Remote sensing applied to agronomic and environmental systems

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Definition

Remote sensing:"obtaining information about **objects** . . . by using electromagnetic radiation without being in direct contact with the object"

Geographic remote sensing: obtaining information about the **Earth's surface** . . . by using electromagnetic radiation without being in direct contact with the Earth's surface

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Why use remote sensing?

- **Uniform coverage** of “large” areas
  - especially with Earth-orbiting satellites

- **Consistent** and **objective** information over a wide area

- **Repeat sensing** of same areas by same or similar systems
  - → monitoring, change detection

- **Low cost** per unit area (even at commercial prices)
  - If successful, avoids costly or even impossible field work.
  - Results from accessible areas can be extrapolated to inaccessible areas

- **Inference** about objects imaged by the **physics** of their interactions with energy

- **Inference** about objects imaged by **data mining** or **statistical models** (e.g., land cover classification)

Physics

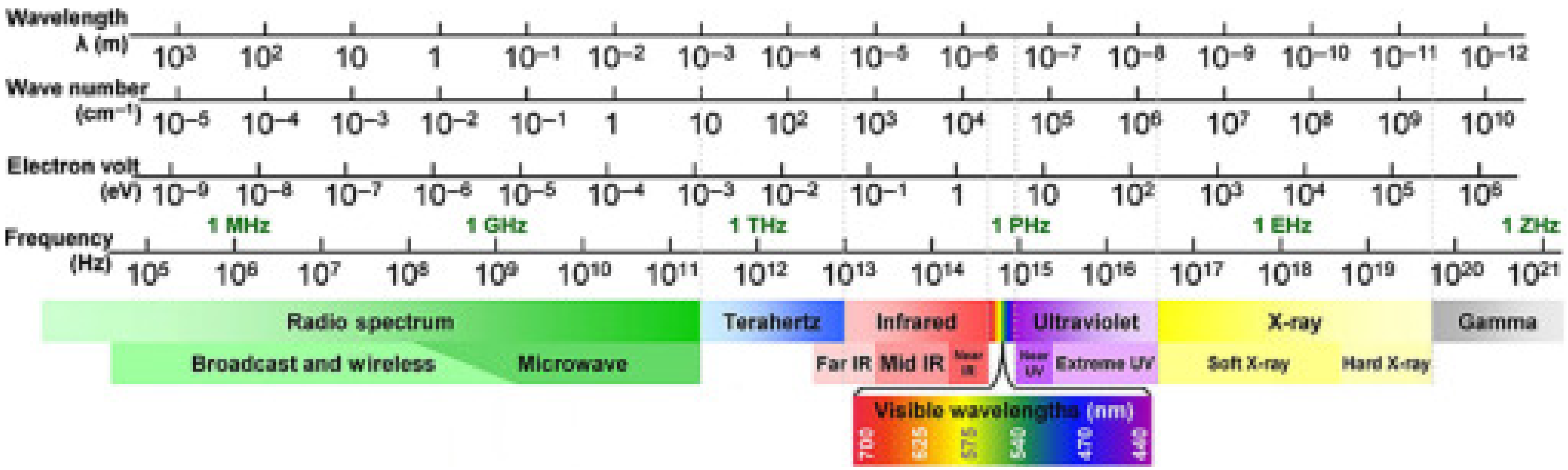
1. the **source** of the electromagnetic energy (active vs. passive sensors)

2. the **path** through the atmosphere

3. the **interaction** with the object

4. the **recording** of the radiation by the sensor.

The electro-magnetic spectrum



Base-10 logarithmic scales – energy per photon decreases 10x at each division

e.g., mid-IR has 10x less energy per photon than near UV.

Note very narrow range of visible light.

Source: Viscarra Rossel, R. A., *et al.* (2011). Proximal soil sensing: an effective approach for soil measurements in space and time. In D. L. Sparks (Ed.), Advances in Agronomy, Vol 113 (Vol. 113, pp. 237–291). San Diego: Elsevier Academic Press Inc. `http://dx.doi.org/10.1016/B978-0-12-386473-4.00005-1`

Sources

1. **no external** energy source, **emitted** from object
   - e.g., γ-rays from radioactive decay of minerals
2. energy emitted from **sun**, (part) **reflected** from object (most common, visible-NIR energy) – **passive** sensor systen
3. energy emitted from **sensor system**, (part) reflected from object – **active** sensor system
   - e.g., microwave radar “backscatter”; lidar (visible light energy)
4. energy emitted from **sun**, (part) **re-emitted** (with delay) from object
   - e.g., land surface thermal

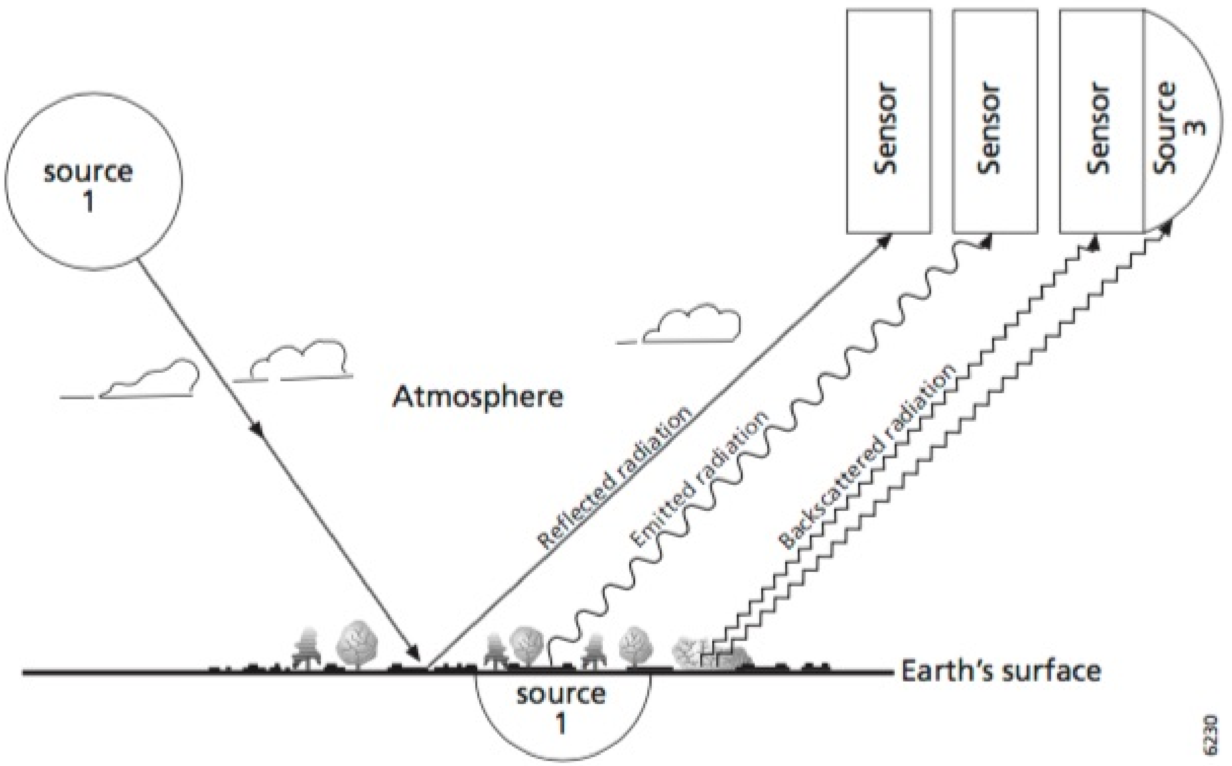
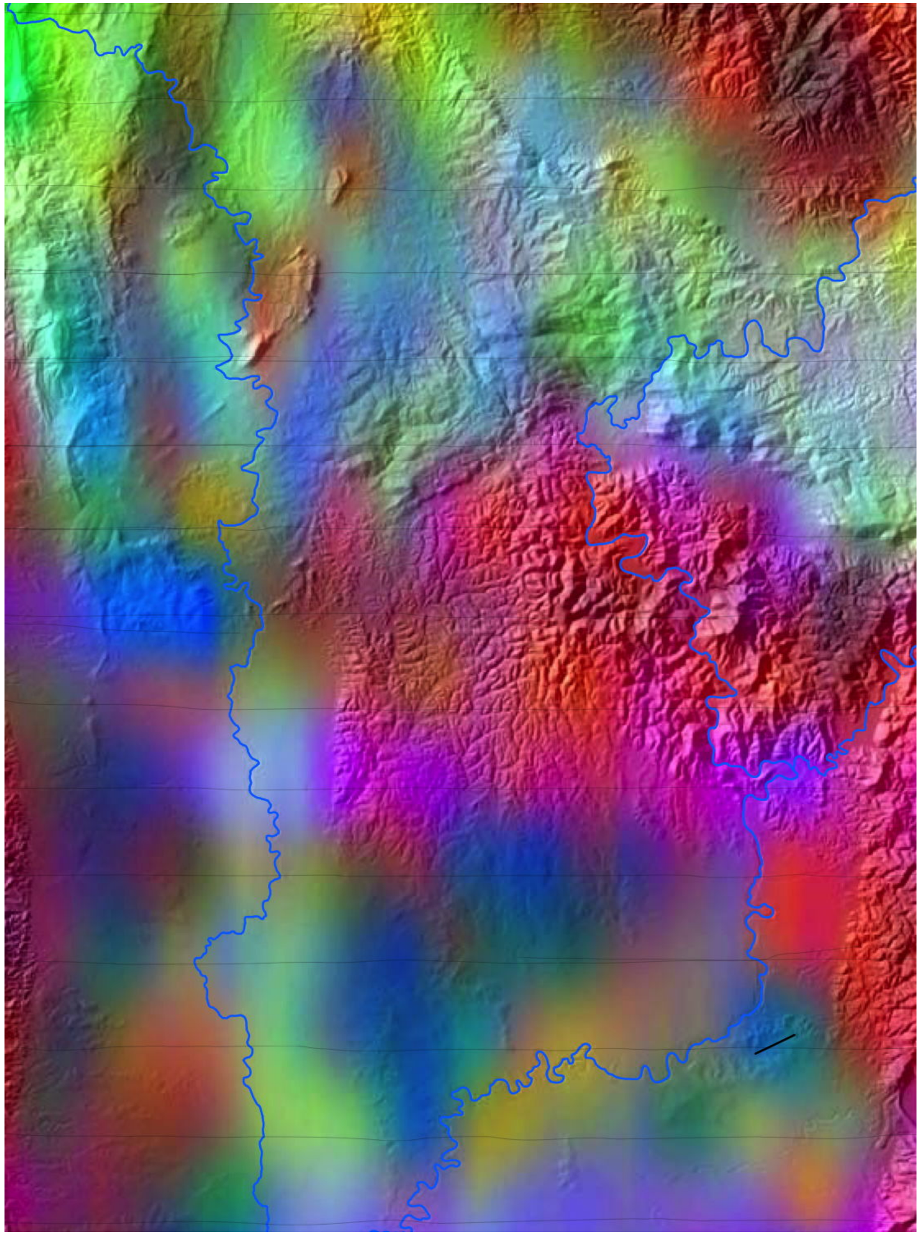


Figure 1.1 – The remote sensing system (modified from Curran, 1985).

Source: Jong, S. M. de, Meer, F. D. van der, & Clevers, J. G. P. W. (2004). **Basics of Remote Sensing.** In *Remote sensing image analysis: including the spatial domain* (pp. 1–15).
`http://dx.doi.org/10.1007/978-1-4020-2560-0_1`

No external energy – γ-rays



Airborne γ-ray survey, flying height 400 m above terrain, flight lines spaced 2 km

Interpolated to 400 x 400 m pixels

Red: K; Green: Th; Blue: U

Superimposed on hill-shaded DEM

Upper Pasak watershed, Petchaboon province, Thailand

Interaction with atmosphere

- Atmosphere transmits/absorbs electromagnetic energy

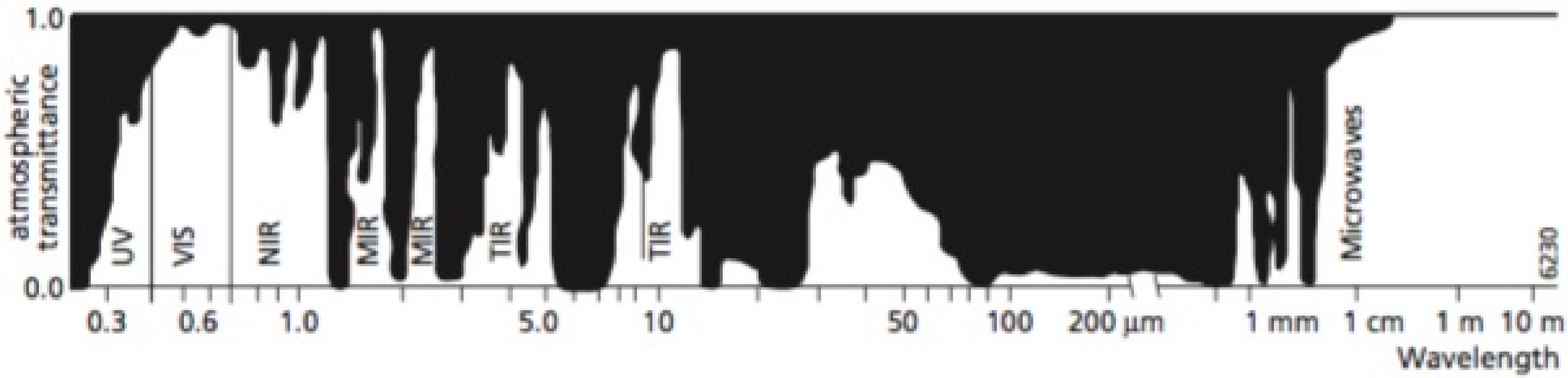


Figure 1.2 – Atmospheric transmittance for radiation as a function of the wavelength (modified from Lillesand and Kiefer, 2000).

