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GEOBIA 2016 Doctoral Colloquium – 12-13 September 2016

Earth observation big data pre-preprocessing and analysis in operating mode: OBIA system design, process and outcome innovations

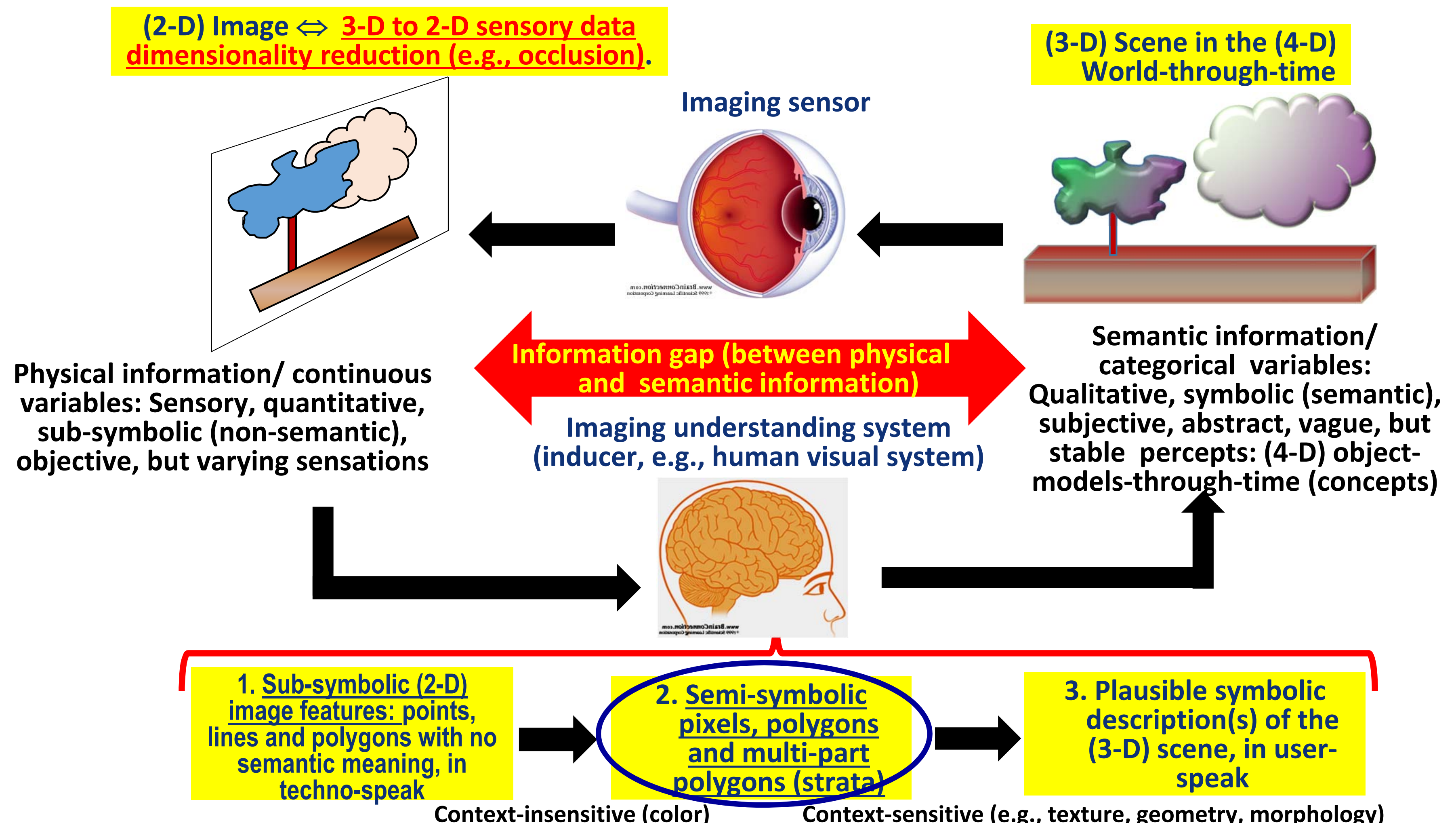
(“In general, process is easier to measure, outcome is more important”, Measurement: Process and Outcome Indicators, Duke Center for Instructional Technology, 2016.)

