical expression of the radiation–matter interactions of Chapter 2 (Chuvieco, 2016). Characteristic examples include:

- **Healthy vegetation:** low reflectance in the red owing to chlorophyll absorption, rising sharply to high reflectance in the near-infrared — the "red edge" exploited by vegetation indices (Tucker, 1979).
- **Water:** moderate reflectance in the visible and strong absorption in the near-infrared, so water appears dark in NIR imagery (Lillesand et al., 2015).
- **Built-up surfaces:** a relatively flat, moderate response across the visible and infrared, often with elevated reflectance in the SWIR that indices such as NDBI exploit (Zha et al., 2003).

Because these signatures differ systematically, they allow surfaces to be identified and separated — the foundation of image classification.

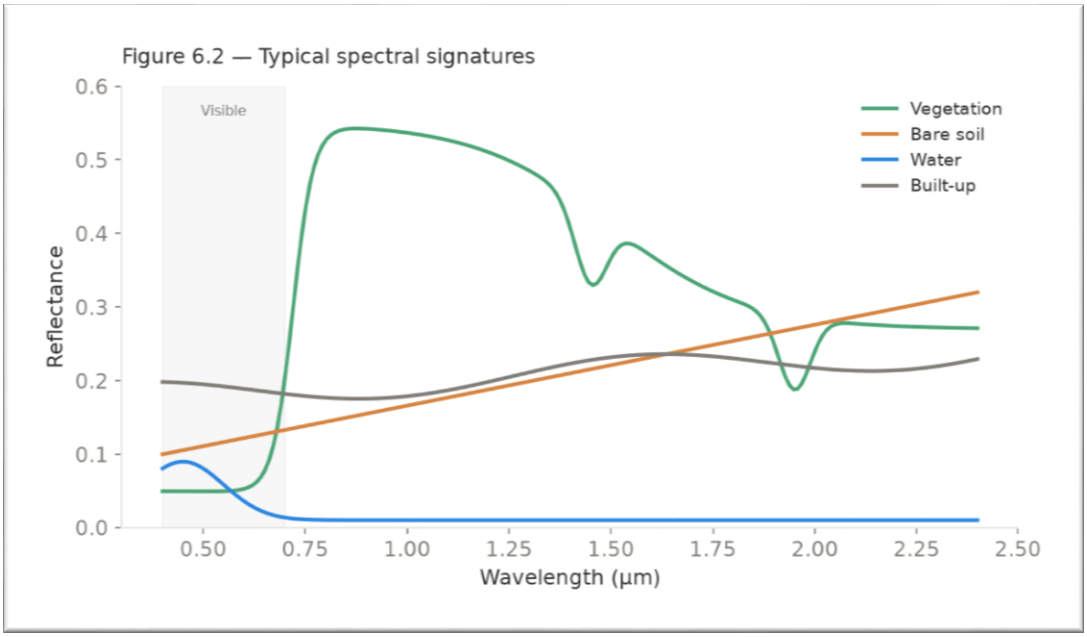


Figure 6.2 — Typical spectral signatures of vegetation, water, and soil

6.4 Colour Composites

Since display screens combine red, green, and blue (RGB) channels, multispectral data are visualised by assigning three chosen bands to these channels (Jensen, 2015):

- A **true-colour composite** assigns the red, green, and blue bands to the corresponding channels, producing a scene that resembles natural vision.
- A **false-colour composite** assigns non-visible bands to visible channels — classically near-infrared to red, red to green, and green to blue — so that vigorous vegetation appears bright red. This standard combination is widely used because it emphasises the vegetation response that the eye cannot see directly (Lillesand et al., 2015).

Colour composites are an interpretive aid rather than an analytical result; the same bands may be combined in many ways to highlight different features.

6.5 The Feature Space

Because each pixel carries a vector of band values, an image can be represented in a multi-dimensional **feature space** whose axes are the spectral bands (Richards, 2013). In this space, pixels belonging to the same surface type cluster together while different surfaces occupy different regions — the geometric intuition underlying classification in Chapter 8. Adjacent bands are often

strongly correlated, carrying overlapping information; techniques such as principal component analysis compress this redundancy into fewer, uncorrelated components, easing visualisation and reducing data volume (Jensen, 2015). Understanding the feature space clarifies why adding well-chosen bands improves class separability while adding highly correlated bands adds little — an insight that connects spectral resolution (Chapter 4) to classification performance (Chapter 8).

Conclusion

This chapter has shown that a satellite image is a stack of raster bands whose pixels store digital numbers, that these numbers must be calibrated to reflectance for quantitative use, and that the resulting per-pixel spectra — spectral signatures — make surfaces distinguishable. It has also explained how true- and false-colour composites render multi-band data visible. These fundamentals are the immediate prerequisite for the corrections, enhancements, and indices of Chapter 7, which transform raw imagery into analysis-ready products.

✓ Key points

- Images are rasters of pixels; each pixel holds a digital number (DN) requiring calibration to reflectance.
- Multispectral images are stacks of co-registered bands, giving each pixel a spectral vector.
- Every surface has a diagnostic spectral signature; vegetation, water, and built-up areas differ systematically.
- True- and false-colour composites display selected bands in the RGB channels.

Review questions

34. What is a pixel, and what does its digital number represent?
35. Why must digital numbers be converted to reflectance before multi-date comparison?
36. Describe the spectral signature of healthy vegetation and explain the "red edge."
37. Why does vegetation appear bright red in a standard false-colour composite?
38. Distinguish true-colour from false-colour composites and give a use for each.

Chapter 7 — Image Processing

Introduction

Raw satellite data are rarely fit for immediate analysis: they contain sensor artefacts, atmospheric effects, and geometric distortions, and their information is not always presented in the most useful form. Image processing is the set of operations that turns raw data into analysis-ready products and then extracts thematic information from them. This chapter treats the three stages that structure the syllabus's "imagery and processing" component: geometric correction and georeferencing; radiometric and atmospheric correction; and enhancement, colour composites, and filters, concluding with the spectral indices central to urban analysis (Jensen, 2015; Richards, 2013).

