



Computer Vision

Lecture 1: Introduction to Digital Image Analysis & Processing

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Module overview

Computer Vision = 6 ECTS.

Divided in 2 modules (3 ECTS each):

- Image Analysis
- Image Processing

But Image Analysis & Processing are closely related!

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(from a computer science perspective)

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Discussion

Experience in EO software?

What image analysis/processing functionalities have been used?

Lecturers

Three lecturers (all at IUT), but **contact me** for any question / issue

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All are senior researchers within the OBELIX group, with specific expertise in:

- efficient image analysis/processing through graph/tree structures
- and/or deep learning for computer vision
- but also with background knowledge in image analysis/processing

Module contents

The module will build upon lecturers' expertise to include both

- a broad coverage of computer vision
- and an in-depth coverage of specific topics

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- morphological, tree-based, graph-based processing
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but will avoid redundancy with other modules,
e.g. machine learning, deep learning, data mining, remote sensing

Components of a Digital Image Analysis System

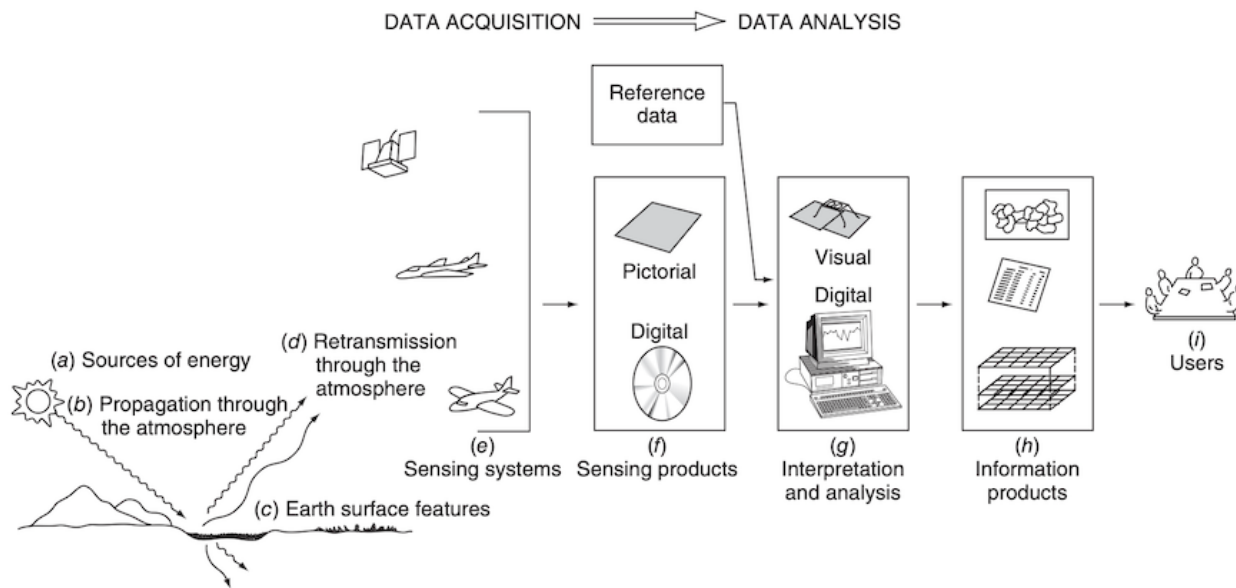


Figure 1.1 Electromagnetic remote sensing of earth resources.

Components of a Digital Image Analysis System

- data acquisition & storage
- preprocessing: restoration, registration, fusion, ...
- enhancement
- segmentation
- feature extraction
- classification, clustering
- visualization

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Discussion

Knowledge of some existing methods?

Capable of implementing some algorithms?

References

Many books have been published, and numerous online resources are available

- [A Computational Introduction to Digital Image Processing](#); McAndrew; CRC Press
- [Digital image processing](#); Gonzalez, Woods; Pearson
- [Image Operators Image Processing in Python](#); Kinser; CRC Press
- [Image processing, Analysis, and Machine Vision](#); Sonka, Hlavac, Boyle; Cengage
- [Introduction to Digital Image Processing](#); Pratt; CRC Press
- [Practical algorithms for image analysis description, examples, and code](#); Seul, O'Gorman, Sammon; Cambridge