GEOBIA 2016 Doctoral Colloquium – 12-13 September 2016

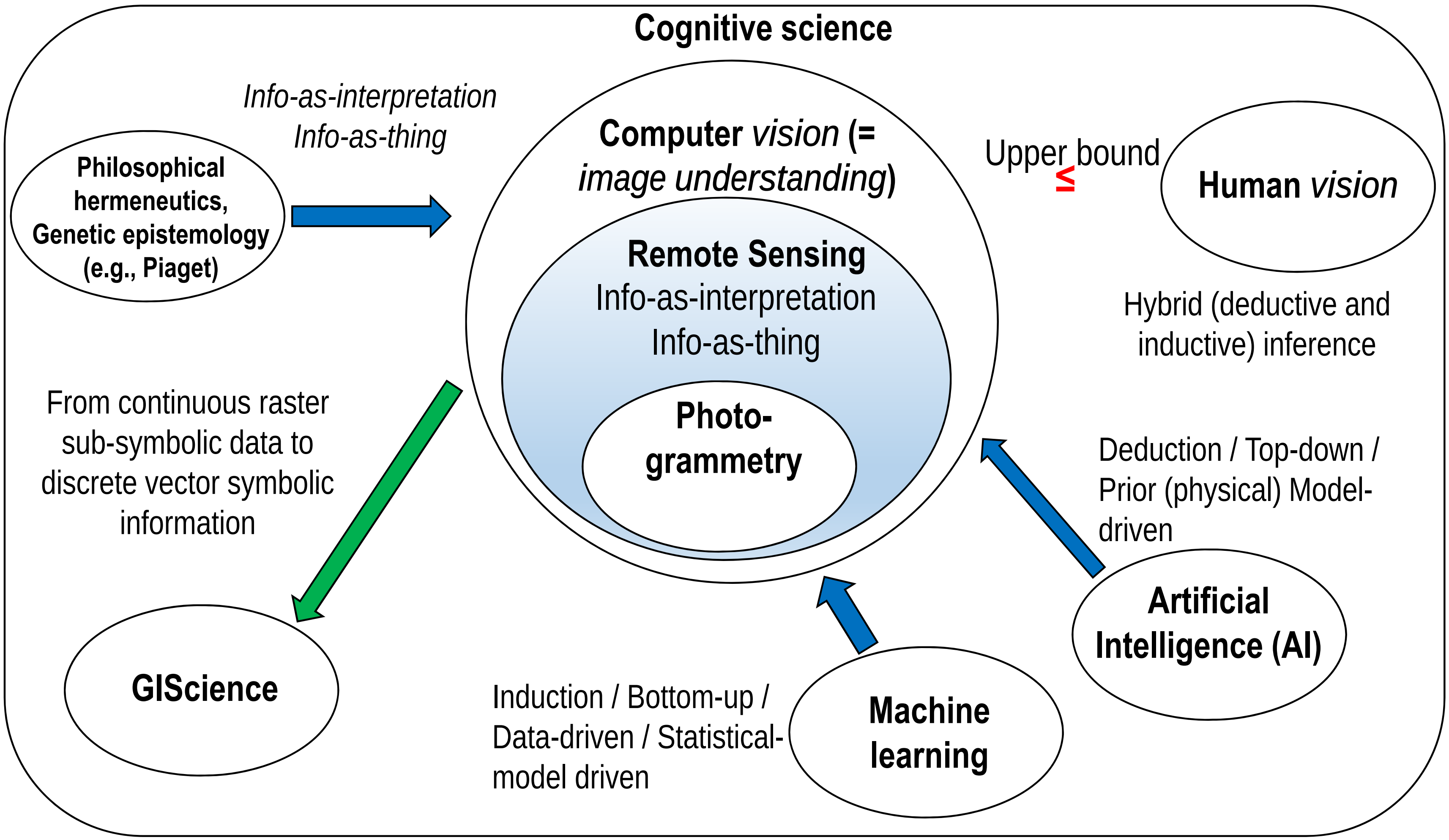
Recommended topics of interest:

- Big Earth data: pre-classification and integrated workflow strategies
- OBIA-specific change detection and accuracy assessment
- Increasing classification transferability and OBIA operationalization
- 3D data processing and object generation

Intro - What is (human) vision? To be mimicked by computer vision.