7.1 Pre-processing: Geometric Correction and Georeferencing

Geometric correction (*correction géométrique*) removes the spatial distortions introduced by the Earth's curvature and rotation, terrain relief, and sensor viewing geometry, so that image pixels correspond to their true positions on the ground (Lillesand et al., 2015). **Georeferencing** then assigns a map coordinate system — for Algeria typically a UTM projection on a suitable datum — allowing the image to be overlaid accurately with maps and GIS layers (Longley et al., 2015). Without accurate geometry, multi-date comparison and integration with other spatial data are impossible, because apparent change would be confounded with misregistration (Singh, 1989).

7.2 Pre-processing: Radiometric and Atmospheric Correction

Radiometric correction (*correction radiométrique*) compensates for sensor-related errors — detector miscalibration, striping, and dropped lines — and converts digital numbers to physically meaningful radiance and reflectance (Jensen, 2015). **Atmospheric correction** (*correction atmosphérique*) then removes the scattering and absorption effects described in Chapter 2 to yield **surface reflectance**, the quantity required for consistent comparison across dates and sensors (Chuvieco, 2016). Atmospheric correction is particularly important for change detection and for computing spectral indices, whose values would otherwise drift with atmospheric conditions rather than with the surface itself.

7.3 Image Enhancement, Colour Composites, and Filters

Enhancement improves the visual interpretability of an image without altering the analytical conclusions drawn from calibrated data (Richards, 2013):

- **Contrast enhancement / stretching** (*rehaussement du contraste*) redistributes digital numbers across the available display range — by linear stretching, histogram equalisation, or similar methods — so that subtle differences become visible.
- **Colour composites** (*compositions colorées*) assign spectral bands to the red, green, and blue channels to highlight particular features, as described in Chapter 6.
- **Filters** (*filtres*) are moving-window operations applied over the image:
- Low-pass (smoothing) filters average neighbouring pixels to reduce noise, at the cost of fine detail.
- High-pass filters emphasise abrupt changes and so sharpen the image.
- Edge-detection filters such as the Sobel and Laplacian operators isolate boundaries, helping to delineate roads, field edges, and building outlines (Gonzalez & Woods, 2018).

Enhancement and filtering are interpretive tools; because they are applied to display or derived layers, they must be distinguished from the corrections of §7.1–7.2, which restore physical fidelity.

7.4 Spectral Indices

Spectral indices combine two or more bands arithmetically to accentuate a target property while suppressing irrelevant variation (Chuvieco, 2016). The most important for urban studies are:

- **NDVI** (Normalized Difference Vegetation Index): NDVI = (NIR − Red) / (NIR + Red), which measures vegetation vigour on a scale from −1 to +1 and is the most widely used index in the discipline (Rouse et al., 1974; Tucker, 1979).
- **NDBI** (Normalized Difference Built-up Index): NDBI = (SWIR − NIR) / (SWIR + NIR), which highlights impervious, built-up surfaces (Zha et al., 2003).
- **NDWI** (Normalized Difference Water Index): NDWI = (Green − NIR) / (Green + NIR), which delineates open water bodies (McFeeters, 1996).

Indices are valued because they are simple, physically interpretable, and largely comparable across dates once atmospheric correction has been applied, which makes them ideal inputs to change analysis and classification.

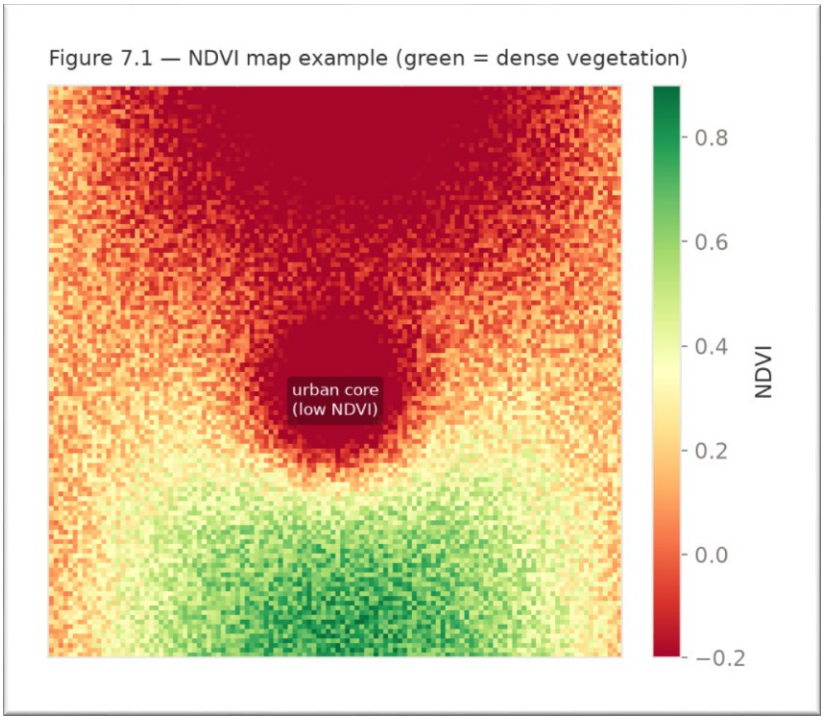


Figure 7.1 — NDVI map example (high values = dense vegetation)

7.5 Error Propagation and Good Practice

Each processing step can introduce or amplify error, and a professional workflow manages this explicitly (Jensen, 2015). Residual geometric misregistration between dates produces false change along every edge; incomplete atmospheric correction biases index values; and aggressive contrast stretching, if mistaken for an analytical result, can mislead interpretation (Lu et al., 2004). Good practice therefore includes checking registration accuracy to a fraction of a pixel, using surface-reflectance products for any quantitative comparison, keeping enhancement strictly separate from analysis, and documenting every parameter so the result can be reproduced (Congalton & Green, 2019). Treating error as something to be quantified and reported, rather than ignored, is a hallmark of sound remote-sensing work and a habit students should cultivate from the outset.