References

There are also books dedicated to remote sensing data

- [Computer Processing of Remotely-Sensed Images](#); Mather; Wiley
- [Digital Analysis of Remotely Sensed Imagery](#); Gao; McGraw Hill
- [Image Analysis, Classification, and Change Detection in Remote Sensing With Algorithms for Python](#); Canty; Taylor & Francis
- [Image processing and GIS for remote Sensing: Techniques and applications](#); Liu & Mason; Wiley Blackwell
- [Introductory Digital Image Processing: A Remote Sensing Perspective](#); Jensen; Pearson
- [Learning Geospatial Analysis with Python](#); Lawhead; Packt Publishing
- [Remote Sensing and Image Interpretation](#); Lillesand, Kiefer, Chipman; Wiley
- [Remote Sensing Digital Image Analysis: An Introduction](#); Richards, Jia; Springer

Agenda

12 sessions x 3h, 1-3 per week

Each focused on a specific topic including both theory and practice

Today is an **introductory** session (and further if time allows).

Evaluation based on several (theoretical/practical) assignments

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Image analysis and processing closely related.

Topics are artificially assigned to one single module.

Image processing	Image analysis
Mathematical morphology	General (non-deep) topics in Computer Vision
Efficient processing/analysis with structures (trees and graphs)	Deep Learning for Computer Vision

Agenda

Module program (tentative)

Image processing	Image analysis
Introduction (SL 14/9)	Point analysis (SL 5/10)
Binary Morphology (SL 15/9)	Spatial analysis (SL 21/10)
Gray Morphology (SL 23/9)	Image features (SL 26/10)
Color Morphology (SL 27/9)	Geometry (SL 9/11)
Morphological Trees (FM 6/10)	Selected (non-deep) topics (SL 16/11)
Attribute Profiles (FM 13/10)	Image classification (MTP 29/11)
Pattern Spectra (SL 18/10)	Semantic segmentation 1 (SL 30/11)
Graphs from pixels (MTP 19/10)	Semantic segmentation 2 (SL 3/12)
Graphs from superpixels (MTP 25/10)	Object detection (MTP 6/12)
Multiscale segmentation (MTP 27/10)	Instance segmentation (MTP 13/12)

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Discussion

Knowledge on these topics?

Specific interest in additional topics?

Labs

All practical will be (probably) done in Python.

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Many Python libraries for Computer Vision

- NumPy/SciPy
- scikit-image
- PIL/Pillow
- OpenCV
- SimpleCV
- & deep/machine learning toolboxes

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And even some dedicated to remote sensing data:

- GDAL
- Orfeo Toolbox (OTB)
- RSGISLib, Rasterio, Fiona, GeoPandas, ...

Terminology

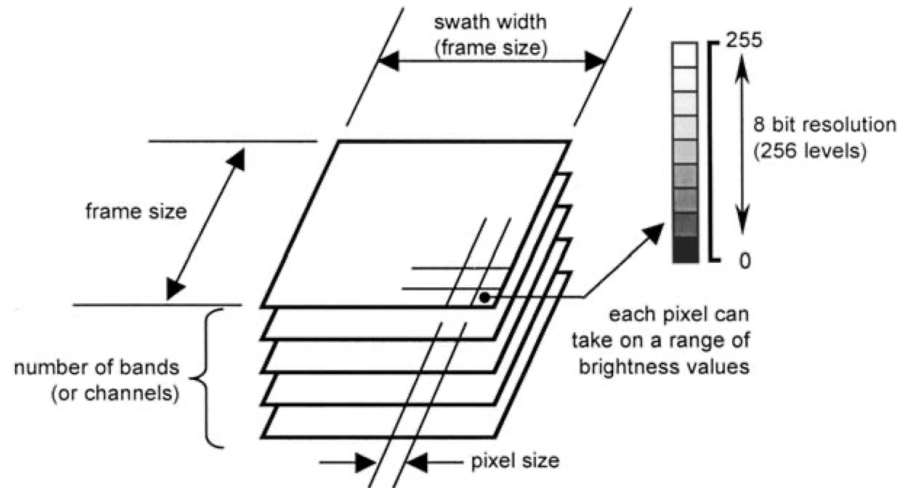


Fig. 1.2. Technical characteristics of digital image data

A **pixel** is assigned some values (a.k.a. **Digital Number** - DN)

A digital image is an approximation of the real world.