(Note logarithmic scale of wavelengths)

Interaction with objects

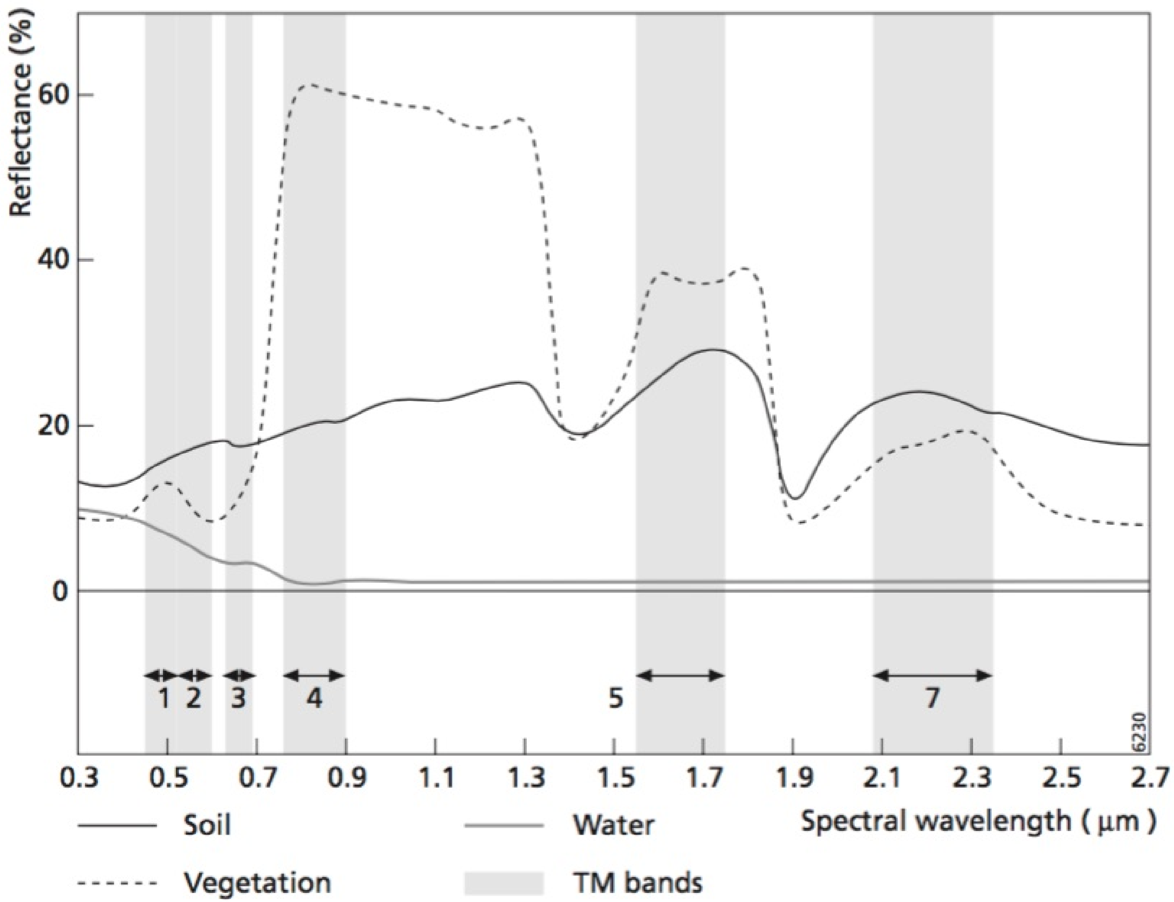


Figure 1.4 – Typical spectral reflectance curves for water, soil and vegetation.

This allows differentiation of objects based on their **spectra**

Sensor system

- **reception**, **transmission**, and **pre-processing** of the recorded radiance

- **post-processing** to remove “noise” vs. desired “signal”
  - atmospheric correction – this is usually “noise” but can be “signal” for some applications
  - land cover change studies vs. atmospheric pollution studies

Resolutions

Can be described on four axes:

spatial (smallest object imaged – averaged in the instantaneous field of view (IFOV)) mini

spectral (number of bands, their width)

radiometric (number of digital levels detectable by sensor)

temporal (repeat interval)

E.g., LANDSAT 4/5: 30x30 m, 8 bands (4 visible, 3 NIR, 1 thermal); 256 levels; 16 day repeat

Platforms

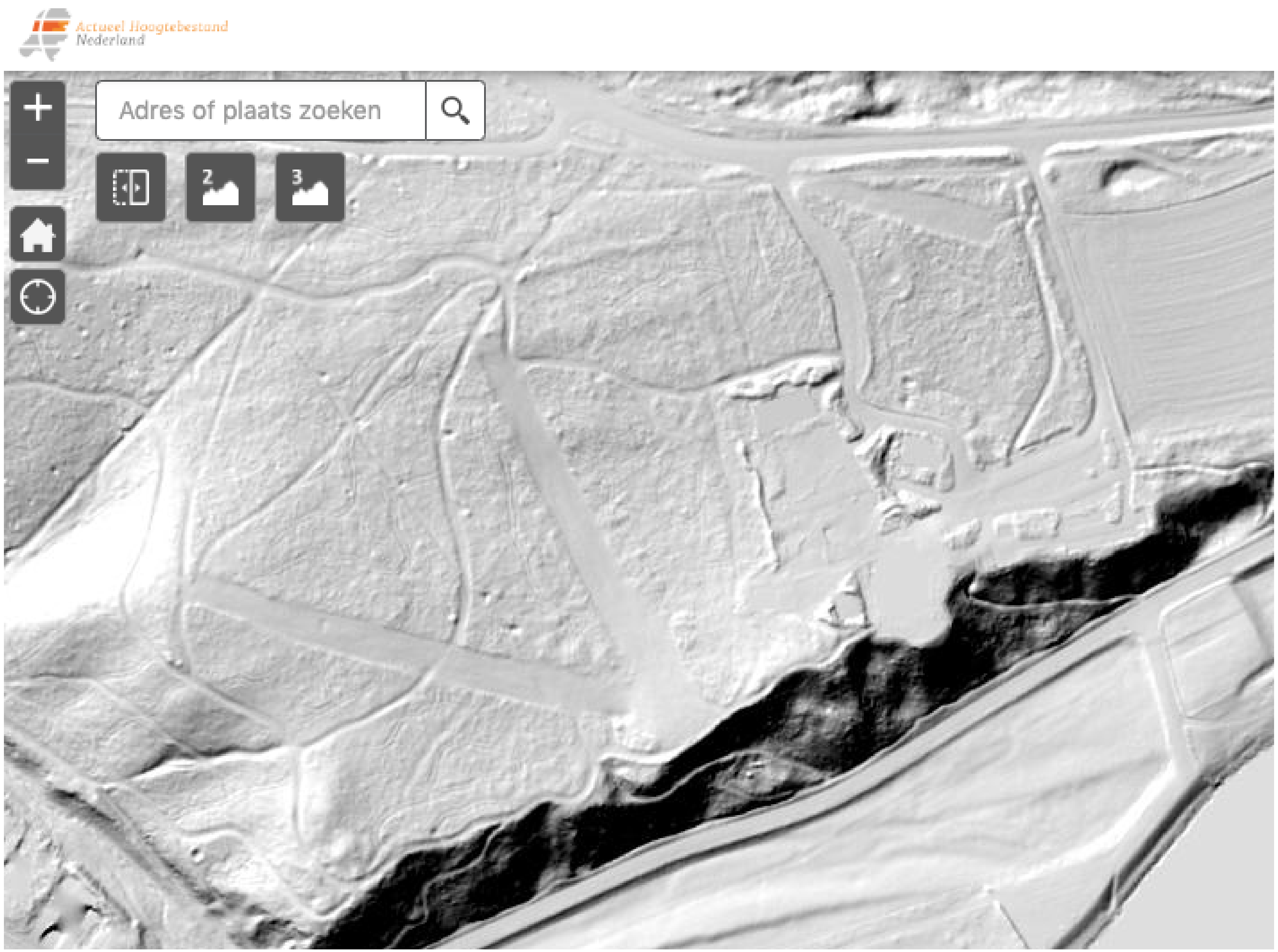
Earth-observation satellites e.g., Landsat, SPOT, MODIS, AVHRR, Quickbird, Ikonos, ASTER (Terra/Aqua), RADARSAT; GOES (geostationary), Cartosat

Aircraft often used for LIDAR (elevation models, forest inventory), γ-ray

- much closer to object, allows finer spatial and spectral resolution, detection of low-energy photons

Drones precision agriculture, infrastructure mapping

Elevation model from airborne LIDAR



Westerbouwing, Oosterbeek (NL); Source: `https://www.ahn.nl/ahn-viewer`

Lists of satellite sensor systems

- https://en.wikipedia.org/wiki/Category:Earth_observation_satellites
- https://en.wikipedia.org/wiki/Remote_sensing_satellite_and_data_overview

These pages point to specific information for each system. Examples:

MODIS https://en.wikipedia.org/wiki/Remote_sensing_satellite_and_data_overview

LANDSAT https://www.usgs.gov/land-resources/nli/landsat

ASTER http://asterweb.jpl.nasa.gov

The conceptual remote sensing model (1) – scene vs. image

- **scene**: "the spatial and temporal distribution of matter and energy fluxes from which the sensor draws measurements"

- **image**: "a collection of measurements from a sensor that are arrayed in a systematic fashion"

Reference: Strahler, A. H., Woodcock, C. E., & Smith, J. A. (1986). **On the nature of models in remote sensing.** *Remote Sensing of Environment*, 20(2), 121–139. http://doi.org/10.1016/0034-4257(86)90018-0

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The conceptual remote sensing model (2) – models

1. **scene model**

   "the form and nature of the energy and matter within the scene and their spatial and temporal order"

2. **atmospheric model**

   "the interaction between the atmosphere and the energy entering and being emitted from the scene"

3. **sensor model**

   "the behavior of the sensor in responding to the energy fluxes incident upon it and in producing the measure- ments that constitute the image"

The remote sensing problem

“inferring the order in the properties and distributions of matter and energy in the scene from the set of measurements comprising the image.”

- “simple”: soil moisture by direct physical measurements and a physical model
- “complex”: land use

These all require explicit models (scene, atmospheric, sensor).

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Processing levels

- From sensor to scene. Terminology varies a bit, but these are typical:

  Level 0 raw instrument data (generally not distributed)

  Level 1A corrected for instrument variations
  - e.g., among the detectors along a scan line

  Level 1B corrected for sensor platform geometry
  - note: platform is moving during acquisition of a single scene

  Level 2A mapped into a projection based on expected sensor position (not ground control)
  - geolocation accuracy not good, typically > 100 m

  Level 2B mapped into a projection based on ground control
  - geolocation accuracy similar to pixel size

  Level 3A also corrected for elevation displacements (ortho-rectification)

- For use in a GIS or for co-registration with other sources, Level 2B (no mountains) or 3A (mountains) are needed.

- Analyst can perform 1B to 2B, 3A with sufficient ground control and (3A) a digital elevation model (DEM).

Resolution in scene models

L-resolution : scene elements are **smaller** than the resolution cells

- "L" ≈ "Low", here with a specific definition, depends on the size of the **scene elements**
- scene elements are *not* individually detectable
- cells ("pixels") are an area-weighted average of scene elements, i.e., *mixed* pixels
- (note: weighting by *point-spread function* of the sensor)
- low spatial correlation
- may attempt *spectral unmixing* of compound pixels to determine proportion of "pure" components
- may attempt *image fusion* with higher-resolution imagery to disaggregate mixed pixels

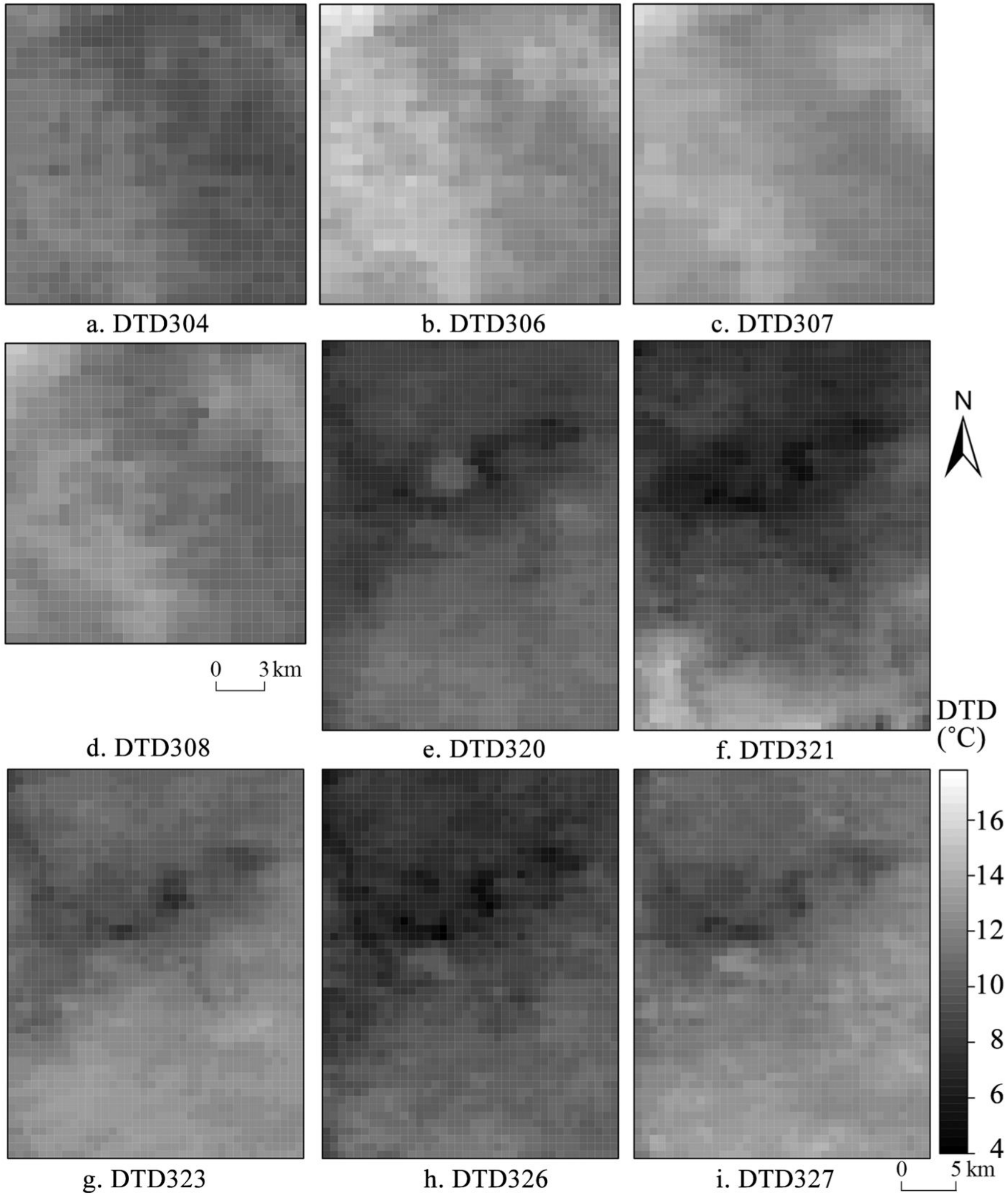
(continued) . . .