Conclusion

This chapter has followed the processing pipeline from raw data to information: geometric correction and georeferencing to fix position, radiometric and atmospheric correction to restore physical values, enhancement and filtering to aid interpretation, and spectral indices to distil target properties. The essential distinction is between corrections, which recover fidelity and are

indispensable for quantitative comparison, and enhancements, which serve visual interpretation. With analysis-ready imagery and indices in hand, the student can proceed to classification, the subject of Chapter 8, where images are converted into thematic maps.

✓ Key points

- Pre-processing = geometric correction + georeferencing + radiometric and atmospheric correction.
- Georeferencing aligns imagery with GIS layers and enables multi-date comparison.
- Enhancement (stretching, composites, filters) aids interpretation but does not restore physical fidelity.
- NDVI, NDBI, and NDWI highlight vegetation, built-up areas, and water, respectively.

Review questions

39. Why is atmospheric correction necessary before multi-date comparison?
40. Write the NDVI formula, state its range, and interpret high and low values.
41. Which index would you use to map built-up expansion, and why?
42. Distinguish enhancement from correction with an example of each.
43. Describe the effect of low-pass, high-pass, and edge-detection filters.

Chapter 8 — Image Classification

Introduction

Classification is the operation that transforms a continuous image into a discrete thematic map — the land-use / land-cover product that most urban applications ultimately require. This chapter sets out the principle of classification, contrasts the unsupervised and supervised approaches, explains how classification accuracy is assessed, and introduces object-based image analysis for high-resolution urban scenes. Together these topics equip the student to produce and, crucially, to validate thematic maps (Lu & Weng, 2007; Congalton & Green, 2019).

8.1 Principles of Classification

Classification (*classification*) assigns every pixel, or every image object, to one of a set of predefined **classes** such as water, vegetation, built-up, and bare soil, thereby converting a multi-band image into a thematic map (Richards, 2013). The procedure exploits the fact that different surfaces occupy different regions of the multi-dimensional feature space defined by the spectral bands; classification is, in essence, the partitioning of that feature space (Lu & Weng, 2007).

8.2 Unsupervised Classification

In **unsupervised classification** (*classification non supervisée*) the software groups pixels into spectral clusters using an algorithm such as **K-means** or **ISODATA**, and the analyst subsequently attaches thematic labels to the clusters (Jensen, 2015). This approach requires little prior knowledge and is useful for exploratory analysis or where reference data are scarce, but the clusters produced are spectral rather than thematic and may not correspond neatly to the classes of interest.

8.3 Supervised Classification

In **supervised classification** (*classification supervisée*) the analyst first delineates **training samples** (*échantillons d'entraînement*) for each known class, and an algorithm then labels the whole image by comparison with these examples (Richards, 2013). Classical algorithms include the **Maximum Likelihood** classifier, while modern practice increasingly favours machine-learning methods such as **Random Forest** (Breiman, 2001) and **Support Vector Machines**, which cope well with high-dimensional data and complex class boundaries (Lu & Weng, 2007). Supervised methods are generally more accurate than unsupervised ones when representative training data are available.

8.4 Accuracy Assessment

A classification is not complete until its accuracy has been quantified against independent **reference data** (Congalton & Green, 2019). The standard tool is the **confusion matrix** (*matrice de confusion*), which cross-tabulates classified against reference labels and from which several measures are derived: **overall accuracy** (the proportion of correctly classified samples), **producer's and user's accuracies** for individual classes, and the **kappa coefficient**, which adjusts agreement for that expected by chance (Cohen, 1960; Foody, 2002). Reporting accuracy honestly is an ethical as well as a technical obligation, because downstream planning decisions depend on it (Congalton & Green, 2019).

8.5 Object-Based Image Analysis (OBIA)

Object-Based Image Analysis (OBIA) first segments the image into homogeneous **objects** — groups of adjacent, similar pixels — and then classifies these objects using spectral, textural, geometric, and contextual attributes (Blaschke, 2010). OBIA is particularly effective on very-high-resolution urban imagery, where the single-pixel "salt-and-pepper" noise of per-pixel methods is severe and where shape and context help distinguish, for example, a road from a rooftop of similar spectral response (Blaschke, 2010).

8.6 Reading a Confusion Matrix

To make accuracy assessment concrete, consider a small confusion matrix in which 100 reference points are compared with a classification. If 92 points fall on the diagonal (correctly classified), the **overall accuracy** is 92 %. Individual classes may nonetheless perform unevenly: if only 25 of 30 reference "vegetation" points were labelled correctly, the producer's accuracy for vegetation is 83 %, revealing a weakness the overall figure conceals (Congalton & Green, 2019). The **kappa coefficient** adjusts the 92 % for the agreement expected by chance; a kappa of about 0.88 would indicate strong agreement beyond chance (Cohen, 1960; Foody, 2002). This example shows why several measures are reported together: overall accuracy summarises performance, per-class accuracies expose specific confusions, and kappa guards against over-optimistic interpretation.

Conclusion

This chapter has explained how images become thematic maps through classification, contrasting unsupervised clustering with supervised, training-based methods, and highlighting the modern shift toward machine-learning classifiers. It has stressed that accuracy assessment through the confusion matrix, overall accuracy, and kappa is an indispensable part of the process, and it has shown why object-based analysis suits high-resolution urban scenes. Classified maps are the raw material of the applications examined in Chapter 9, where remote sensing is put to work on concrete urban problems.