The level of approximation is related to **resolution**:
spatial, spectral, temporal, radiometric

Spatial resolution

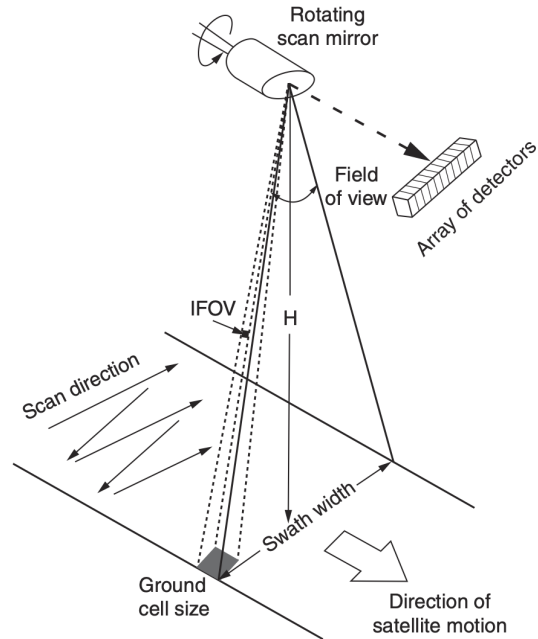


FIGURE 1.7 Relationship among spatial resolution of satellite imagery, satellite altitude (H), and IFOV (α) of the scanner.

Spatial resolution

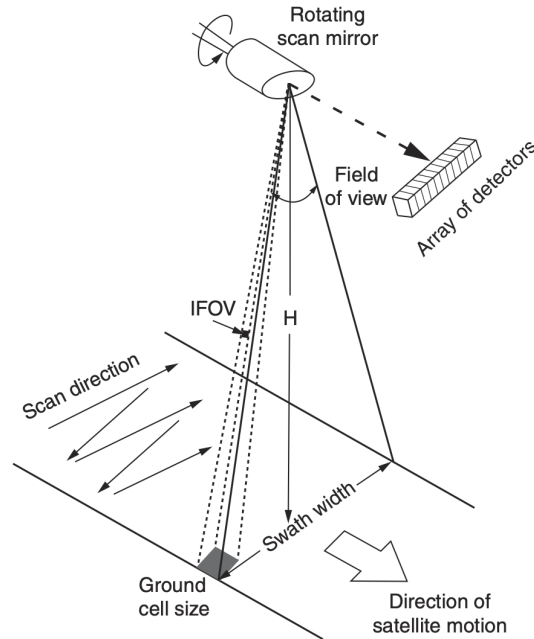


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Discussion

Spatial resolution of remote sensing sources?
+/- of high spatial resolution?

Spectral resolution

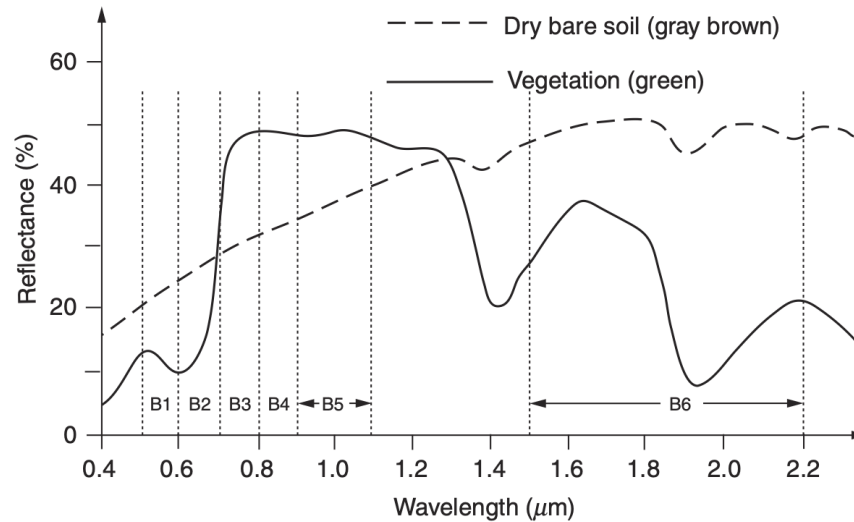


FIGURE 1.9 Spectral resolution of imagery. It is defined as the width of a spectral band. As illustrated in this figure, band 6 has the coarsest spectral resolution against bands 1 and 2. Spectral resolution affects the spectral separability of covers.