. . . (continued)

H-resolution : scene elements are **larger** than the resolution cells

- “H” ≈ “High”, here with a specific definition, depends on the size of the **scene elements**
- only mixed pixels are at boundaries
- higher resolution, larger scene objects → fewer mixed pixels
- high spatial correlation
- allows **object-based** image analysis (OBIA), *texture* analysis

Example L-resolution image



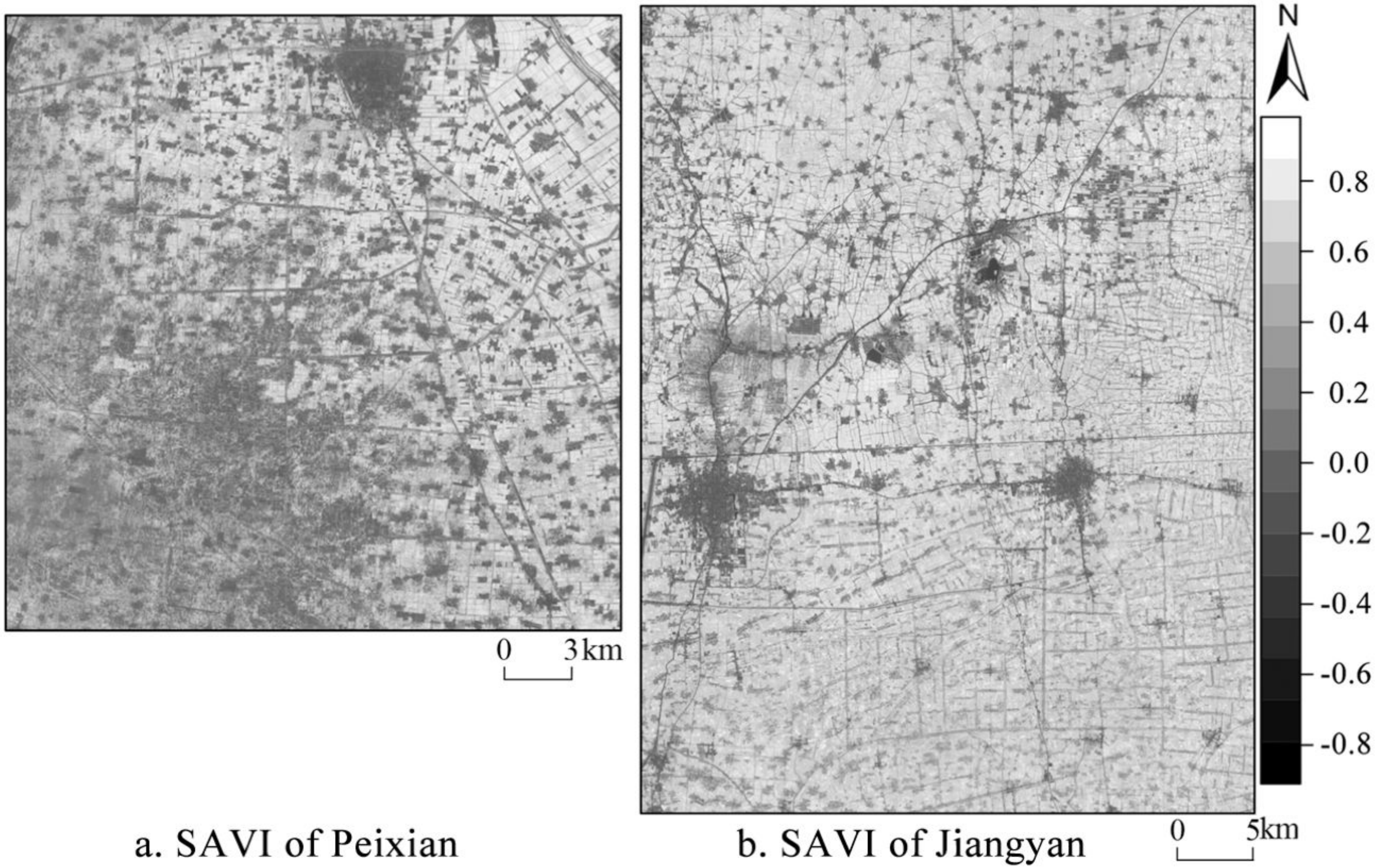
Scene elements in this application are **individual farm fields**

typical size ≈ 1 ha (100x100 m)

Resolution of MODIS: 1x1 km pixels

Scene elements not resolved in the images

Example H-resolution image



a. SAVI of Peixian

b. SAVI of Jiangyan

Soil-adjusted vegetation index (SAVI) from Landsat 8: 30x30 m pixels
Individual fields are resolved

Topic: Properties inferred by remote sensing

1. **Physical** properties – directly-sensed, using *physical* models

2. **Conceptual** properties – inferred, using *knowledge* models

Properties inferred by remote sensing & *physical* models

These use a direct physical interaction between the sensor system and the property of interest.

- Chlorophyll concentration
- Green vegetation intensity; vegetative vigour (red-edge); phytoplankton
- Surface temperature (e.g., volcanoes, fire detection); thermal capacity (a property of materials and moisture)
- Soil moisture, actual evapotranspiration
- Ice

Properties inferred by remote sensing & *knowledge* models

These require *conceptual* definitions, and a way to relate the physics of remote sensing (and often ancillary information as other GIS coverages) to these concepts.

Two levels of abstraction, depending on how close the physics are to the concept. E.g.,

- Land **cover** – requires a model of how different land covers relate to the sensor model

- Land **use** – requires a model of how cover relates to use; requires a defined **ontology** of land use

Land cover mapping (1/3)

Three main approaches:

1. *Unsupervised* pixel-based

- Machine-learning algorithms cluster pixels in spectral space
  - multivariate (hierarchical) clustering, multiple regression classifiers, random forests, artificial neural networks ...
- Analyst assigns labels to clusters, by ground or airphoto inspection of some examples
- Analyst may **merge** clusters that represent the same land cover (e.g., type of vegetation at different growth/maturity stages)
- Analyst assigns class labels to (possibly merged) clusters
  - names based on what could be distinguished in the imagery
  - or, the classes may be assigned to pre-defined legend classes

...

Land cover mapping (2/3)

. . .

(2) *Supervised* pixel-based

- *a priori* list of classes
- Analyst identifies areas in the scene known to be in the various classes
- Spectral characteristics of these are extracted from the image(s) → distribution; often assumed multivariate normal
  - n.b., problems if one class has several realizations in the scene
- Each pixel in image is matched to the most likely distribution, usually by maximum likelihood

Land cover mapping (2/3)

...

(3) *Object-oriented* (contextual)

- Considers the **context** of a pixel, not in isolation
- (see below, “Object-oriented” classification)

Land cover mapping – example (1/3)

Reference: Friedl, M. A., *et al.* (2002). **Global land cover mapping from MODIS: Algorithms and early results. Remote Sensing of Environment**, 83(1-2), 287-302. https://doi.org/10.1016/S0034-4257(02)00078-0

- Legend: land cover categories; here from IGBP
  - IGBP = International Geosphere-Biosphere Programme[1]
  - **categories** and **level of detail** are from the client/user
    example: "Evergreen needleleaf forests (127): Lands dominated by needleleaf woody vegetation with a percent cover >60% and height exceeding 2 m. Almost all trees remain green all year. Canopy is never without green foliage."
  - the imagery may or may not be able to distinguish these
    - maybe with ancillary information, e.g., *a prior* land cover maps from an independent source

[1] http://www.igbp.net/

Land cover mapping – example (2/3)

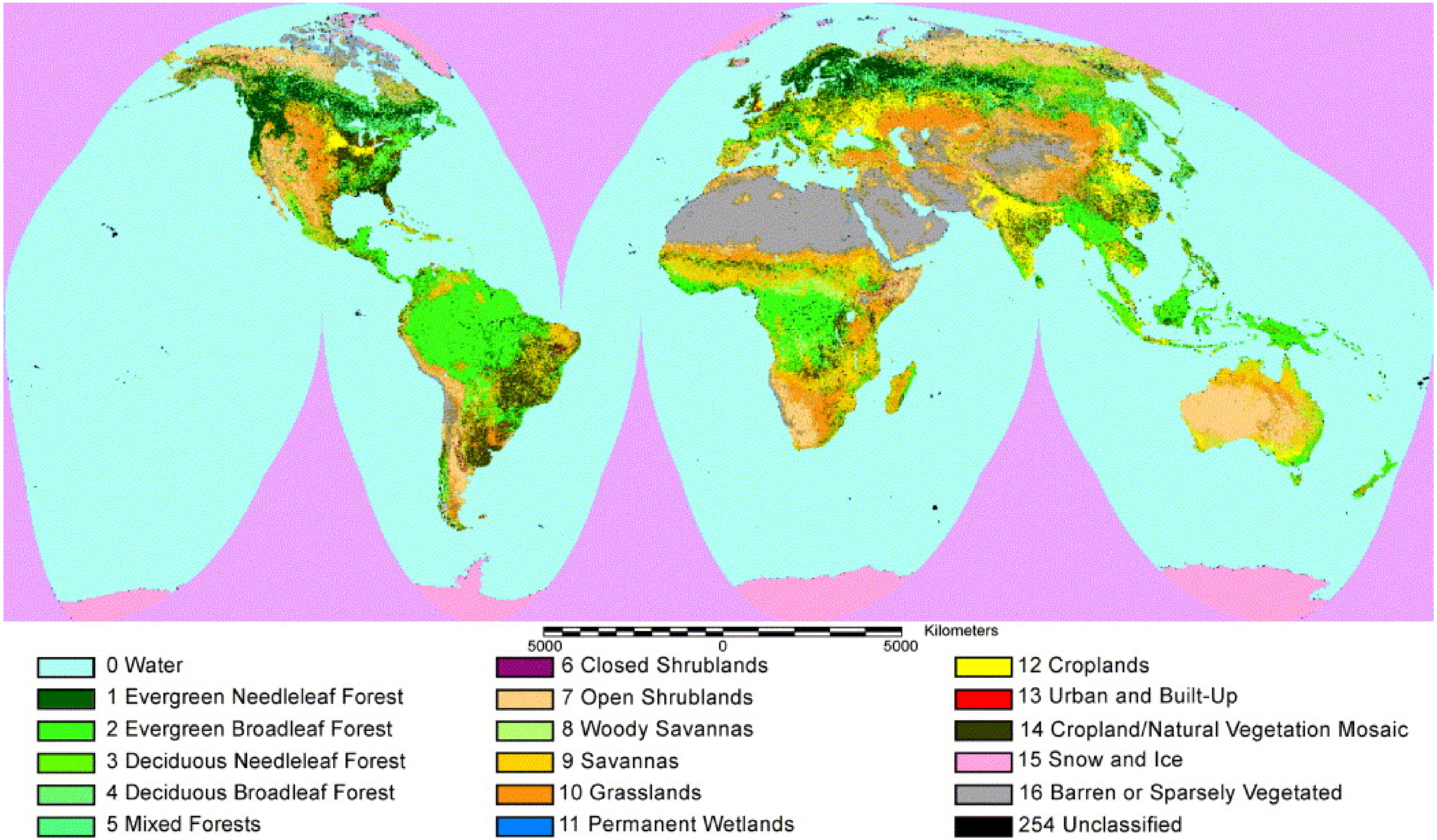
- Supervised classification
  - **training sites**, must be representative
  - some classes may need sites with different characteristics (e.g., spectral characteristics depends on growth stage), mapped separately, later to be merged

    These authors used the System for Terrestrial Ecosystem Parameterization (STEP): “a classification-free and versatile database structure for site-based characterization of global land cover . . . explicitly designed as a general purpose database for ecological studies.”
  - **algorithms**: C4.5 decision trees; Artificial Neural Networks