Intro - Interdisciplinary cognitive science



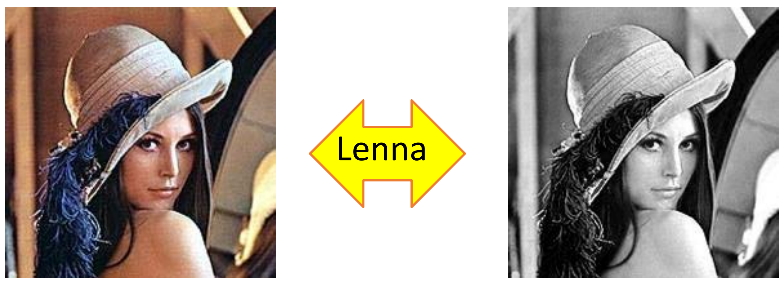
Intro - Spatiotemporal information dominates color information in the (4D) world and in (2D) images

Fact: human chromatic and achromatic visions are nearly as effective in scene-from-image representation

1. **Spatiotemporal information dominates color information in both [8]:**
   I. **the 4D world-through-time domain (scene-domain).**
   II. **The (2D) image domain ⇔ OBIA paradigm** [56], also refer to (Adams et al., 1995) [55].

Experimental proof that primary spatial information is thoroughly investigated by a CV system for scene-from-image representation:

Seamless (near lossless) scalability of a CV system from color to panchromatic image analysis ought to be considered mandatory.



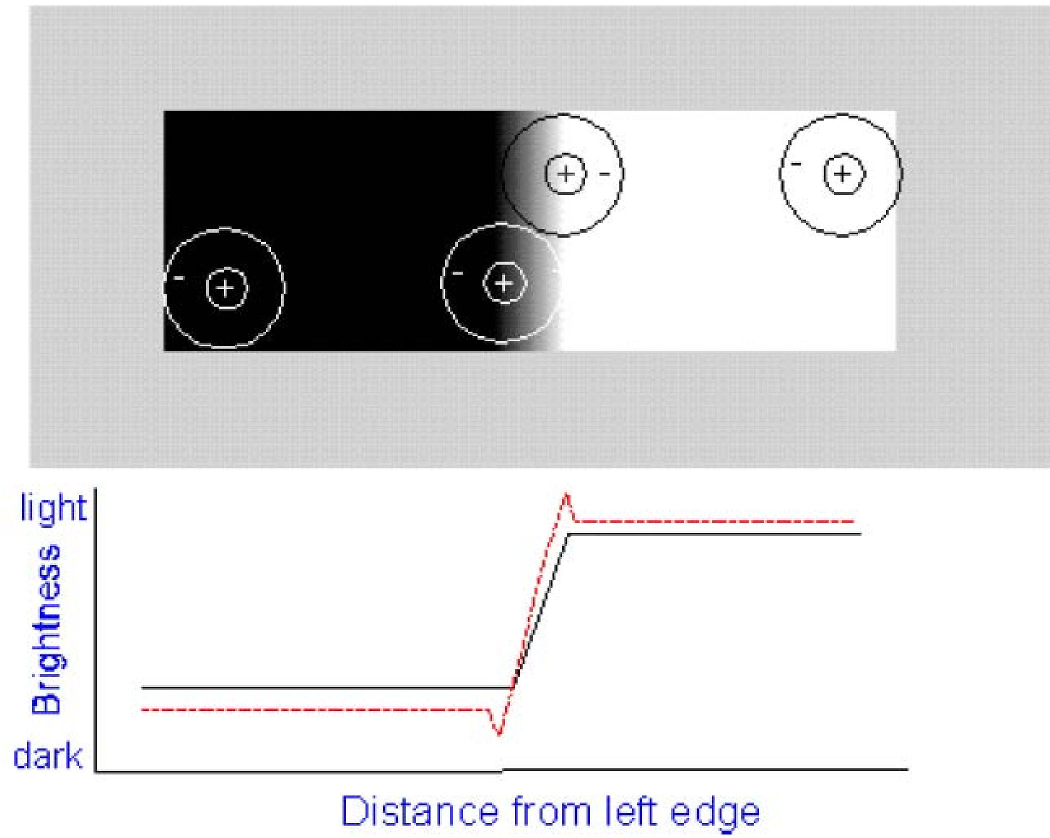
2. **Image non-contextual information: color.** It is the only visual information available at pixel resolution! Easy to deal with...
3. **Image contextual information.**
   I. **Texture** = visual effect generated by the spatial distribution of texture elements (texels) = superpixels = connected sets of pixels featuring the same color name.
   II. **Geometric (shape) and size properties** of image-objects = Marr's zero-crossing segments ⇔ polygons (OGC) [58].
   III. **Inter-object spatial relationships**.
      - **Topological**, e.g., inclusion, adjacency.
      - **Non-topological**, e.g., metric distance, inter-angle measure.
4. **Non-spatial semantic relationships,** e.g., part-of, subset-of. Impossible to learn from (sub-symbolic) sensory data with machime learning-from-data approaches**.**

Intro: Visual illusions - Mach bands

Mach band illusion

One of the best-known brightness illusions (where brightness is defined as the subjective / perceived luminance of a surface) is the psychophysical phenomenon of the Mach bands: where a luminance (radiance, intensity) ramp meets a plateau, there are spikes of brightness, although there is no discontinuity in the luminance profile. As a consequence, human vision detects two boundaries, one at the beginning and one at the end of the ramp in luminance.