Spectral resolution

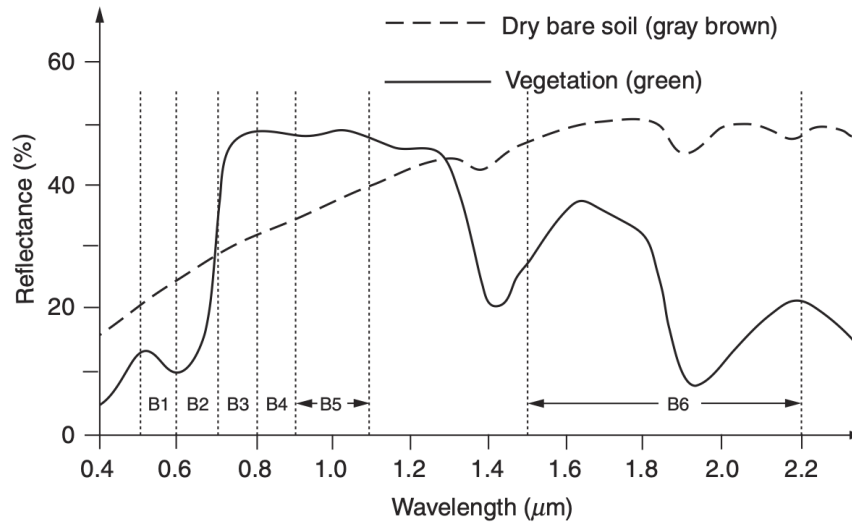


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Radiometric resolution

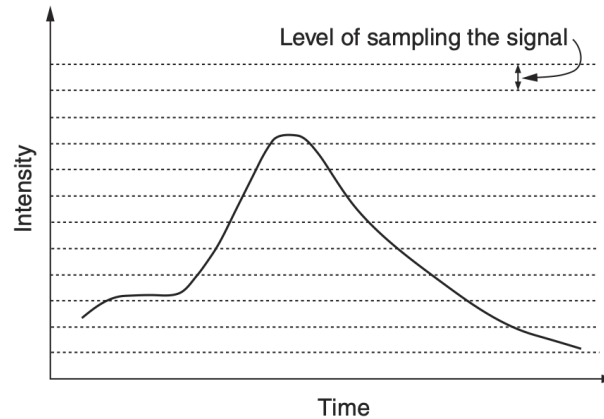


FIGURE 1.11 Quantization of energy reflected from a ground target is converted into an electrical signal whose intensity is proportional to its reflectance. The interval of sampling the signal intensity determines the radiometric resolution of the satellite imagery, or its ability to discriminate subtle variation in reflectance.

Radiometric resolution

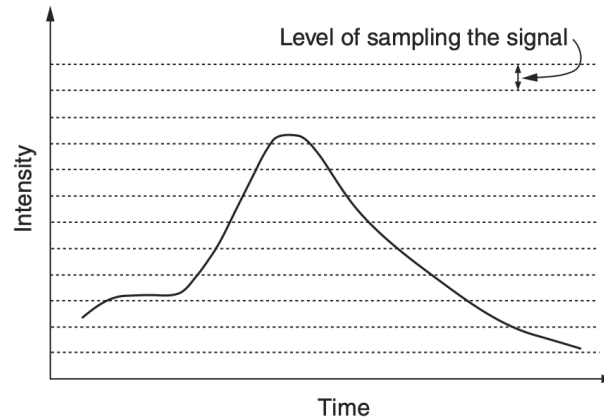


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Radiometric resolution of remote sensing sources?
+/- of high radiometric resolution?