✓ Key points

- Classification turns imagery into thematic (land-cover) maps by partitioning feature space.
- Unsupervised: the software clusters and the analyst labels afterwards.
- Supervised: the analyst provides training samples first; Random Forest and SVM are now common.
- Accuracy is judged with a confusion matrix, overall accuracy, and the kappa coefficient.
- OBIA classifies image objects and excels on very-high-resolution urban imagery.

Review questions

44. Contrast supervised and unsupervised classification.
45. What is a training sample, and why must it be representative?
46. Explain the roles of the confusion matrix, overall accuracy, and kappa.
47. Why is OBIA advantageous for very-high-resolution urban imagery?
48. Name two machine-learning classifiers and one advantage they offer over Maximum Likelihood.

Chapter 9 — Urban Applications

Introduction

The preceding chapters built the theory and technique of remote sensing; this chapter demonstrates their payoff for urban techniques management. It reviews the principal application domains — land-use/land-cover mapping, monitoring of urban sprawl, green-space inventory, urban heat islands, and change detection — showing in each case which data, indices, and methods are appropriate and what decisions they support. The applications are illustrated with reference to the challenges facing rapidly growing cities, a context directly relevant to Algerian urban management (Weng, 2012; Patino & Duque, 2013).

9.1 Land Use / Land Cover (LULC) Mapping

Land use / land cover (LULC) mapping classifies the territory into categories such as built-up, vegetation, water, bare soil, and transport surfaces, and it is the foundational product of urban remote sensing (Anderson et al., 1976). Land cover describes the physical material of the surface, whereas land use describes its human function; the two are related but distinct, and remote sensing observes cover directly while use is often inferred from context (Cihlar & Jansen, 2001). A current LULC map provides the spatial baseline for master plans, zoning, and the calculation of indicators such as impervious-surface fraction (Weng, 2012).

9.2 Monitoring Urban Sprawl

Urban sprawl (*étalement urbain*) is the outward, frequently low-density and poorly coordinated expansion of the built-up area, and it is one of the most consequential processes in contemporary cities (Ji et al., 2006). By comparing classified images from successive years, analysts can quantify the area of land converted to urban use, identify the direction and rate of growth, and detect informal settlements that official records may miss (Patino & Duque, 2013). Such evidence is essential for planning infrastructure and services ahead of, rather than behind, the advancing urban front.

9.3 Green Space Inventory and Management

Using NDVI together with classification, remote sensing can inventory **urban green spaces** — parks, gardens, street trees, and peri-urban agriculture — monitor their health, and assess whether their distribution matches the population's needs (Tucker, 1979; Weng, 2012). This is especially

important in dense cities, where equitable access to vegetation has recognised benefits for public health and microclimate, and where remote sensing offers the only practical means of a complete and repeatable census of greenery.

9.4 Urban Heat Islands

Thermal-infrared bands, such as those on Landsat, permit the estimation of **Land Surface Temperature (LST)** and thereby the mapping of **urban heat islands** (*îlots de chaleur urbains*) — zones significantly warmer than their surroundings owing to dense construction, impervious materials, and a deficit of vegetation (Oke, 1982; Voogt & Oke, 2003). Because LST is closely linked to surface cover and to the impervious fraction, remote sensing can both map heat islands and diagnose their causes, supporting climate-sensitive planning and the targeting of green-infrastructure interventions (Weng, 2009).

9.5 Change Detection

Change detection (*détection des changements*) compares imagery from two or more dates to reveal where and how the surface has changed — new construction, loss of vegetation, or conversion of agricultural land (Singh, 1989). Common techniques include image differencing, index differencing (for example of NDVI), and post-classification comparison, each with characteristic strengths and error sources (Lu et al., 2004). Reliable change detection depends critically on the accurate geometric and radiometric pre-processing of Chapter 7, without which spurious change is inevitable.

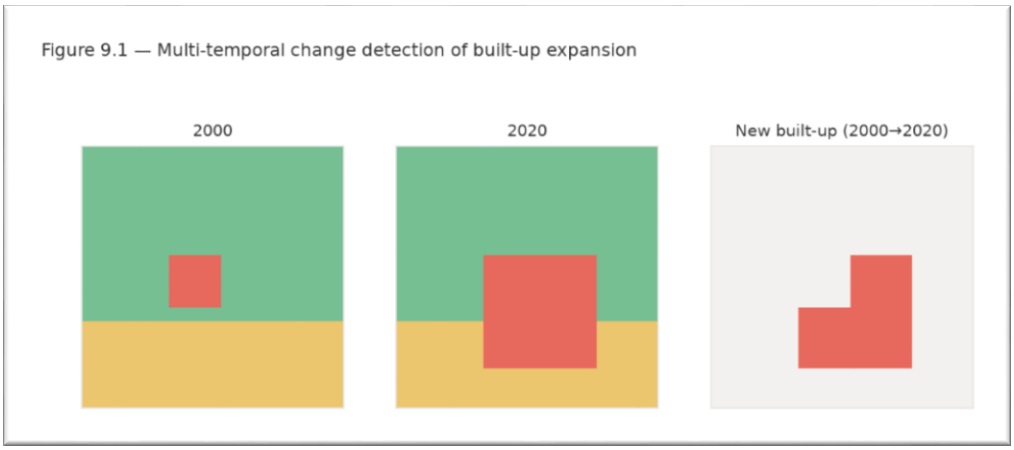


Figure 9.1 — Multi-temporal change detection of built-up expansion

9.6 Hazard and Risk Applications

Beyond growth and greenery, remote sensing supports the management of urban hazards, an increasingly urgent concern under climate change (Patino & Duque, 2013). Radar imagery from Sentinel-1, unaffected by cloud, is widely used to map flood extent during and after events, when optical sensors are obscured (Torres et al., 2012). NDWI and related indices help delineate standing water from optical data once skies clear (McFeeters, 1996), while InSAR measures the slow ground deformation that threatens buildings and networks (Ferretti et al., 2001). Combined in a GIS with data on population and infrastructure, these products allow planners to identify exposed zones and prioritise mitigation — a direct contribution of remote sensing to urban resilience that is especially relevant to cities with steep terrain such as Constantine.