"**If we require that a brightness model should at least be able to predict Mach bands, the bright and dark bands which are seen at ramp edges, the number of published models is surprisingly small**" (Pessoa, 1996) [32]



CONCLUSION: traditional local contrast (gradient of I, I • ∂G/ ∂x) with thresholding IS NOT consistent with the Mach band effect.

Intro: Process (P) and outcome (O) quantitative quality indicators (Q^2Is) $\pm \delta$ (degree of tolerance) $\subseteq$ QA4EO *Val*

Fact 1: A minimally dependent and maximally informative (mDMI) set of Q^2Is must be community-agreed upon.

Fact 2: Every P-Q^2I and/or O-Q^2I must be provided with its degree of tolerance in measurement.

Definition: To be considered in **operating mode, an information processing system must score "High" in every Q^2I.**

LOW
MEDIUM
HIGH

Legend of fuzzy sets of a quantitative variable.

Process Q^2Is and Outcome Q^2Is $\pm \delta \subseteq$ QA4EO *Val*	Example: System 1
Degree of automation (P): (a) number, physical meaning and range of variation of user-defined parameters, (b) collection of the required training data set, if any.	HIGH
Effectiveness (O): for example, (a) thematic Qis (TQIs) and (b) spatial Qis (SQIs), provided with a degree of uncertainty in measurement $\pm\delta$.	HIGH
Semantic information level (P)	MEDIUM
Efficiency (P): for example, (a) computation time and (b) memory occupation.	LOW
Robustness to changes in input image (P), e.g., large spatial extent data mapping (no toy problems).	MEDIUM
Robustness to changes in input parameters (P), e.g., sensitivity analysis.	HIGH
Scalability to changes in the sensor's specifications or user's needs (P), e.g., panchromtc/chrmtc.	HIGH
Timeliness (P), from data acquisition to high-level product generation, increases with manpower and computing power.	HIGH
Costs (P), increasing with manpower and computing power.	HIGH

This system is NOT in operating mode

Definition: Big data (en.wikipedia.org/wiki/Big_data)

“Big data requires exceptional technologies to efficiently process large quantities of data within tolerable elapsed times… The challenges include capture, curation, storage, search, sharing, transfer, analysis and visualization… What is considered "big data" varies depending on the capabilities of the organization managing the set, and on the capabilities of the applications that are traditionally used to process and analyze the data set in its domain… Real or near-real time information delivery is one of the defining characteristics of big data analytics.”

Definition: EO Level 2 product (Sentinel-2 User Handbook, ESA, 2015)

1. A multi-spectral (MS) image corrected for:

- **I. Absolute calibration: digital numbers (DNs) ⇒ Top-of-atmosphere (TOA) radiance ⇒ TOA reflectance (TOARF).**
- **II. Atmospheric effects.**
- **III. Topographic effects (requires a Digital Surface Model, DSM, in addition to sensory data).**
- **IV. Adjacency effects ⇒ Bottom-of-atmosphere (BOA) reflectance (BOAR) = SURF values.**

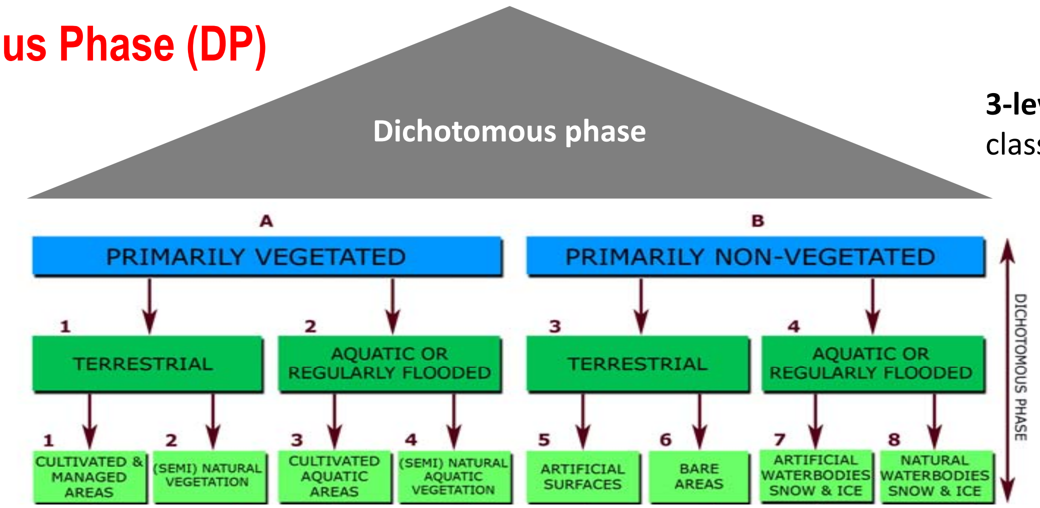
2. A scene classification map (SCM).