Land cover mapping – example (3/3)

- RS products used as predictors in the classification algorithm:
  - MODIS reflectance,
  - MODIS Enhanced Vegetation Index
  - MODIS Bi-directional reflectance
  - USGS land/sea mask
  - MODIS snow/ice
  - maximum MODIS surface temperature
  - USGS DEM elevation, slope aspect, slope gradient

IGBP first-level categories



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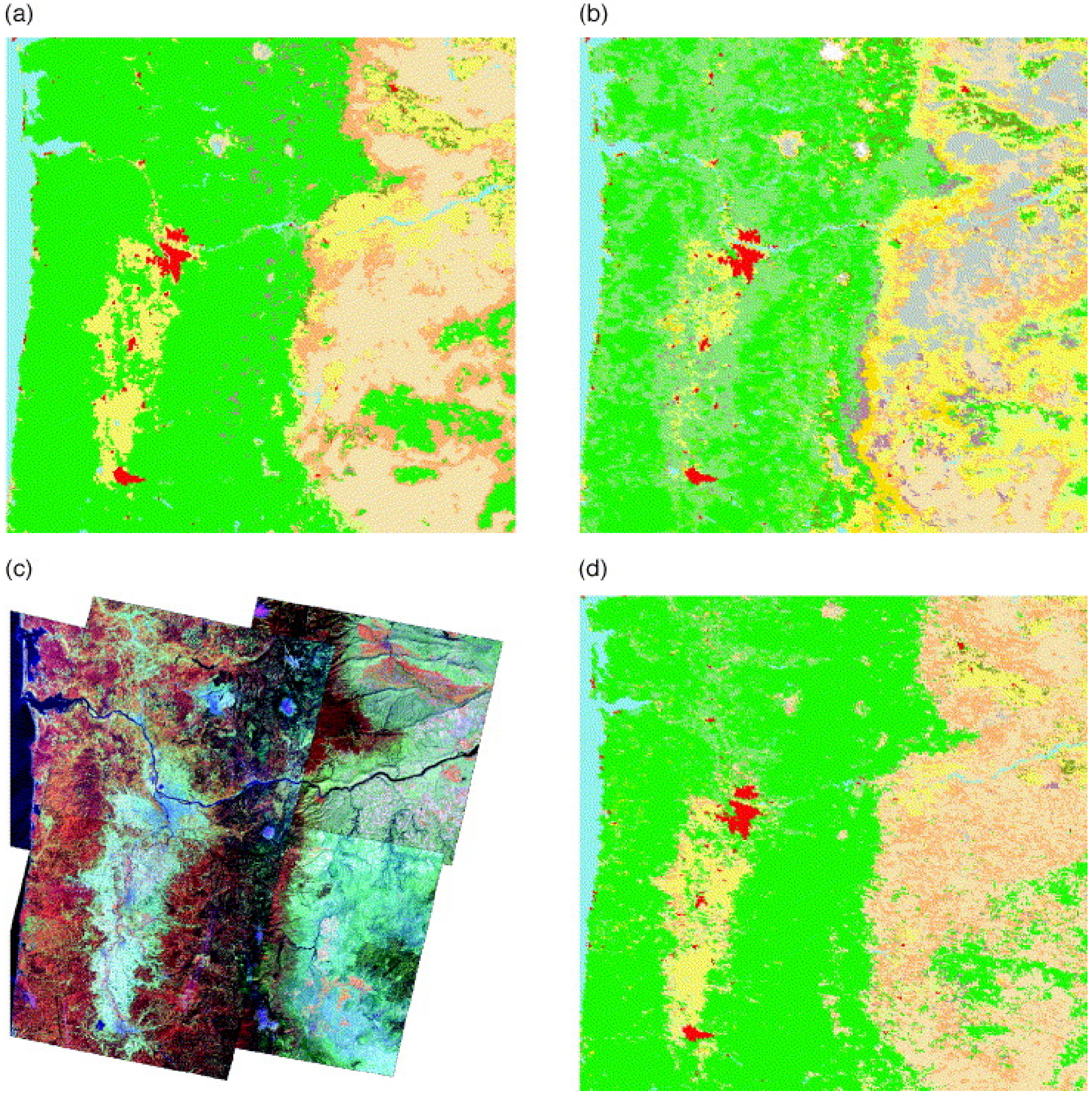
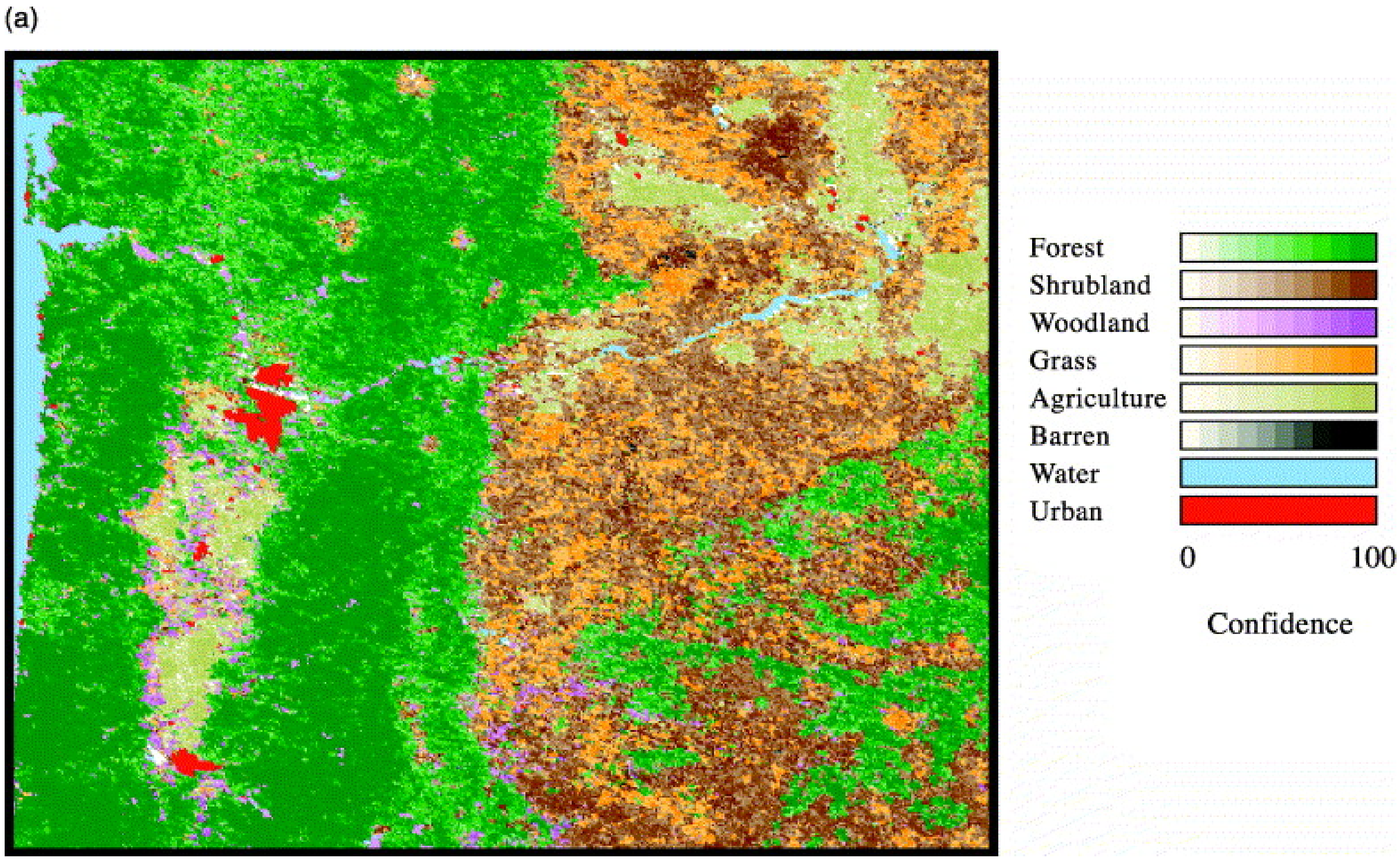
Improving land cover mapping with newer products



(a) previous map; (b) prototype land cover map from AVHRR; (c) four Landsat TM images;(d) the MODIS Beta release classification

Per-pixel confidence for first mapped class



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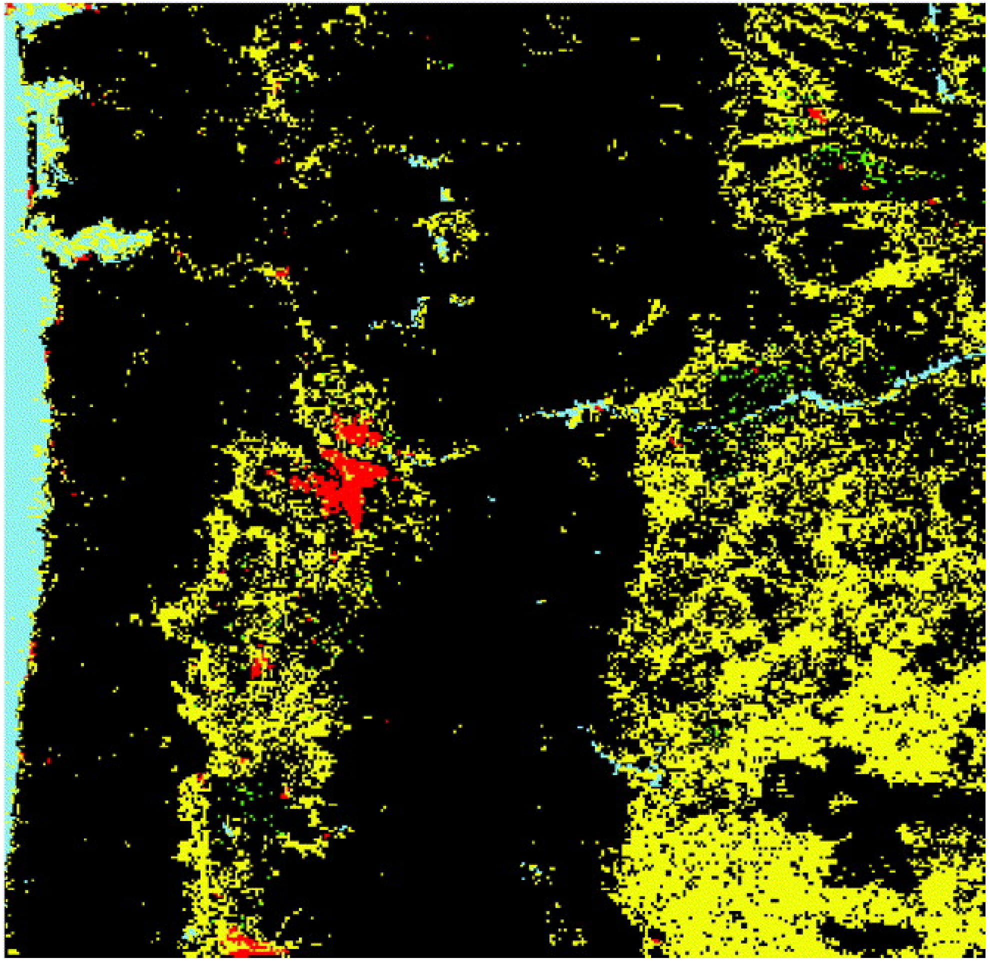
Using ancillary information



Classification changes due to inclusion of **prior probabilities** for agriculture: *yellow* = change from agriculture to natural vegetation; *green* = change from natural vegetation to agriculture.

Land use mapping

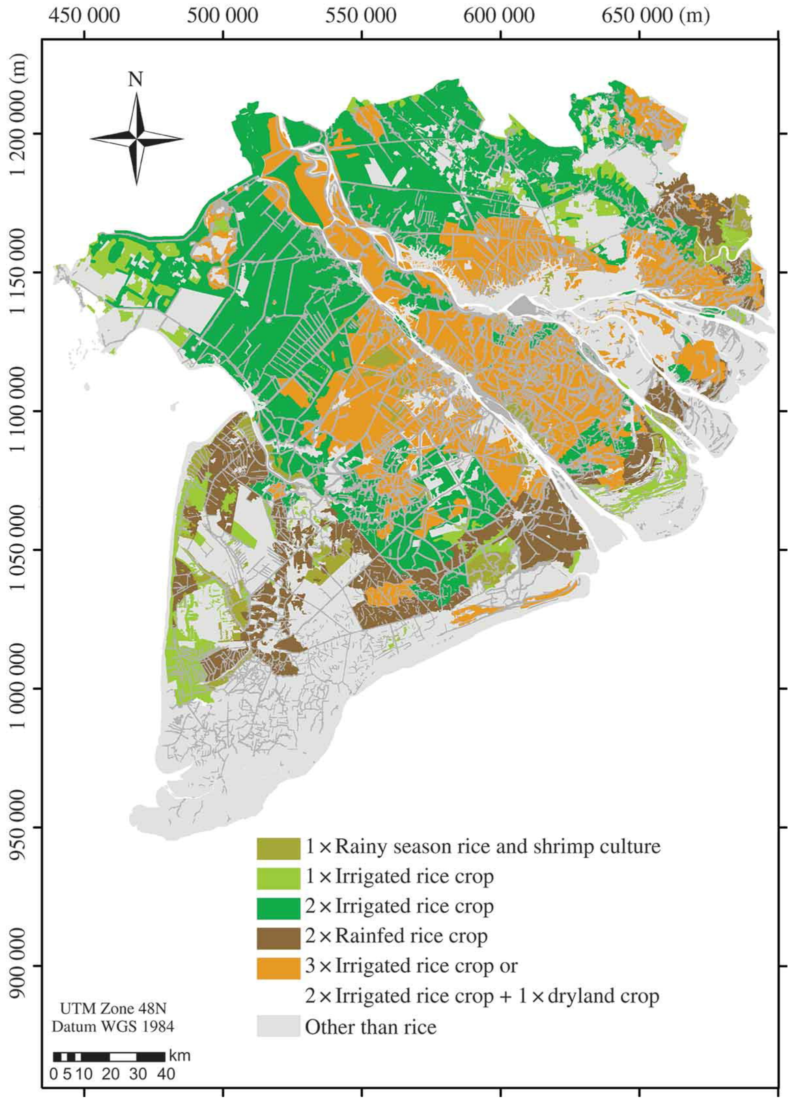
- What is a “land use?” – must have a **legend** according to client/user needs
- What **land covers** are possible within a **land use**?
  - e.g., grassland cover could be a golf course (*recreational* land use), pasture (*agricultural*), large lawn (*residential*)
- Ancillary information is needed
  - e.g., grass on very steep slope on mountainside, in a “finger” pattern is likely a ski slope (*recreation*).
- A single **land use** may include **diverse land covers** in a spatial arrangement
  - e.g., dairy farms with buildings, pasture, cropland