Conclusion

This chapter has shown how the tools of remote sensing address concrete urban problems: LULC maps provide the spatial baseline, multi-temporal analysis quantifies sprawl and change, NDVI supports green-space management, and thermal data reveal heat islands and their causes. In every case the value of the technique depends on sound data selection and pre-processing, reinforcing the lessons of earlier chapters. These applications rarely stand alone, however; their full utility is realised when the results are integrated with other spatial data in a GIS, the subject of Chapter 10.

✓ Key points

- LULC maps distinguish physical cover from human use and form the urban spatial baseline.
- Multi-temporal analysis quantifies urban sprawl and detects informal growth.
- NDVI underpins green-space inventory; thermal data map urban heat islands and their causes.
- Change detection requires careful geometric and radiometric pre-processing.

Review questions

49. Distinguish land use from land cover and explain how remote sensing relates to each.
50. How can multi-temporal imagery quantify urban sprawl?
51. Which data and physical concept underlie urban-heat-island mapping?
52. Name three change-detection techniques and one error source for each.
53. Why does change detection depend on accurate pre-processing?

Chapter 10 — Integration with GIS (SIG)

Introduction

Remote sensing rarely delivers final decisions on its own; its products acquire full value when combined with other spatial data in a Geographic Information System. This chapter explains how imagery-derived information becomes a GIS layer, how remote sensing and GIS complement one another in decision-making, and what a typical end-to-end urban workflow looks like. It thereby connects the analytical chapters to the practical case study of Chapter 11 (Longley et al., 2015; Burrough et al., 2015).

10.1 From Image to Geographic Data

Remote sensing produces information in **raster** form, whereas many planning datasets — parcels, roads, administrative boundaries — are held as **vector** features (points, lines, and polygons) (Longley et al., 2015). A **Geographic Information System (GIS / SIG)** stores, integrates, and analyses both models, so a classified land-cover raster or a vectorised built-up boundary can be overlaid, queried, and combined with existing municipal data (Burrough et al., 2015). This conversion — from image to geographic layer — is what makes remote-sensing output actionable within established planning systems.

10.2 Remote Sensing + GIS for Decision-Making

The integration of remote sensing with GIS enables **multi-criteria analysis**, in which imagery-derived layers such as land cover, NDVI, and surface temperature are combined with data on population, zoning, elevation, and networks to answer planning questions (Malczewski, 2004). Typical applications include siting public facilities, delineating flood-prone or heat-vulnerable zones, and prioritising investment in green infrastructure. The analytical power comes precisely from the overlay: neither the imagery nor the ancillary data alone would support the decision, but together they do (Weng, 2012).

10.3 A Typical Urban Management Workflow

A complete workflow links the operations of the previous chapters into a repeatable sequence (Jensen, 2015):

54. **Acquire** suitable imagery (for example Sentinel-2 for medium-resolution monitoring).
55. **Pre-process** through radiometric/atmospheric correction and georeferencing.

56. **Analyse** using enhancement, spectral indices, and classification.

57. **Validate** the results with an accuracy assessment.

58. **Integrate** the validated products into the GIS alongside other layers.

59. **Produce** maps and quantitative indicators for decision-makers.

Documenting each step ensures the analysis is transparent, reproducible, and defensible — qualities that matter when results inform public policy (Congalton & Green, 2019).

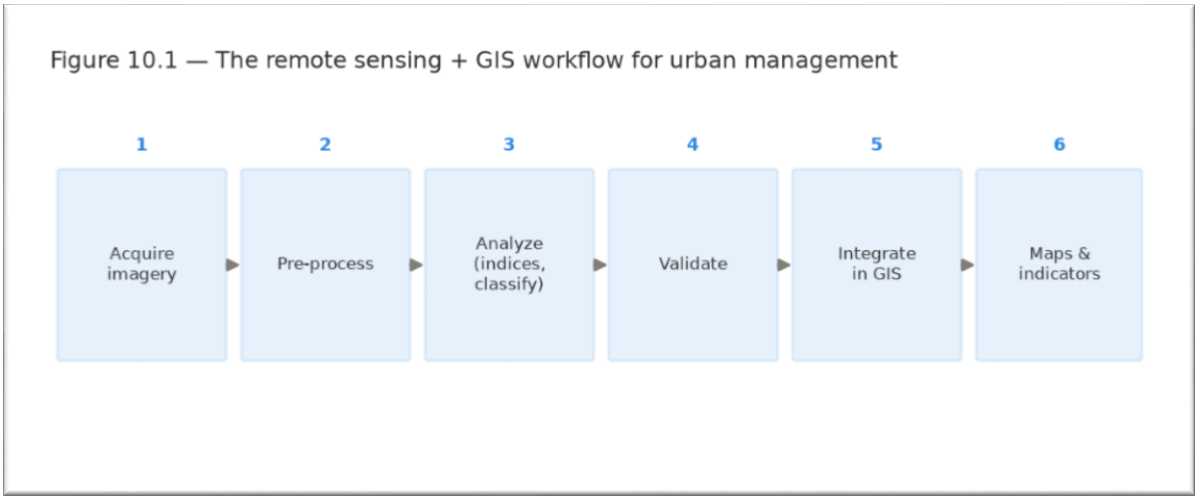


Figure 10.1 — The remote sensing + GIS workflow for urban management

10.4 Data Quality, Scale, and Interoperability

Integrating remote-sensing products into a GIS raises practical issues that determine whether the analysis is trustworthy (Longley et al., 2015). All layers must share a common coordinate reference system and be co-registered, or overlay analysis will be meaningless. Layers must also be compatible in scale and resolution: overlaying a 30 m land-cover raster with a cadastral map surveyed at parcel precision requires care about what conclusions the coarser layer can legitimately support (Burrough et al., 2015). Finally, metadata and standardised formats ensure that data can be shared and reused across departments — an interoperability concern that open standards from bodies such as the Open Geospatial Consortium seek to address. Attending to these matters is what turns a visually plausible map into a defensible basis for decisions.