- **I. 8-class Dichotomous Phase of the Food and Agriculture Organization of the United Nations (FAO) - Land Cover Classification System (LCCS) taxonomy: (i) vegetation / non-vegetation, (ii) terrestrial / aquatic, (iii) Managed / natural semi-natural [4].**
- **II. Cloud / Cloud-shadow quality layers.**

Intro: FAO Land Cover Classification System (LCCS) taxonomy

- **FAO-LCCS: Dichotomous Phase (DP)**

"EASY" DP layers - Very substantial contribution by pixel-based MS reflectance space polyhedralization = MS color naming, e.g., SIAM's



3-level 2-4-8 dichotomous land cover classes, **APPLICATION INDEPENDENT!**

DIFFICULT DP layer. Managed / Natural, semi-natural features high-level SEMANTICS!

A. Primarily vegetated

A11	cultivated and managed terrestrial areas (**agricultural fields**)	**Terrestrial**
A12	natural and semi-natural terrestrial vegetation (e.g., **forest**)	
A23	cultivated aquatic or regularly flooded areas	**Aquatic**
A24	natural and semi-natural aquatic or regularly flooded vegetation	

B. Primarily non vegetated

B35	artificial surfaces and associated areas (roads, built-up, impervious surfaces, e.g., parking lots)	**Terrestrial**
B36	bare areas (non agricultural fields)	
B47	artificial waterbodies, snow and ice	**Aquatic**
B48	natural water bodies, snow and ice	

- **FAO-LCCS Modular Hierarchical Phase (MHP), consisting of a hierarchical battery of one-class LC classifiers**

EO Problem identification

Fact 1

To date no EO data-derived Level 2 prototype product has ever been generated systematically at the ground segment (Sentinel-2 User Handbook, ESA, 2015)⇔ The **Global Earth Observation System of Systems (GEOSS)** implementation plan for years 2005-2015, subject to the **Cal/Val requirements of the Quality Assurance Framework for Earth Observation (QA4EO) guidelines**, has not been accomplished yet. GEOSS is expected to systematically transform multi-source EO “big data” into **timely, comprehensive and operational information products**. Fact: **the percentage of EO data ever downloaded from the European Space Agency (ESA) databases is estimated at about 10% or less.** Conclusion**: the RS community is overwhelmed by EO data…**

Fact 2

To date **no semantic content-based image retrieval (SCBIR) system exists** in operating mode. SCBIR ≠ traditional CBIR whose queries are input with text information, summary statistics or by either image, object or multi-object examples.

Fact 3

If we require that a computational vision model should at least be able **to predict Mach bands**, the bright and dark bands which are seen at ramp edges, the number of published models is surprisingly small (Pessoa, 1996).

Fact 4

Chromatic and achromatic primate visions are nearly as effective in scene-from-image representation. It means that **spatial information dominates color information in the 2D image-domain and in the 4D spatiotemporal scene-domain**. **Experimental proof** that primary spatial information is thoroughly investigated by a CV system: **Seamless scalability from color to panchromatic image analysis**.

Fact 5

In general, “**process** is easier to measure, **outcome** is more important”. (Measurement: Process and Outcome Indicators, Duke Center for Instructional Technology, 2016).