Land use mapping – example

Reference: Nguyen, Thu Thi Ha, *et al.* (2012). *Mapping the irrigated rice cropping patterns of the Mekong delta, Vietnam, through hyper—Temporal SPOT NDVI image analysis*. **International Journal of Remote Sensing**, 33(2), 415–434. https://doi.org/10.1080/01431161.2010.532826

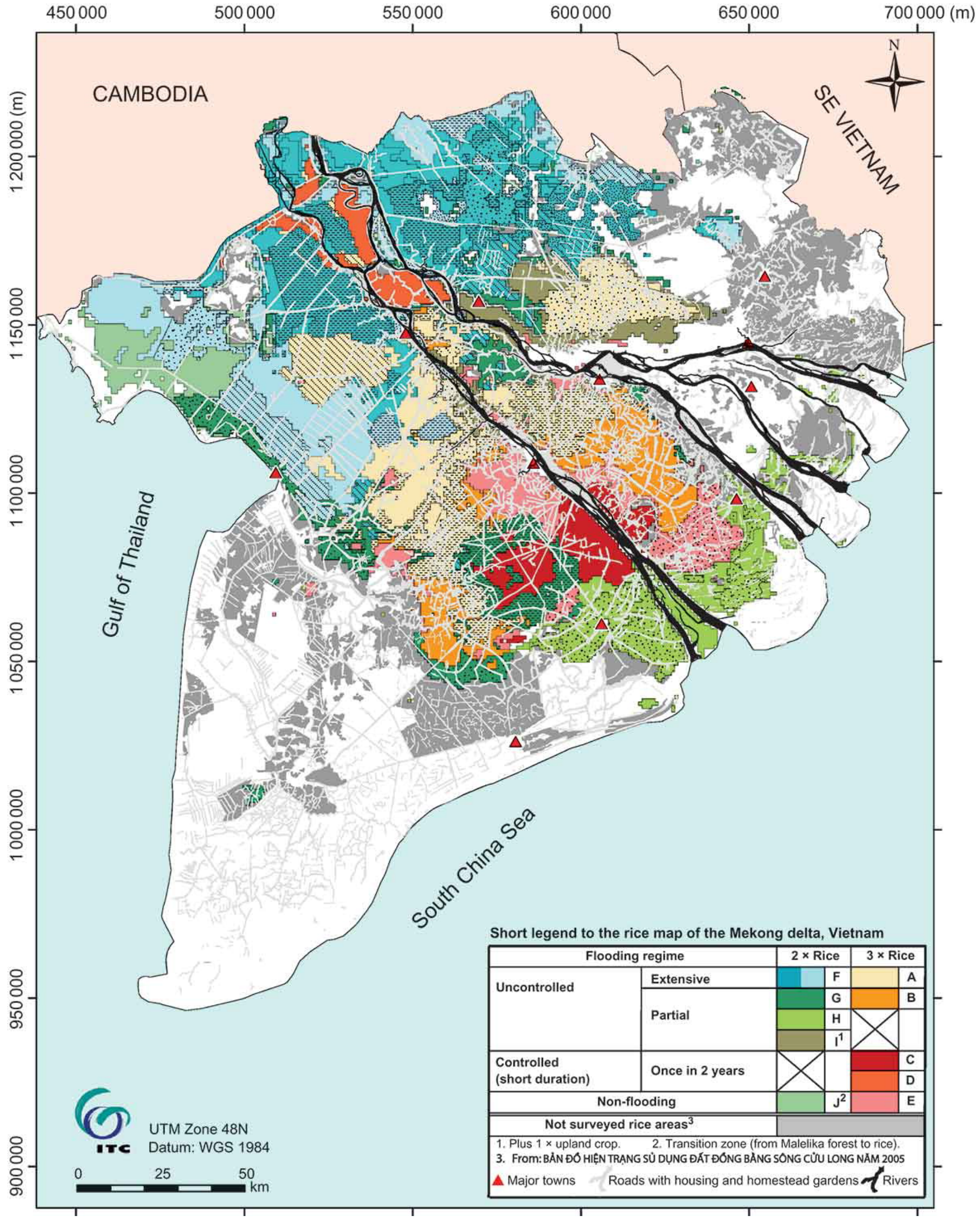
- Land uses: **cropping systems**
- Imagery: long time-series – to capture detailed **phenology**

Prior land use map by ground survey

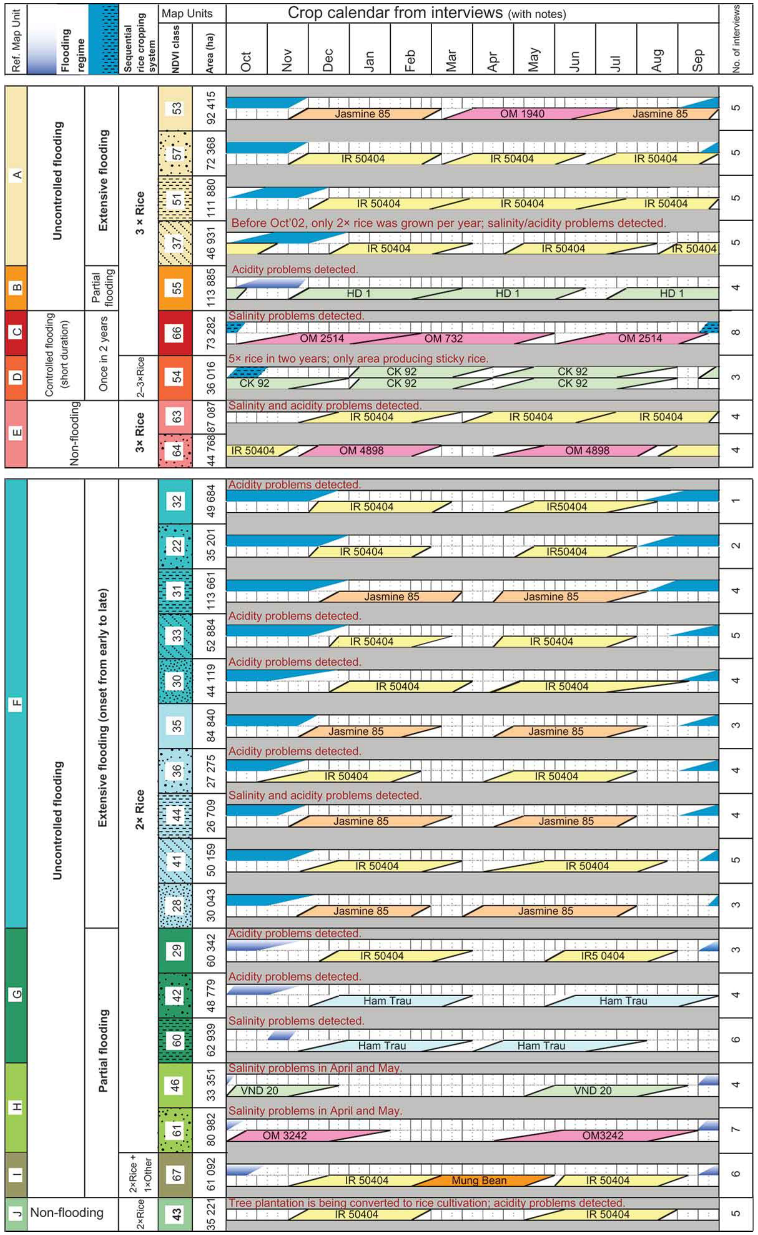


Notice fairly general legend – six cropping categories

Land use map by hyper-temporal remote sensing



Cropping patterns time-sequence



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Accuracy assessment

- Must compare **predicted** land cover or land use class with **actual** class
- This requires a **probability sample** (simple random, stratified random . . .) across the map of **ground truth** points
  - field sampling or identification with air photos/very high-resolution imagery
  - problem of yes/no identification → **fuzzy** accuracy assessment
- Compare actual vs. predicted with a **cross-classification** (also called **confusion**) matrix
- Compute accuracy statistics

Accuracy statistics

Overall accuracy proportion of ground truth samples where actual = predicted

- **diagonal** of cross-classification matrix

User's accuracy or "map unit purity" (Brus 2011); per-class predicted = actual

- **rows** of cross-classification matrix

Producer's accuracy or "class representation" (Brus 2011); per-class actual = predicted

- **columns** of of cross-classification matrix

τ corrects these for prior probabilities, assessed mapper skill (replaces the obsolete, incorrect κ)

Sample cross-classification matrix

Table 5
Conventional accuracy assessment of the regional land cover map at the super-alliance level

Predicted		Observed data set (field data)																											
		Subclass code																											
		1100			1200						1300			3100			5100				5400	6300		7000	8000			Row	User's
Land cover type		1	3	4	5	6	7	8	9	10	11	12	13	20	22	24	30	31	32	36	37	43	45	50	60	61	62	total	(%)
Spruce-fir	1	**67**	13	3	26	1	0	2	0	0	0	195	4	0	0	0	2	8	0	0	1	0	0	2	0	0	0	324	21
Evergreen wetland	3	22	**26**	2	6	0	1	4	0	0	0	79	1	0	5	0	0	6	0	0	0	0	0	7	0	0	1	160	16
Evergreen plantation	4	0	0	**57**	0	1	2	4	0	0	0	36	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	101	56
Sugar maple mesic	5	2	2	14	**554**	186	325	51	0	3	0	196	1	37	11		172	2	0	1	124	0	1	3	2	13	22	1722	32
Oak	6	0	0	2	91	**241**	94	14	2	4	1	91	0	9	0	0	41	1	0	1	25	0	0	2	0	5	23	647	37
Successional hardwoods	7	0	0	7	167	94	**455**	46	0	4	1	151	1	27	10	0	108	4	0	0	74	0	0	2	0	4	33	1188	38
Deciduous wetland	8	3	2	0	33	17	47	**96**	0	0	0	35	4	3	14	0	22	28	0	0	15	0	0	27	2	1	6	355	27
Orchard/vineyard	9	0	0	0	0	0	0	0	**4**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0
Appalachian oak–pine	10	0	0	13	21	32	10	7	0	**5**	0	71	0	0	0	0	11	1	0	1	0	0	1	1	0	1	14	188	0
Pitch pine–oak	11	0	0	0	0	25	2	3	0	0	**49**	3	0	1	0	0	0	0	2	0	0	1	0	1	0	9	28	125	40
Evergreen–northern hardwood	12	30	5	142	205	67	119	49	0	3	0	**1205**	5	12	15	0	29	9	0	0	13	0	0	5	4	2	10	1929	62
Mixed wetland	13	0	0	3	5	0	5	2	0	0	0	44	**1**	1	1	0	3	2	0	0	1	0	0	2	0	2	4	76	1
Successional shrub	20	0	0	2	17	11	72	8	0	0	2	17	0	**42**	0	2	72	1	3	0	55	0	0	1	4	18	32	359	12
Shrub swamp	22	4	7	0	7	0	12	8	0	0	0	7	1	1	**10**	0	12	8	0	0	20	0	2	7	1	2	5	115	9
Salt shrub/maritime shrubland	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**	0	0	0	0	0	0	0	0	0	0	0	0	0
Old field/pasture	30	0	0	2	16	12	38	8	1	0	0	4	0	35	1	5	**406**	0	0	9	230	2	0	0	6	20	53	848	48
Emergent marsh/open fen/wet meadow	31	1	1	3	0	0	4	10	0	0	0	8	3	5	2	0	13	**26**	0	0	16	0	2	8	2	1	0	105	25
Salt marsh	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**30**	1	0	0	0	0	0	0	2	34	88
Golf course/park/lawn	36	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	6	1	0	**9**	0	0	0	0	0	0	1	18	0
Cropland	37	0	2	3	17	18	29	3	4	0	2	11	0	21	2	0	334	12	0	11	**610**	0	2	1	2	33	39	1156	53
Sand dunes/flats	43	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	**7**	0	0	1	13	5	28	25
Barren	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	**1**	0	0	8	2	14	7
Open water	50	1	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	5	0	0	0	1	0	**121**	0	0	0	131	92
Road	60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	**12**	0	0	14	86
Urban	61	0	0	0	0	1	0	0	0	0	0	1	0	1	0	1	3	0	0	0	0	0	0	0	12	**35**	20	74	47
Suburban	62	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	3	**22**	30	73
Column total		130	58	253	1166	707	1215	315	11	19	56	2157	21	195	71	11	1240	114	35	33	1185	11	9	190	51	170	322	9745	
Producer's (%)		52	45	23	48	34	37	30	36	26	88	56	5	22	14	0	33	23	86	27	51	64	0	64	24	21	7		

Total correct = 4091; overall accuracy (%) = 42.0; Kappa=.345.