Conclusion

This chapter has shown that GIS is the environment in which remote-sensing products deliver their value, integrating raster imagery with vector planning data to support multi-criteria decision-making. The six-step workflow — acquire, pre-process, analyse, validate, integrate, produce — provides a template that the student will now apply concretely. Chapter 11 puts the entire course into practice through a guided case study and a programme of practical works.

Key points

- GIS integrates raster (imagery) and vector (planning) data in one analytical environment.
- Remote sensing + GIS enables multi-criteria decision-making that neither could support alone.
- The standard workflow runs from acquisition through validation to map and indicator production.
- Documenting each step makes the analysis reproducible and defensible.

Review questions

60. Differentiate raster and vector data models with an urban example of each.
61. Give one decision-support application of combined remote sensing and GIS.
62. List the six steps of the workflow and state the purpose of each.
63. Why is validation placed before integration in the workflow?

Chapter 11 — Practical Exercise / Case Study: Constantine

Introduction

This chapter consolidates the whole course in a single, realistic application: mapping and interpreting the built-up expansion of Constantine using free Landsat data. It presents the study area, a step-by-step method, a template for results and interpretation, a guided student exercise, and the official programme of practical works (TP/TD). The aim is to move the student from understanding to doing, so that the concepts of the previous chapters are exercised end-to-end on a concrete Algerian city (Weng, 2012).

11.1 Study Area

Constantine, in north-eastern Algeria, is a major regional city distinguished by rapid demographic and spatial growth, a dramatic topography incised by the Rhumel gorges, and expansion toward new urban poles such as Ali Mendjeli. These characteristics — strong growth pressure, constrained physical setting, and planned satellite development — make it an instructive case for studying urban sprawl and land-cover change with remote sensing (Patino & Duque, 2013).

11.2 Data and Method (Step by Step)

Objective: map and quantify built-up expansion between two dates, for example 2000 and 2020.

64. **Data:** obtain two cloud-free Landsat scenes (for example 2000 and 2020), available free from USGS EarthExplorer (Wulder et al., 2019).
65. **Pre-processing:** apply radiometric and atmospheric correction and verify georeferencing between the two dates (Jensen, 2015).
66. **Indices:** compute NDVI and NDBI for each date to emphasise vegetation and built-up surfaces (Rouse et al., 1974; Zha et al., 2003).
67. **Classification:** perform a supervised classification into four classes — built-up, vegetation, water, and bare soil — using representative training samples (Richards, 2013).
68. **Accuracy assessment:** build a confusion matrix and compute overall accuracy and the kappa coefficient for each date (Congalton & Green, 2019).
69. **Change detection:** apply post-classification comparison to quantify the built-up gain in hectares and its direction (Singh, 1989).

11.3 Results and Interpretation (Template)

Class	Area 2000 (ha)	Area 2020 (ha)	Change (ha)
Built-up	…	…	+…
Vegetation	…	…	−…
Bare soil	…	…	…
Water	…	…	…

Students complete the table from their own results and interpret it: where did the city expand, at the expense of which land classes, and what are the implications for infrastructure, services, and environmental quality? A sound interpretation links the measured change to the physical constraints and planning history of the city (Patino & Duque, 2013).

11.4 Guided Student Exercise

Your task

70. Download two Landsat scenes of Constantine (for example 2000 and 2020).
71. Compute NDVI and NDBI for both dates.
72. Perform a supervised classification into four classes and assess its accuracy with a confusion matrix and kappa.
73. Quantify the built-up change and write a half-page interpretation accompanied by one map figure.

11.5 Practical Works Programme (TP / TD)

The official course includes a set of practical and tutorial sessions (*travaux pratiques / travaux dirigés*). A suggested programme, fully reproducible with free data and software, is:

74. **Physical bases of remote sensing** — exercises on the spectrum, wave–matter interactions, and spectral signatures.
75. **Working with satellite images** — opening a scene, exploring bands, and reading metadata (for example a Landsat image).
76. **Image pre-processing** — radiometric and geometric corrections and georeferencing.
77. **Colour composites** — constructing true-colour and false-colour composites.

78. **Filters** — applying low-pass, high-pass, and edge-detection filters.
79. **Georeferencing** — assigning a coordinate system and checking accuracy against reference data.

Recommended free software includes **QGIS** with the Semi-Automatic Classification Plugin, and ESA's **SNAP** toolbox for Sentinel data (Congedo, 2021).

 TP tip: every practical above can be completed with free Landsat or Sentinel imagery and free, open-source GIS software, so the programme is fully reproducible without commercial licences.

11.6 Extending the Case Study

The Constantine exercise can be extended in several instructive directions (Weng, 2012). Students may add a third date to reveal the tempo of growth across two decades rather than a single interval, or incorporate a thermal analysis to relate the observed built-up expansion to rising land-surface temperature and emerging heat islands (Voogt & Oke, 2003). A further extension overlays the classified change with slope and the Rhumel gorges to examine how topography has channelled development toward Ali Mendjeli and other poles. Each extension reuses the same core workflow while deepening the interpretation, illustrating how a single, well-designed study can grow into a research programme. Students are encouraged to reproduce the exercise on their own home city to consolidate the skills acquired.