State-of-the-art: EO CBIR systems, supporting no semantic querying

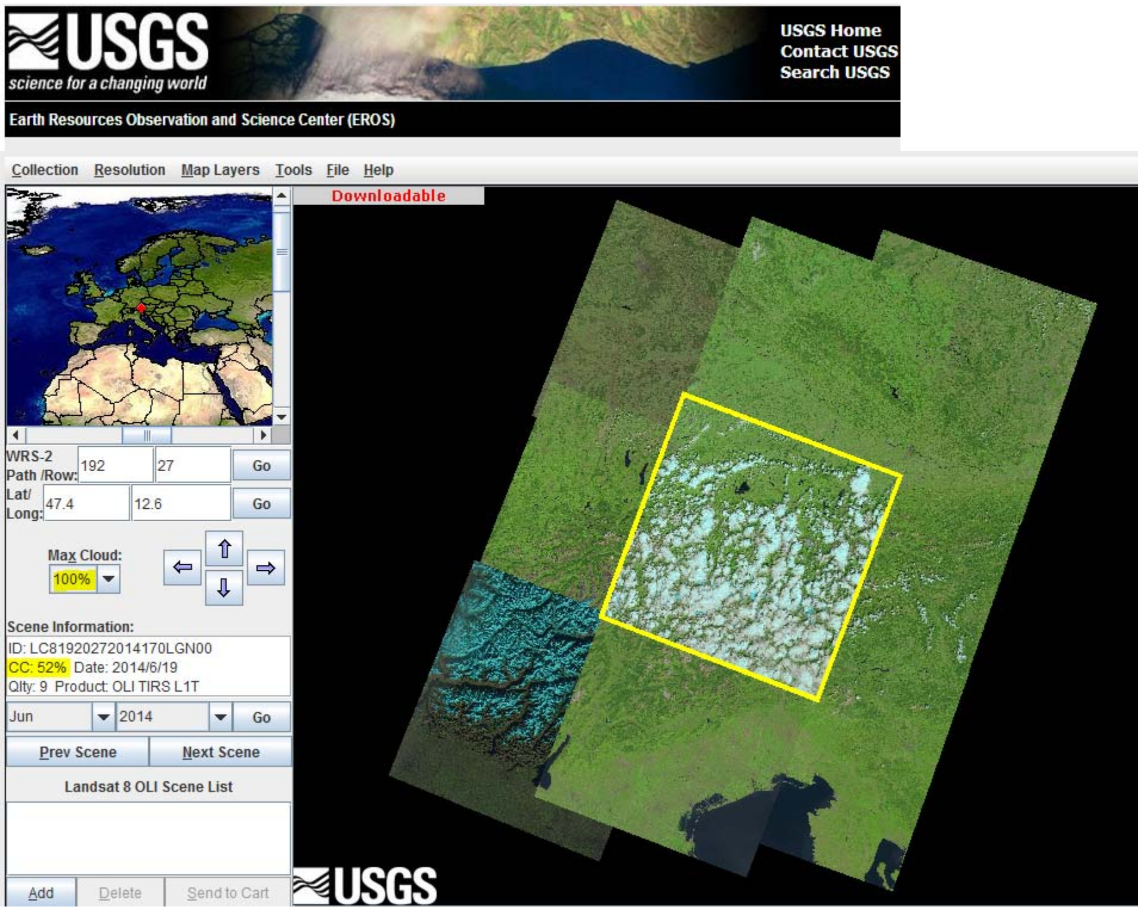


Image querying by:

- metadata text information (acquisition time, target geographic area).
- Summary statistics (e.g., image-wide cloud cover).

- **No semantic content-based querying of images**
- **No spatiotemporal image-content extraction to generate either quantitative or qualitative information products, e.g., cloud cover map.**

Project requirements specification: EO image understanding for semantic querying (EO-IU4SQ)

1) EO-IU subsystem. Systematic generation of EO Level 2 products in operating mode (all OP-Q^2Is must score “high”) at the ground segment. Never done before!
   - ➢ EO data pre-processing: Automated stratified atmospheric and topographic correction.
   - ➢ SCM legend = 3-level 8-class FAO-LCCS Dichotomous Phase.
   - ➢ Hybrid inference design: Alternate deductive/ top-down/ learning-by-rule/ physical data models with inductive/ bottom-up/ learning-from-data/ statistical data models.
   - ➢ Feedback loops, to enforce stratified data sampling.
   - ➢ Hierarchical multi-stage convergence-of-evidence approach. Visual features are:
     - o Color values $\Rightarrow$ Categorical color names.
     - o Local shape.
     - o Texture = spatial distribution of texels = superpixels = connected sets of pixels with the same color name.
     - o Inter-object spatial topological and non-topological relationships.
2) EO-SQ subsystem. Semantic querying of large-scale EO image databases = Semantic content-based image retrieval (SCBIR) $\neq$ traditional CBIR by metadata text information, summary statistics or by either image, object or multi-object examples.