M. Laba et al. / Remote Sensing of Environment 81 (2002) 443–455

source: Laba *at al.* (2002)

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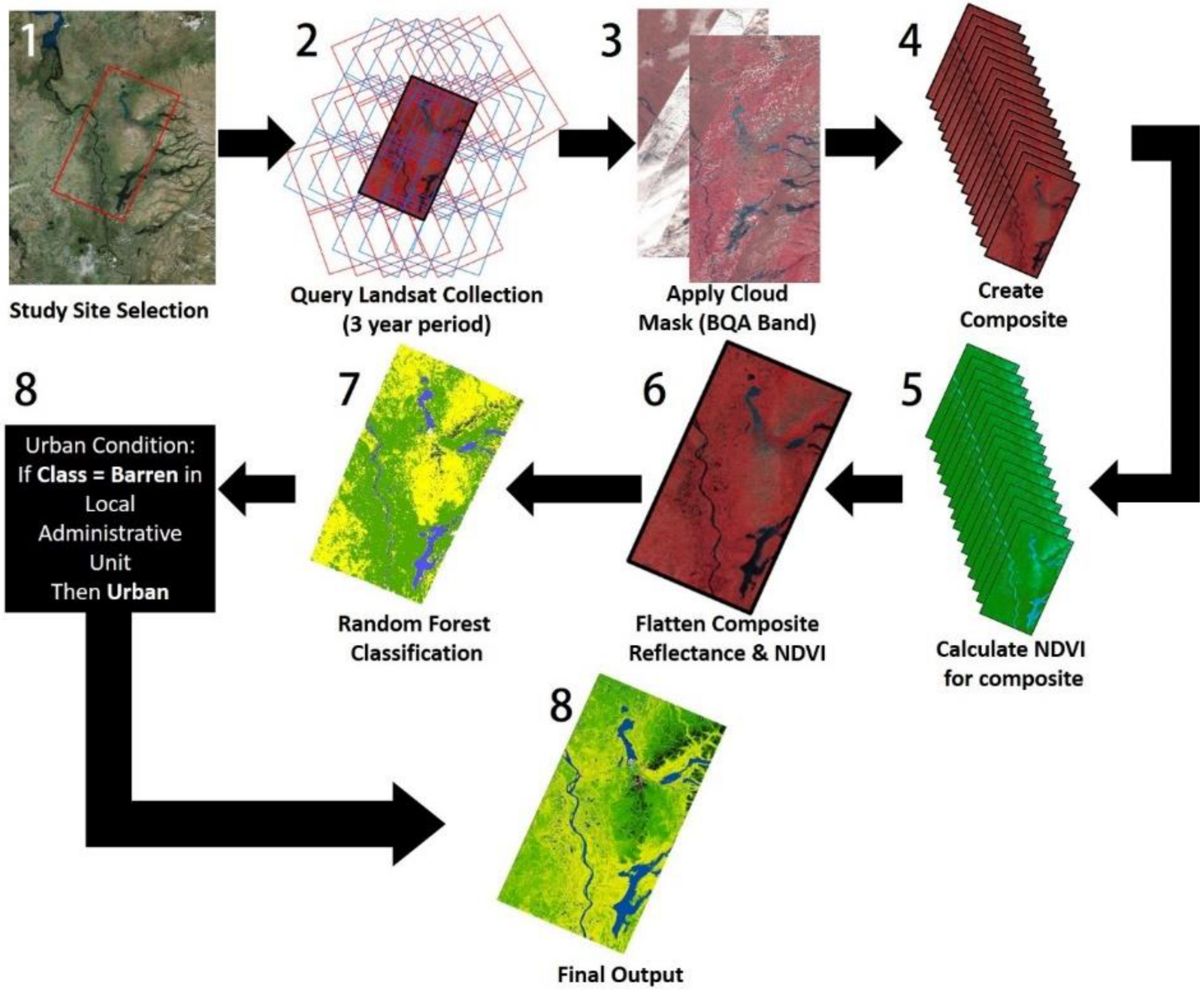
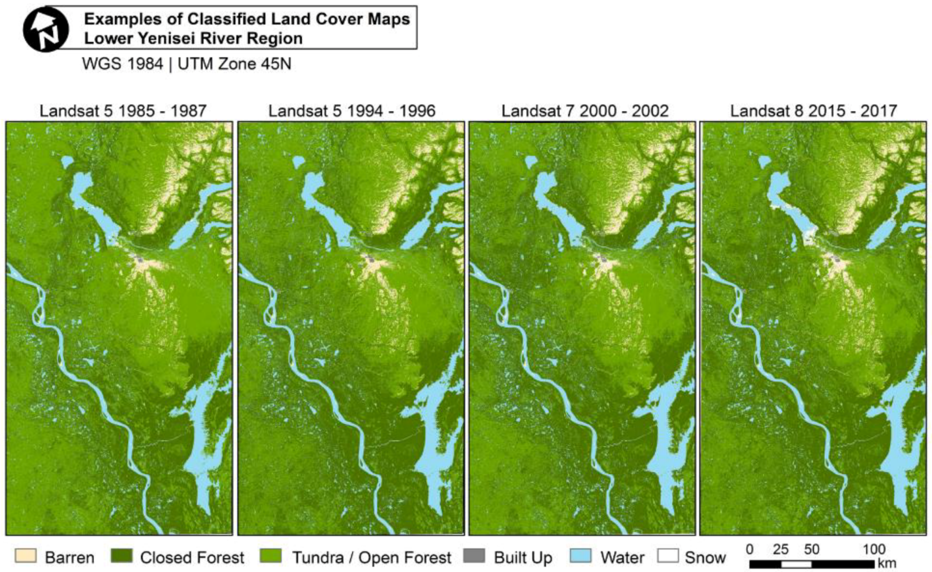
Topic: Change detection

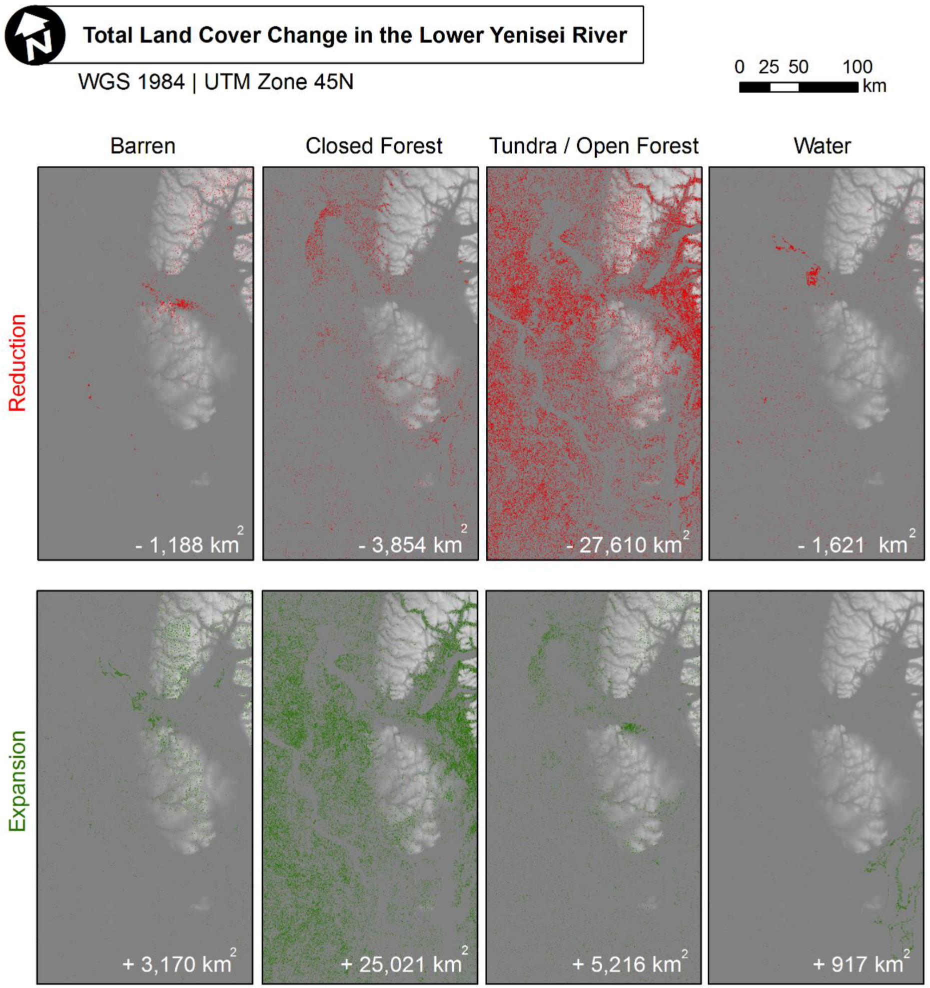
- Two or more images of the same scene – what has changed?
  - in the remote sensing product
  - on the ground
- Method: **pre-classification**: co-registration, change in pixel values
  - problem: exact co-registration
  - problem: comparable digital numbers vs. variable illumination/atmosphere
  - problem: significance of change in values vs. actual change
  - multi-temporal: change **vectors**
- Method: **post-classification**: independent allocation to same classification, co-registration, map overlay to find differences
  - problems: exact co-registration, independent allocations each have (correlated?) errors

Change detection example

Source: Nyland, Kelsey E. *et al.* (2018). Land cover change in the lower Yenisei river using dense stacking of Landsat imagery in Google Earth Engine. **Remote Sensing**, 10(8), 1226. `https://doi.org/10.3390/rs10081226`




Examples of Classified Land Cover Maps
Lower Yenisei River Region
WGS 1984 | UTM Zone 45N
Landsat 5 1985 - 1987
Landsat 5 1994 - 1996
Landsat 7 2000 - 2002
Landsat 8 2015 - 2017
Barren
Closed Forest
Tundra / Open Forest
Built Up
Water
Snow
0 25 50 100
km


Total Land Cover Change in the Lower Yenisei River
WGS 1984 | UTM Zone 45N
0 25 50 100
km
Barren
Closed Forest
Tundra / Open Forest
Water
Reduction
- 1,188 km²
- 3,854 km²
- 27,610 km²
- 1,621 km²
Expansion
+ 3,170 km²
+ 25,021 km²
+ 5,216 km²
+ 917 km²

Time resolution of change detection

1. Seasonal (e.g., vegetation phenology, atmospheric pollution, cloudiness)
   - May look for **cycles**
2. Annual
3. Long-term
   - often to look for **trends**

Reference: Eastman, J. R., *et al.* (2009). Seasonal trend analysis of image time series. International Journal of Remote Sensing, 30(10), 2721–2726. `https://doi.org/10.1080/01431160902755338`

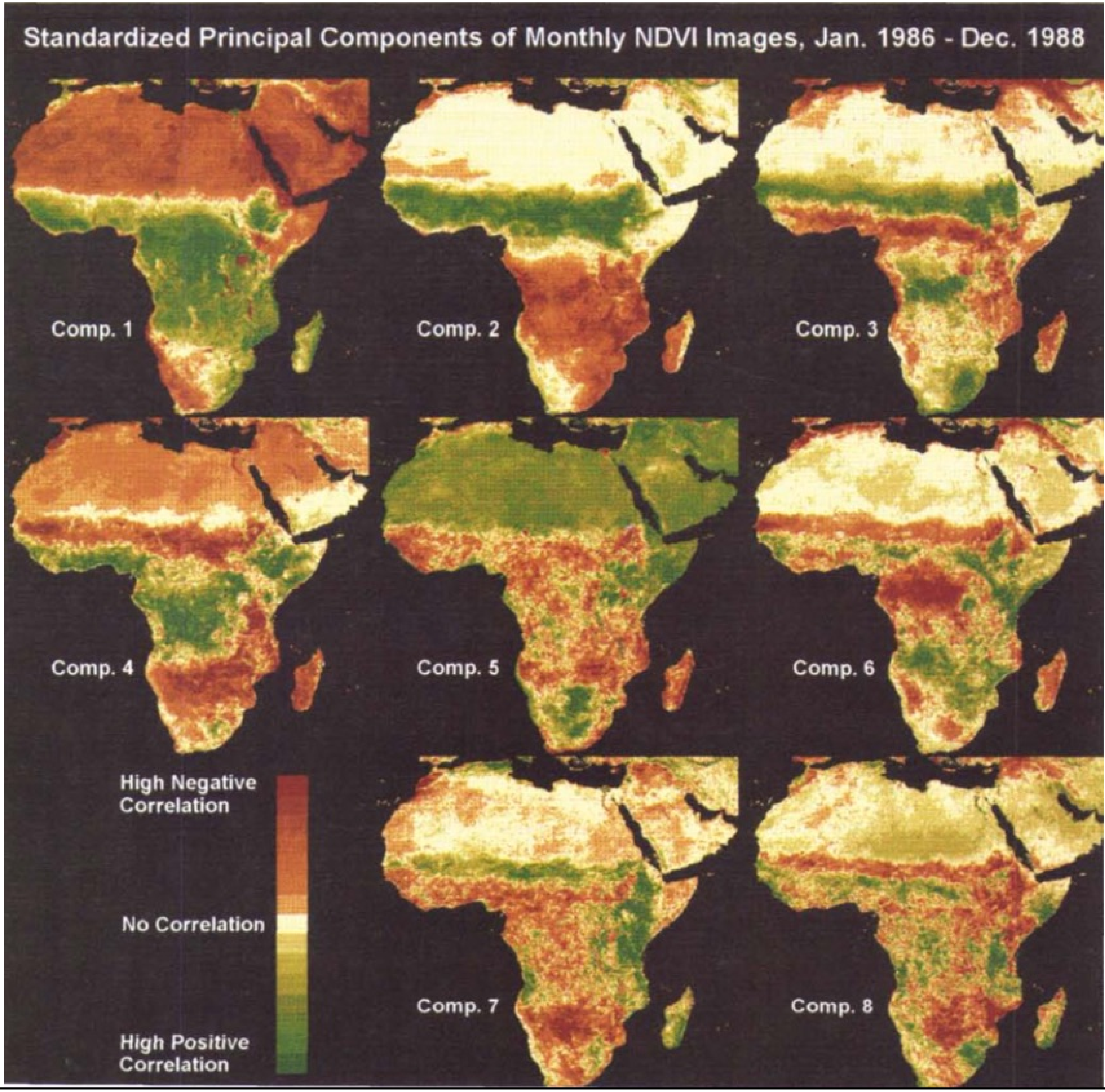
Change detection of a property

- Example: time-series of NDVI to estimate trends in vegetation health or land use

- See example of long-term PCA for Africa

  - Eastman, J., & Fulk, M. (1993). **Long Sequence Time-Series Evaluation Using Standardized Principal Components** (reprinted from Photogrammetric Engineering and Remote-Sensing , Vol 59, Pg 991–996, 1993). *Photogrammetric Engineering and Remote Sensing*, 59(8), 1307–1312.