Conclusion

This chapter has integrated the entire course into a single applied study, from data acquisition and pre-processing through classification and accuracy assessment to change detection and interpretation, and it has set out a practical-works programme that lets students rehearse each skill. Working through the Constantine case demonstrates that the concepts of the handout are not abstract: with free data and open software, a student can measure real urban change and reason about its consequences. Chapter 12 closes the handout with a synthesis and a look ahead.

✓ Key points

- A complete urban study runs from acquisition and pre-processing to classification, accuracy assessment, and change detection.
- NDVI and NDBI emphasise vegetation and built-up surfaces respectively.
- Post-classification comparison quantifies built-up gain and its direction.
- The whole workflow is reproducible with free Landsat/Sentinel data and open-source GIS.

Review questions

80. Why is Constantine a suitable case for studying urban sprawl?
81. List the six methodological steps of the case study in order.
82. Why must accuracy be assessed for each date before change detection?
83. Which free software and data would you use to complete the exercise, and why?

Chapter 12 — Conclusion and Perspectives

Introduction

This final chapter draws the course together. It restates the intellectual arc from physical principles to applied urban analysis, considers the emerging trends that are reshaping the discipline, and offers guidance for the student's continued study. It is followed by the reference material that supports the whole handout: a bilingual glossary, a full bibliography, and a list of figures.

12.1 Synthesis

The handout has progressed logically from foundations to applications. Chapters 1 and 2 established what remote sensing is and the physics on which it rests — electromagnetic radiation, its interactions with matter and atmosphere, the black-body model, and the spectral signature (Rees, 2013; Chuvieco, 2016). Chapters 3 to 5 described the instruments and data: platforms and sensors, the four resolutions, and the main satellite systems (Campbell & Wynne, 2011; Wulder et al., 2019). Chapters 6 to 8 developed the digital and analytical core: image structure, processing and indices, and classification with rigorous accuracy assessment (Jensen, 2015; Congalton & Green, 2019). Chapters 9 to 11 applied these tools to urban techniques management — land cover, sprawl, green space, heat islands, change detection, GIS integration, and a worked case study of Constantine (Weng, 2012). The consistent message is that reliable results depend on understanding the whole chain, from photon to policy.

12.2 Perspectives and Emerging Trends

Remote sensing is evolving rapidly, and several trends will shape its future role in urban management (Zhu et al., 2019). The transition to **free and open data**, led by Landsat and Copernicus, has already democratised access and will continue to do so. **Cloud platforms** such as Google Earth Engine remove the barrier of local storage and computation, allowing continental-scale analysis from a browser (Gorelick et al., 2017). **Machine learning and deep learning**, particularly convolutional neural networks, are achieving unprecedented accuracy in urban feature extraction (Zhu et al., 2017). Finally, the growth of **drones** and **small-satellite constellations** is pushing spatial and temporal resolution to levels once unimaginable. For the Algerian planner, these developments promise ever cheaper, timelier, and more detailed observation of the city.

12.3 Guidance for Further Study

Students wishing to deepen their knowledge should combine textbook study with hands-on practice. The textbooks by Lillesand et al. (2015), Jensen (2015), Campbell and Wynne (2011), and Chuvieco (2016) provide comprehensive coverage, while the journals *Remote Sensing of Environment*, the *ISPRS Journal of Photogrammetry and Remote Sensing*, and the *International Journal of Remote Sensing* report current research. Practical fluency is best acquired by repeating the Constantine workflow on a city of personal interest, using free QGIS and SNAP software (Congedo, 2021).

12.4 Ethical and Practical Considerations

A responsible practitioner recognises that remote-sensing products carry uncertainty and social consequences (Congalton & Green, 2019). Maps of informal settlements, for example, can inform beneficial service provision but could also expose vulnerable communities, so purpose and privacy deserve reflection. Technically, results should always be reported with their accuracy and limitations rather than presented as unquestionable truth. Practically, the discipline rewards reproducibility: documenting data sources, processing parameters, and validation allows others to verify and build on the work. Instilling these habits — humility about uncertainty, transparency of method, and awareness of impact — is as important a learning outcome of this course as any single technique, and it prepares students to use a powerful technology wisely.

Conclusion

Remote sensing has become an indispensable instrument for observing, understanding, and managing the contemporary city. This handout has aimed to give the second-year Licence student both the physical understanding and the practical method needed to use it responsibly, always coupling technique with critical interpretation. Combined with GIS and grounded in sound physical principles, remote sensing offers Algerian urban managers a powerful, accessible, and increasingly affordable means of guiding the sustainable development of their cities.

Key points

- The course forms a chain from physical principles to validated urban applications.
- Free data, cloud platforms, machine learning, and drones are transforming the field.
- Deep competence comes from combining textbook study with repeated hands-on practice.
- Remote sensing with GIS is a strategic tool for sustainable urban management.

Review questions

84. Summarise, in a paragraph, the logical progression of the course.
85. Name three emerging trends and explain how each benefits urban management.
86. Outline a personal study plan combining reading and practice.

General Conclusion

This handout set out to equip students of urban techniques management with both the scientific understanding and the practical competence to use remote sensing responsibly, and its chapters have followed a deliberate path toward that goal. Beginning with the definition and physical foundations of the discipline, the text showed how electromagnetic radiation, its interaction with matter, and the resulting spectral signatures make it possible to identify surfaces from a distance (Rees, 2013; Chuvieco, 2016). It then examined the platforms, sensors, and four resolutions that govern what a given system can observe, and surveyed the satellite missions — from the fifty-year Landsat archive to the free, frequent Sentinel data — on which contemporary urban monitoring relies (Lillesand et al., 2015; Roy et al., 2014).