R&D Project objectives: EO image understanding (EO-IU) for semantic querying (EO-IU4SQ) system

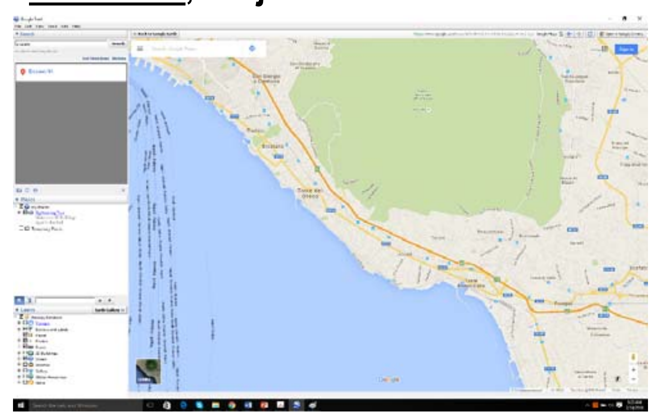
1. **Develop <u>systematic</u> (large spatial extent, coarse-to-fine spatial resolution) <u>automated</u> (without user-interaction) <u>near real-time multi-source</u> EO data-derived <u>Level 2 products</u>, subject to Cal/Val in compliance with the intergovernmental Group on Earth Observations (GEO) - Quality Assurance Framework For EO (QA4EO) guidelines** ⇔ GEO - **<u>Global Earth Observation System of Systems (GEOSS) for Image Understanding</u>** (GEOSS-IU) **<u>in operating mode</u>**.
   Fact 1: To date no EO data-derived Level 2 prototype product has ever been generated systematically at the ground segment [3]. DEF. Level 2 product = Image corrected for atmospheric, topographic and adjacency effects + Scene Classification Map (SCM).
2. Novel **<u>semantic content-based EO image retrieval</u>** (SCBIR) **<u>in operating mode</u>**. **Fact 2: to date no SCBIR exists.**
   - SCBIR ≠ traditional CBIR, employing image query-by-text, summary statistics or by image-example.

Level 2 quantitative outcome, Multi-source EO image, subject to *Cal*, DNs → BOAR

EO-IU automated near real-time process, subject to *Val*

SCBIR process, subject to *Val*

≥ Level 2 qualitative (categorical) outcome, EO image-derived thematic maps, e.g., <u>FAO-LCCS</u>, subject to *Val*



GOAL: EO-IU + SCBIR in operating mode = EO-IU4SQ (Unina & Univ. Salzburg)

Intro - State-of-the-art (knowledge boundary): Object-based image analysis (OBIA) as a new scientific paradigm

1. OBIA is alternative to pixel-based image analysis (p. 187) = 1D and Non-contextual image analysis $\subset$ 1D image analysis.
2. Fundamental tenants (guiding principles) of (GE)OBIA (p. 185). (i) data are Earth (Geo) centric, (ii) its analytical methods are multi-source capable, (iii) geo-object-based delineation is a pre-requisite, (iv) its methods are contextual, allowing for 'surrounding' information and attributes, and (v) it is highly customizable or adaptive allowing for the inclusion of human semantics and hierarchical networks (it incorporates 'the wisdom of the user').
3. Many consider that the ultimate benchmark of GEOBIA is the generation of results equalling or better than human perception, which is far from trivial to numerically quantify and emulate… While biophysical principles like retinal structure and functioning and singular processes such as the cerebral reaction are analytically known, we still lack the bigger 'picture' of human perception as a whole (p. 185).
4. In GEOBIA, image segmentation is not an end in itself. Segmentation is the partitioning of an array of measurements on the basis of "homogeneity". It divides an image – or any raster or point data – into spatially continuous, disjoint and homogeneous regions referred to as 'segments' (p. 186).

PROBLEMS at the very foundation of (GE)OBIA: Underestimation of the complexity of human vision/perception

I. Vecera and Farah (Human vision, 1997) [62]: "we have demonstrated that image segmentation as the dual problem of image-contour detection is an inherently ill-posed problem [63] in the Hadamard sense [53]. It can be influenced by the familiarity of the shape being segmented", "these results are consistent with the hypothesis that image segmentation is an interactive (hybrid inference) process" "in which top-down knowledge partly guides lower level processing".

II. OBIA tolerates a 1D context-sensitive image analysis approach as opposed to a 1D context-insensitive image analysis approach.