Temporal resolution

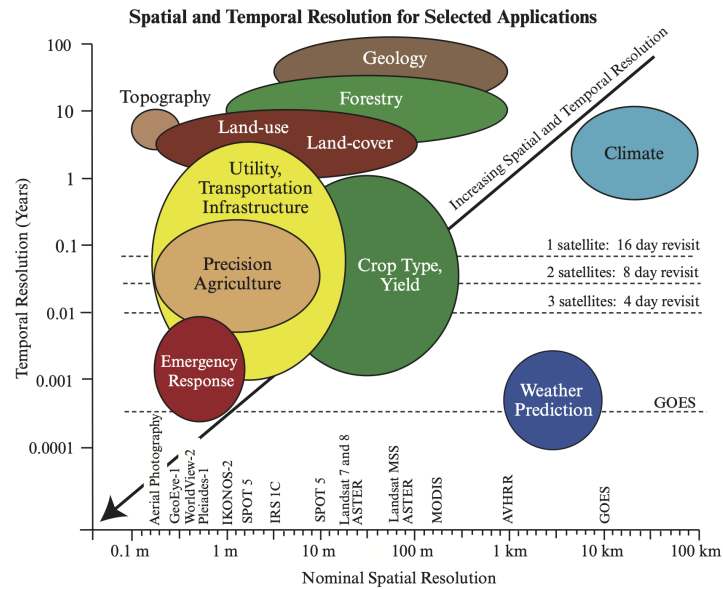


FIGURE 1-10 Spatial and temporal resolution trade-offs must be made when collecting remote sensor data for selected applications. For example, applications such as land use mapping generally require high spatial resolution imagery (e.g., 1 to 5 m) at relatively low temporal resolution (e.g., 1–10 years). Conversely, for weather prediction we are generally content with lower spatial resolution imagery (e.g., 5 × 5 km) if it can be collected frequently (e.g., every half-hour).

Temporal resolution

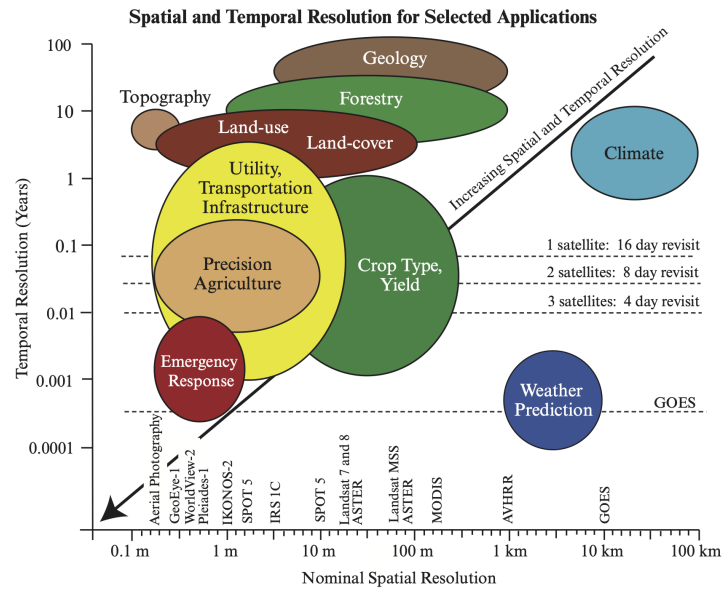


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+/- of high temporal resolution?

Resolution vs. memory

Spatial × Spectral × Temporal × Radiometric resolution = Memory Footprint

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Drawbacks of higher resolutions:

- memory cost (storage, RAM, communication)
- processing cost (CPU/GPU, processing time)
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Discussion

Memory footprint for standard remote sensing images (HSI, VHR, SITS...)

Opportunities & challenges for local processing?

Raw image encoding

There are multiple ways to encode an image.
Specific formats for remote sensing data.

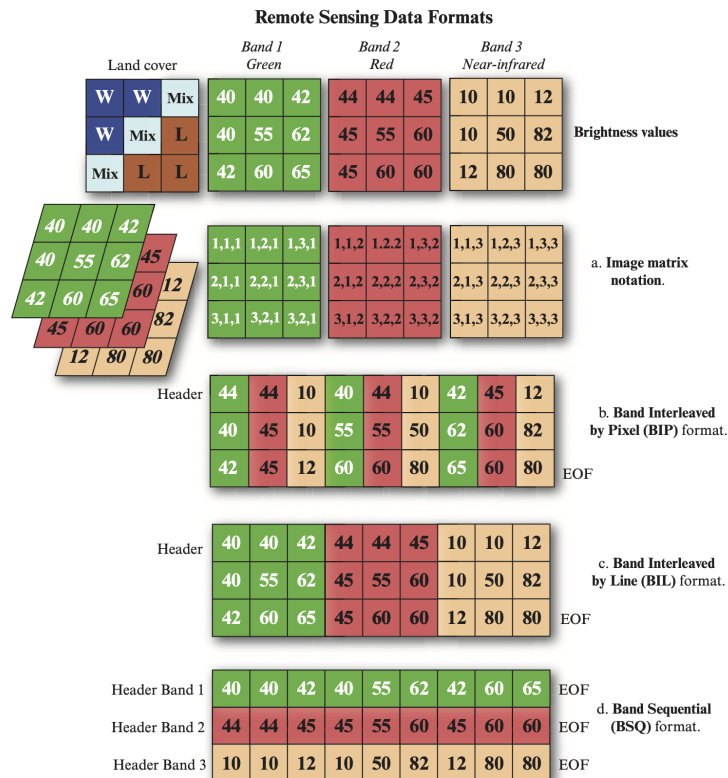


FIGURE 2-58 Selected digital image data formats.