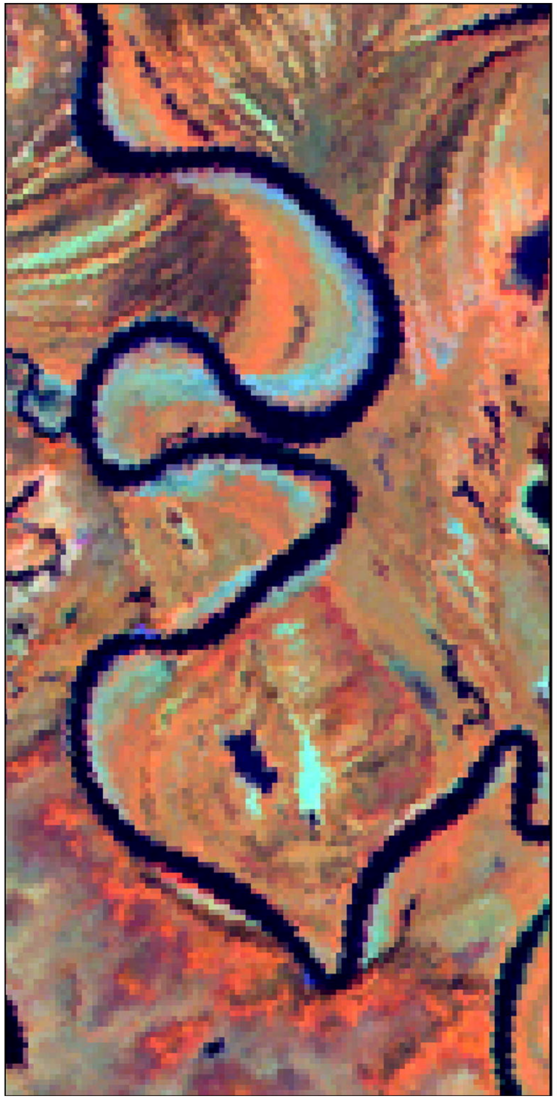
- More explanation in lecture about Principal Components Analysis

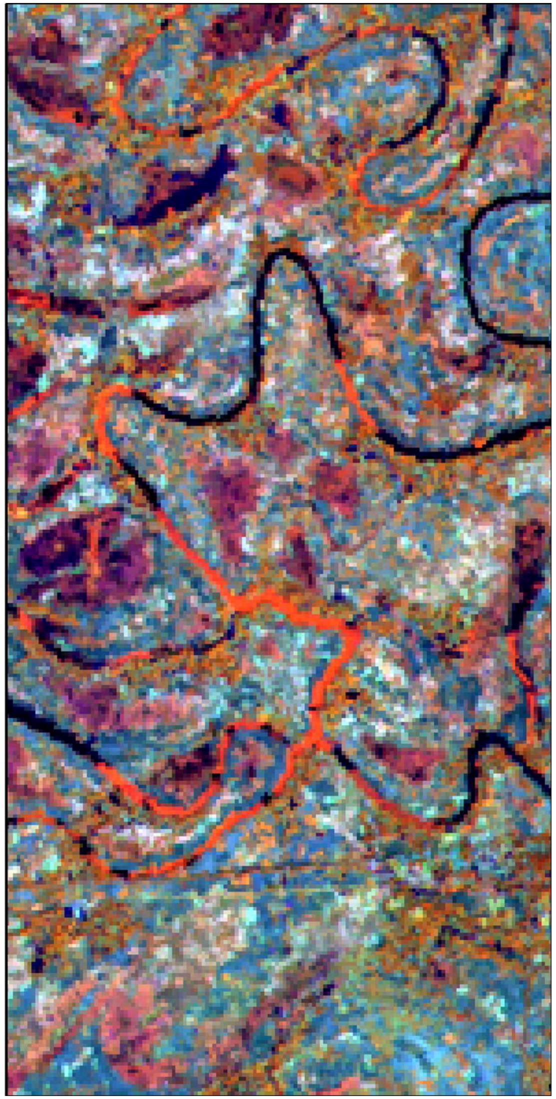

Standardized Principal Components of Monthly NDVI Images, Jan. 1986 - Dec. 1988
Comp. 1
Comp. 2
Comp. 3
Comp. 4
Comp. 5
Comp. 6
Comp. 7
Comp. 8
High Negative Correlation
No Correlation
High Positive Correlation

Topic: Geographic Object-Based Image Analysis (GEOBIA)

- Image is matched to the scene as discrete objects
- Must have H-resolution imagery – objects are made up of groups of pixels
- Hierarchical concept of objects – group low-level objects into higher-level objects
- This requires a definite **ontology**
  - Information science concept: naming and definition of all the entities in some domain (their data types and attributes)
  - Also their permissible **interrelationships**

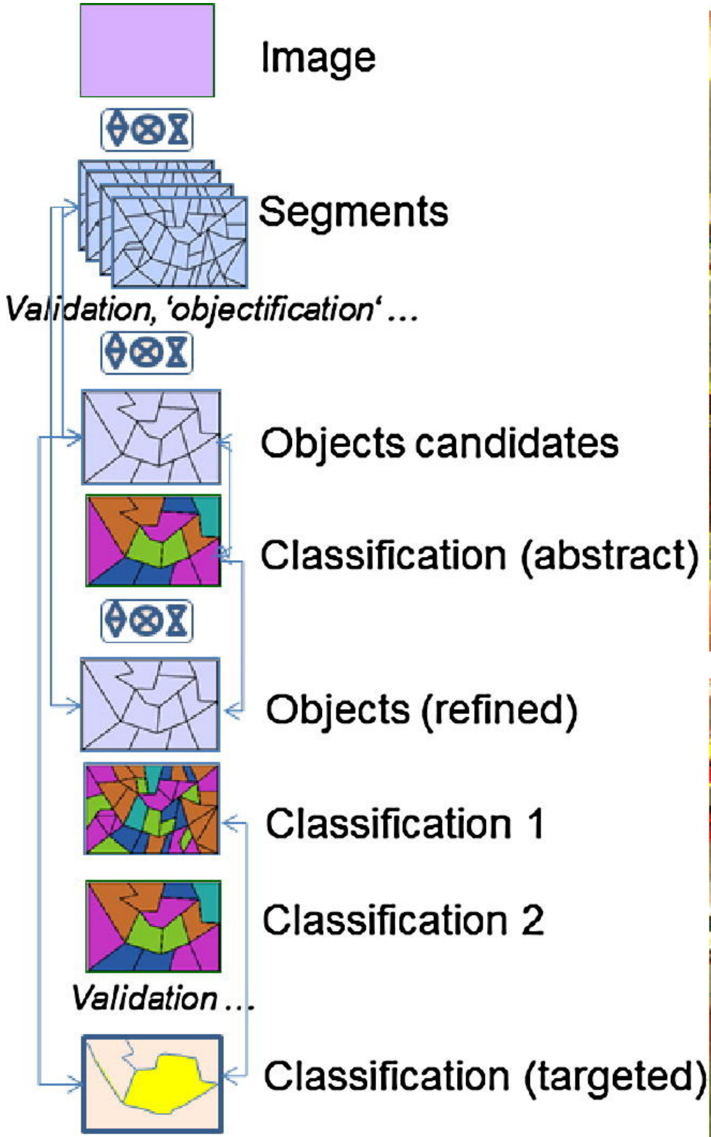
Reference: Blaschke, T., *et al.* (2014). **Geographic Object-Based Image Analysis – Towards a new paradigm.** *ISPRS Journal of Photogrammetry and Remote Sensing*, 87, 180–191. `http://doi.org/10.1016/j.isprsjprs.2013.09.014`



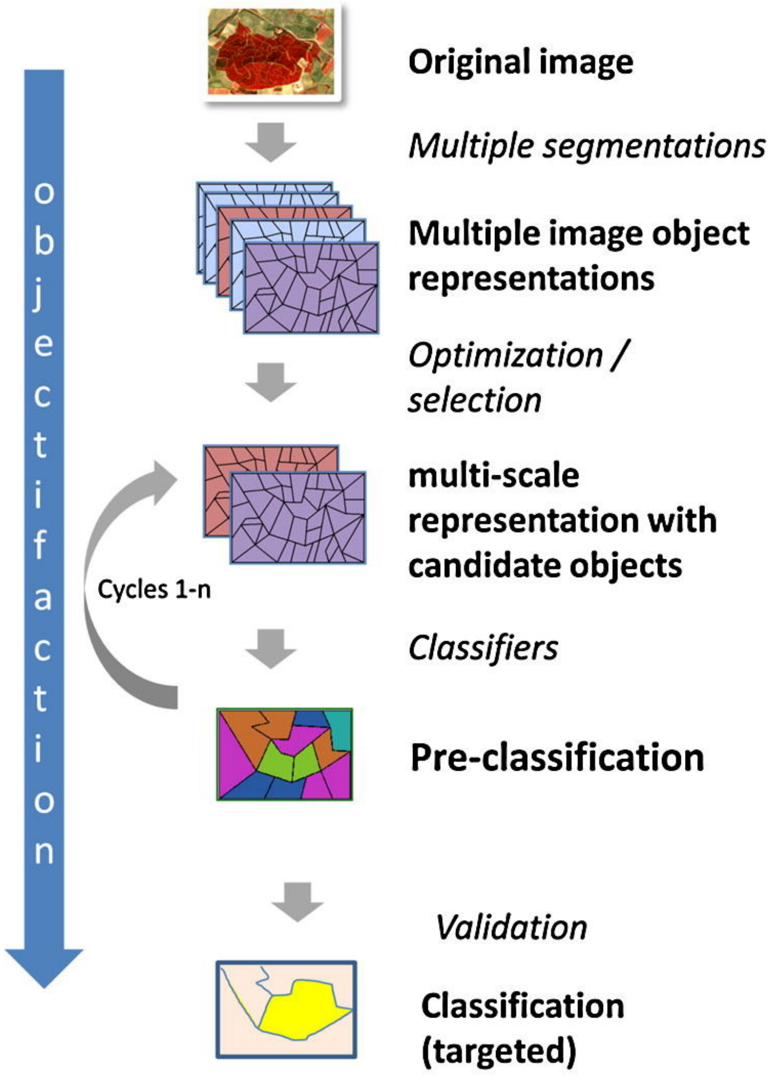


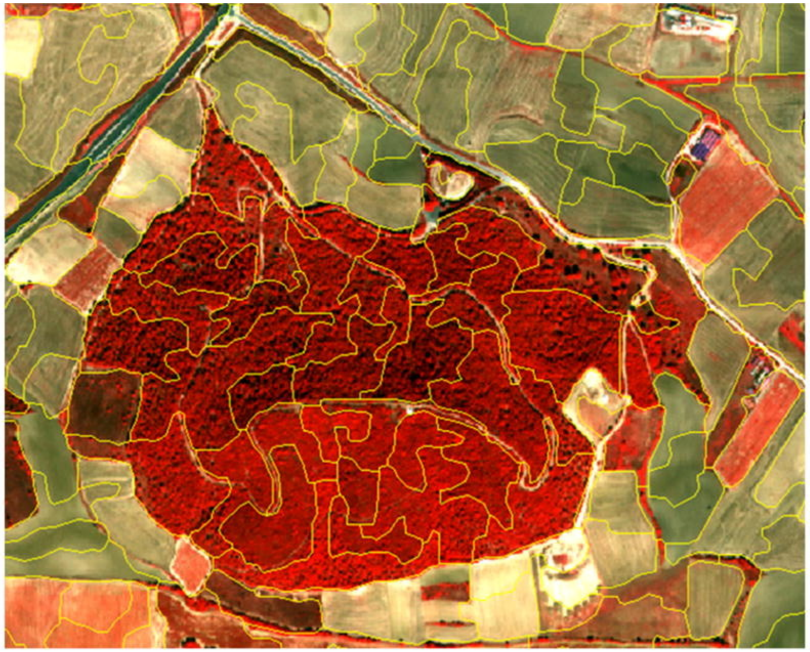
Landsat TM: Alaska
water-filled and sedimented channels intermingled