From these foundations the handout developed the digital heart of the subject: the structure of raster imagery, the corrections and enhancements that make data analysis-ready, the spectral indices that distil target properties, and the classification methods that convert images into thematic maps whose accuracy must always be quantified (Jensen, 2015; Congalton & Green, 2019). These techniques were then put to work on the questions that matter most to the urban manager — land-cover mapping, the measurement of urban sprawl, the inventory of green space, the diagnosis of heat islands, and the detection of change — and were integrated with GIS to support genuine decisions, as demonstrated in the Constantine case study (Weng, 2012; Voogt & Oke, 2003).

Three lessons deserve emphasis as the reader closes the document. The first is that reliability depends on the whole chain: a map is only as trustworthy as its weakest step, from data selection through pre-processing to accuracy assessment, so methodological rigour is not optional (Congalton & Green, 2019). The second is that the discipline is now remarkably accessible: free imagery and open-source tools such as QGIS mean that the principal barrier is no longer data or software but trained analysts — precisely the gap this course seeks to close (Gorelick et al., 2017; Congedo, 2021). The third is that with capability comes responsibility, in the form of honesty about uncertainty, respect for privacy, and clear communication of the limits of the data to those who act on it (Foody, 2002).

The student who has worked through these pages, attempted the review questions, and completed the practical exercises now possesses a coherent and current foundation in urban remote sensing. The cities of Algeria and elsewhere will continue to change, sometimes faster than official records can follow; the graduate of this course is equipped to observe that change objectively, to measure it rigorously, and to contribute the evidence on which wiser urban decisions can be built. The end of this handout is therefore best understood not as a conclusion but as a point of departure for continued learning and professional practice.

Annex A — Worked Examples

Introduction

This annex gathers short numerical illustrations that reinforce the quantitative concepts of the course. Each can be reproduced with free data and a spreadsheet or GIS.

A.1 Computing NDVI

Suppose a pixel of healthy vegetation has a near-infrared reflectance of 0.50 and a red reflectance of 0.08. Applying NDVI = (NIR − Red) / (NIR + Red) gives (0.50 − 0.08) / (0.50 + 0.08) = 0.42 / 0.58 ≈ 0.72, a high value consistent with dense, vigorous vegetation (Rouse et al., 1974). A bare-soil pixel with NIR 0.25 and Red 0.20 yields 0.05 / 0.45 ≈ 0.11, close to zero as expected. Repeating the calculation across an image produces the NDVI map of Figure 7.1.

A.2 Radiometric Levels

An 8-bit sensor stores 2^8 = 256 brightness levels per band, whereas a 12-bit sensor stores 2^12 = 4096 levels (Lillesand et al., 2015). The finer quantisation of the 12-bit sensor allows it to distinguish surface differences — for instance small contrasts in urban surface temperature — that the 8-bit sensor would merge into a single value.

A.3 Estimating Built-up Change

If a supervised classification reports 3,200 ha of built-up land in 2000 and 5,600 ha in 2020, the absolute change is +2,400 ha and the relative change is 2,400 / 3,200 = 75 % over twenty years, roughly 2.8 % per year on a simple average basis (Singh, 1989). Such figures, once validated, translate directly into planning indicators.

A.4 Example Confusion Matrix

The table below is a simplified confusion matrix for a four-class classification validated with 100 reference points; diagonal cells are correct classifications and off-diagonal cells are errors (Congalton & Green, 2019).

Rows: class / Cols: reference	Built-up	Vegetation	Water	Bare soil
Built-up	27	2	0	1
Vegetation	1	25	0	2
Water	0	0	14	0
Bare soil	2	3	0	20

Here 27 + 25 + 14 + 20 = 86 of 100 points are correct, giving an overall accuracy of 86 %. The producer's accuracy for bare soil is 20 / (20 + 3 + 2) = 80 %, showing where most confusion occurs.

Conclusion

These examples show that the core computations of the course are arithmetically simple; their value lies in applying them to correctly pre-processed, validated data and in interpreting the results in their urban context.

Annex B — Formula and Acronym Sheet

Key formulas

- NDVI = (NIR − Red) / (NIR + Red)
- NDBI = (SWIR − NIR) / (SWIR + NIR)
- NDWI = (Green − NIR) / (Green + NIR)
- Radiometric levels = 2 raised to the number of bits
- Overall accuracy = correctly classified samples / total samples

Common acronyms

- **DN** — Digital Number
- **EMR** — Electromagnetic Radiation
- **GIS / SIG** — Geographic Information System / Système d'Information Géographique
- **LULC** — Land Use / Land Cover
- **LST** — Land Surface Temperature
- **NDVI / NDBI / NDWI** — Normalized Difference Vegetation / Built-up / Water Index
- **NIR / SWIR / TIR** — Near / Shortwave / Thermal Infrared
- **OBIA** — Object-Based Image Analysis
- **SAR** — Synthetic Aperture Radar
- **UAV** — Unmanned Aerial Vehicle

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Glossary (English–French)

English	Français
Remote sensing	Télédétection
Wavelength	Longueur d'onde
Spectral band	Bande spectrale
Spectral signature	Signature spectrale
Scattering / Absorption	Diffusion / Absorption
Black body	Corps noir
Specular / Diffuse reflection	Réflexion spéculaire / diffuse
Passive / active sensor	Capteur passif / actif
Spatial resolution	Résolution spatiale
Revisit time / temporal resolution	Résolution temporelle
Radiometric resolution	Résolution radiométrique
Pixel / Digital number	Pixel / Compte numérique
Colour composite	Composition colorée
Classification	Classification
Training sample	Échantillon d'entraînement
Confusion matrix	Matrice de confusion
Accuracy assessment	Évaluation de la précision
Land use / land cover	Occupation / utilisation du sol
Urban sprawl	Étalement urbain
Urban heat island	Îlot de chaleur urbain
Change detection	Détection des changements
GIS	SIG (Système d'Information Géographique)

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