Modeling an image

There are also multiple ways to represent an image.

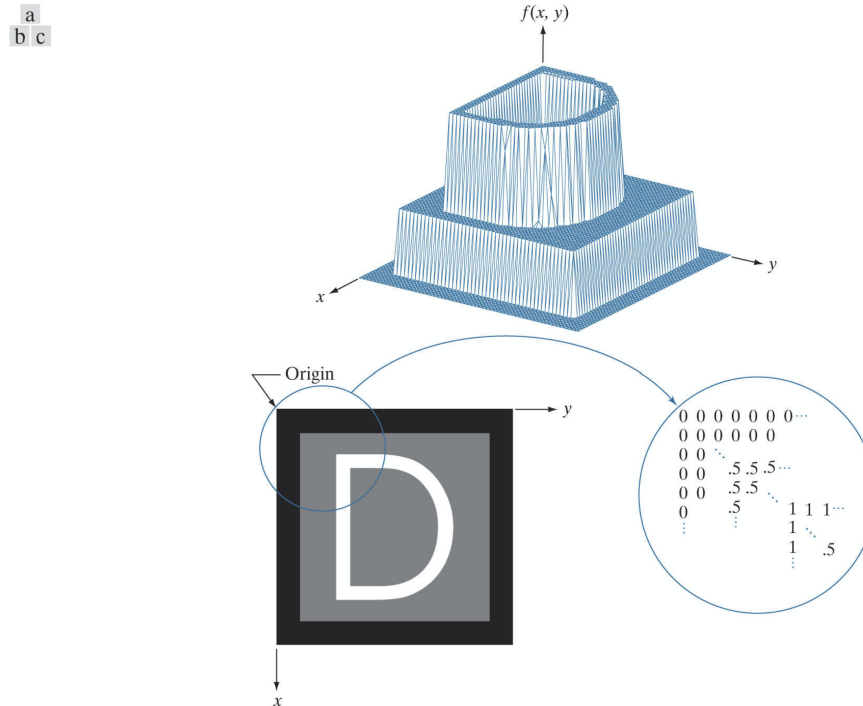


FIGURE 2.18

(a) Image plotted as a surface. (b) Image displayed as a visual intensity array. (c) Image shown as a 2-D numerical array. (The numbers 0, .5, and 1 represent black, gray, and white, respectively.)

Questions?

Lab session

Time to practice a little bit!

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- Jupyter Notebook
- One digital image (at least!)

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Steps

1. load the image file
2. display its properties (dimensions, resolution)
3. display the image

Discussion

Display is straightforward? If no, what to do?

Interest of the different Python image libraries?

Lab session

Understand the effect of the resolution

1. how to reduce the spatial resolution of the image?

Lab session

Understand the effect of the resolution

1. how to reduce the spatial resolution of the image?
2. how to reduce the radiometric resolution of the image?
and extract the so-called bit planes?

MACLEAN 2021

MACLEAN 2021

- 2 keynotes
 - Prof. Begüm Demir, Deep Earth Query: Information Discovery from Big Earth Observation Data Archives
 - Prof. Gustau Camps-Valls, Fitting is not enough: Interpretability and causal inference for the Earth sciences
- 4 papers (10 pages)
 - How to find a good image-text embedding for remote sensing visual question answering?
 - Segmentation of VHR EO Images using Unsupervised Learning
 - SS-HIDA: Semi-Supervised Heterogeneous Image Domain Adaptation
 - Semi-supervised Siamese Networks for Change Recognition with VHR Imagery

First assignment

Write a 2-page summary (format: PDF) of the research paper assigned to you.

The summary should provide the following information:

- what is the problem under study?
- why this problem is important?
- how is solved the problem?
- why does it differ from existing works?
- what is your personal opinion about this paper (including strengths and weaknesses of the paper)