Bangladesh
overgrown channel

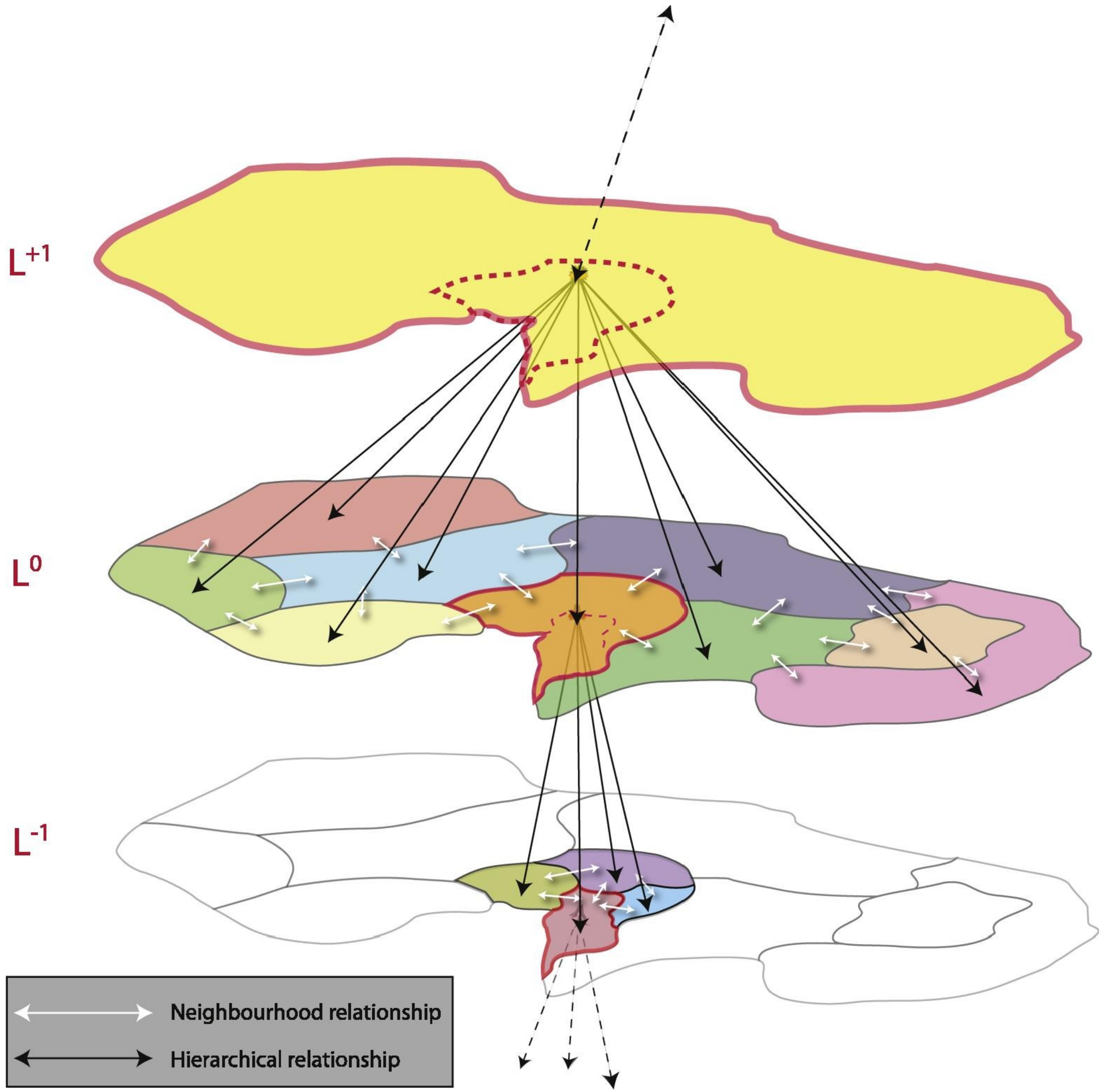


GEOBIA workflow: iterative (1) object building and (2) classification

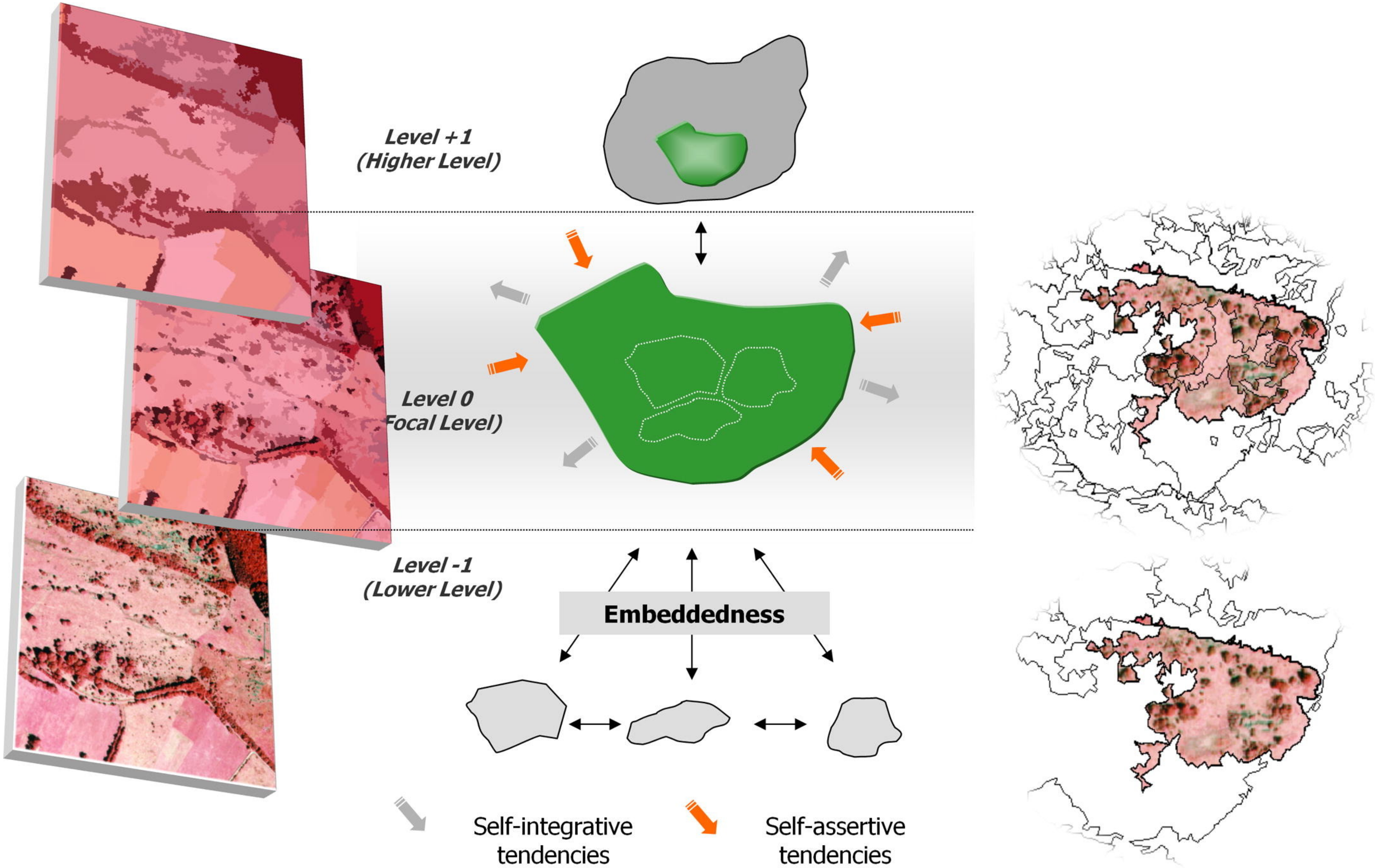




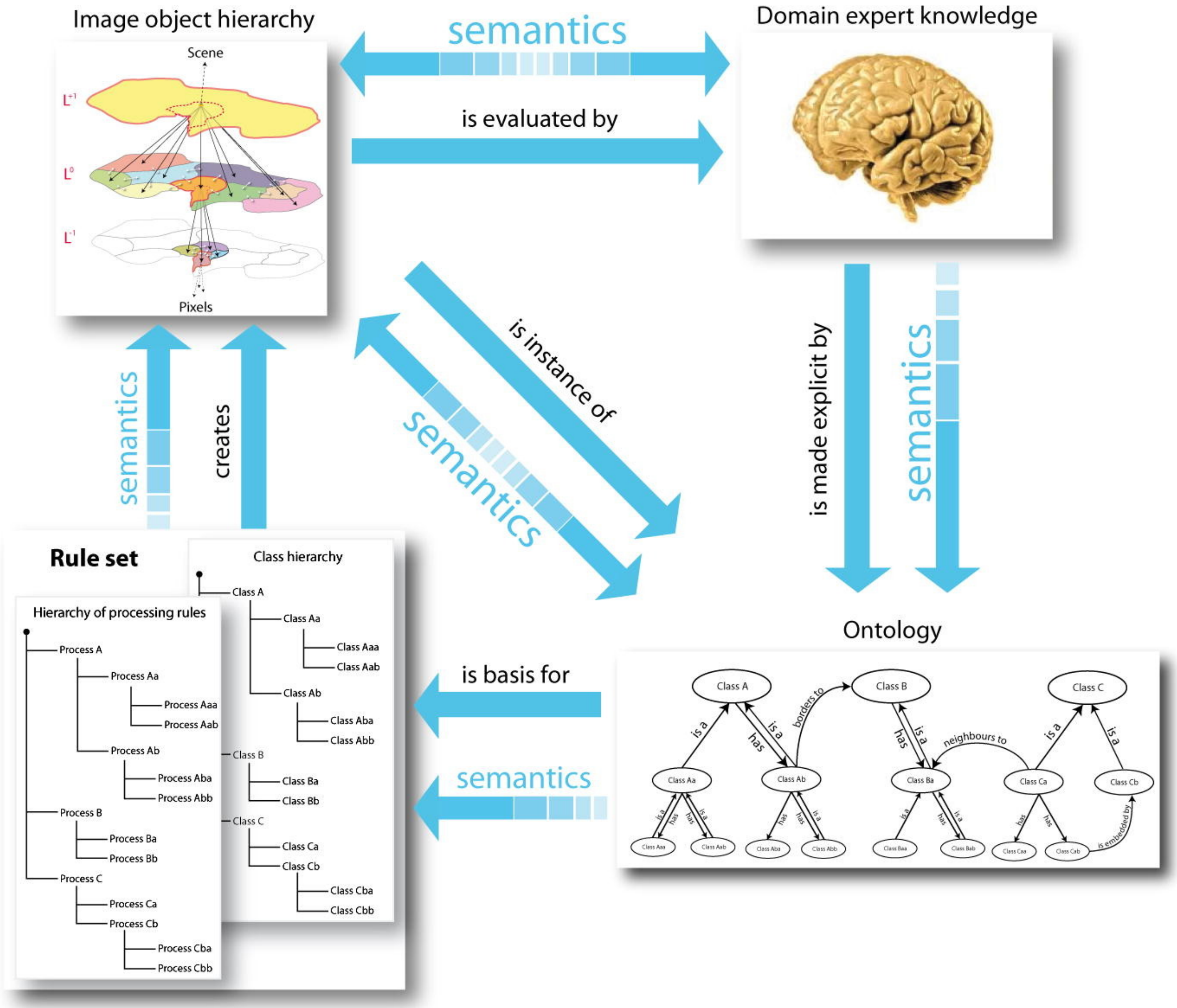
From the image to a classification



Spatial relations across the hierarchy and at one level (topological)



Conceptual illustration of a multi-scale representation of a landscape scene



Semantic/ontological relations between image objects

Topic: Big data in remote sensing

1. Bewildering and ever-expanding sensor systems

2. Ever-increasing data stream: higher spatial/spectral/temporal resolutions

3. Historical archives

4. Opportunity for sophisticated research . . . but how to handle all that data?

Google Earth Engine

- https://earthengine.google.com/
- "A **planetary-scale** platform for Earth science data & **analysis** – Powered by Google's **cloud infrastructure**"
- "hosts satellite imagery and stores it in a **public data archive** that includes **historical earth images** going back more than **forty years** . . . made available for global-scale **data mining**.
- Aimed at consistent Earth-wide analyses, but can be used regionally or locally

Cornell University
College of Agriculture and Life Sciences

Use of GE Engine

- Computation is all done **remotely** (parallel processing)
  - local computer only for coding/viewing
- Accessible via an Application Programming Interface (**API**)
  - Javascript, Python
- Built-in code editor
- Direct access to the datasets
- **Image processing**, **Geometry** algorithms
- **Machine-learning** algorithms: un/supervised classification

Datasets

`https://developers.google.com/earth-engine/datasets/catalog`

- Imagery (Landsat, Sentinel, MODIS . . .)
- Atmospheric conditions (can help correct other products)
- Weather
- Geophysical: terrain (e.g., SRTM), elevation
- Nighlights
- Administrative
- Interpreted: land cover, land use, cropland (e.g., USDA NASS; Global Food Security)

Reference texts

These are entry-level with some applications.

- Lillesand, T. M. (2015). Remote sensing and image interpretation (R. W. Kiefer & J. W. Chipman, Eds.; Seventh edition). John Wiley & Sons, Inc.
- Jensen, J. R. (2007). Remote sensing of the environment: An earth resource perspective (2nd ed.). Pearson Prentice Hall.
- Campbell, J. B., & Wynne, R. H. (2011). Introduction to remote sensing (5th ed). Guilford Press.
- Wang, G., & Weng, Q. (2014). Remote sensing of natural resources. CRC Press; WorldCat.org. http://dx.doi.org/10.1201/b15159