CONCLUSIONS

A. Image segmentation / contour detection is an **ill-posed** problem requiring **hybrid (combined deductive/top-down and inductive/bottom-up) inference** mechanisms.

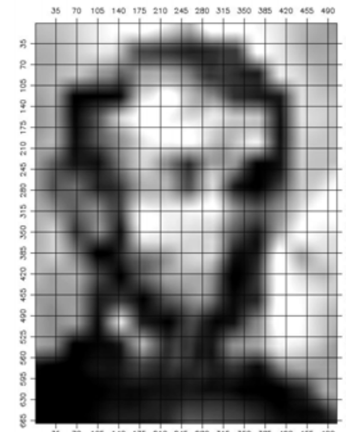
B. **OBIA should be intended as a synonym of 2D image analysis, based on retinotopic/topology-preserving feature maps**.

Intro - Traditional 1D image analysis (spatial topological and/or non-topological info is lost) $\supset$ Pixel-based analysis (spatial topological and non-topological info is lost)

Dali's "Gala contemplating the Mediterranean Sea" at 20 mtr becomes the Lincln portrait, RGB image, $\approx 18 \times 13 = 234$ Dali's square, 504×669 digital pixels

Pnchrmtc image.

Median filter, 35×35 pixels



2D grid, 35×35 pixels

<u>1D image analysis is invariant to permutations in the input sequence, i.e., insensitive to changes in the order of presentation of the input sequence!</u>

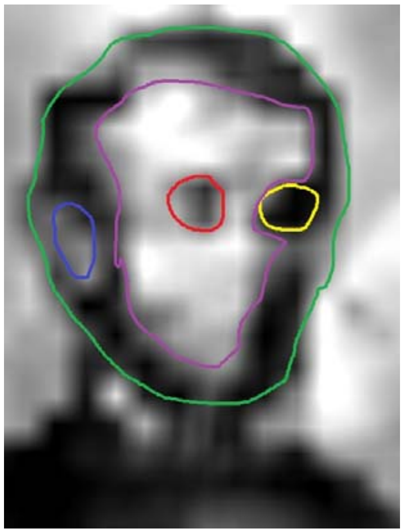
1D image analysis = vector sequence / vector series analysis, where each vector data is either a pixel or context-sensitive

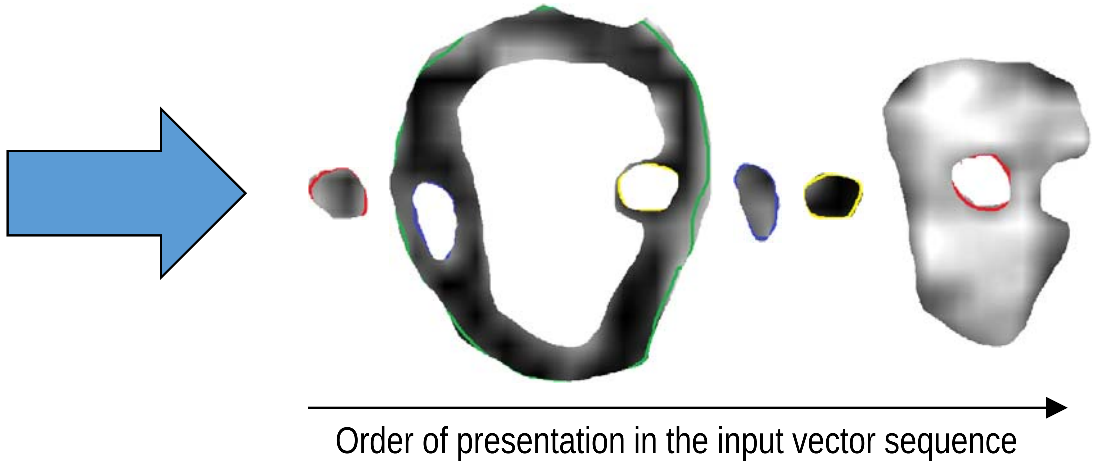
Order of presentation in the input vector sequence

1D image analysis, top 5 lines in the gridded image, spatial unit = local window 35×35 pixels in size (patch-based = context-based) $\approx$ <u>pixel-based image analysis = context-insensitive, insensitive to spatial topological info</u>.
This is WHAT a (pixel-based) inductive data learning classifier looks at!!!!!

Intro - Traditional 1D image analysis (spatial topological and/or non-topological info is lost) $\supset$ Pixel-based analysis (spatial topological and non-topological info is lost)

1D image analysis is invariant to permutations in the input sequence, i.e., insensitive to changes in the order of presentation of the input sequence!

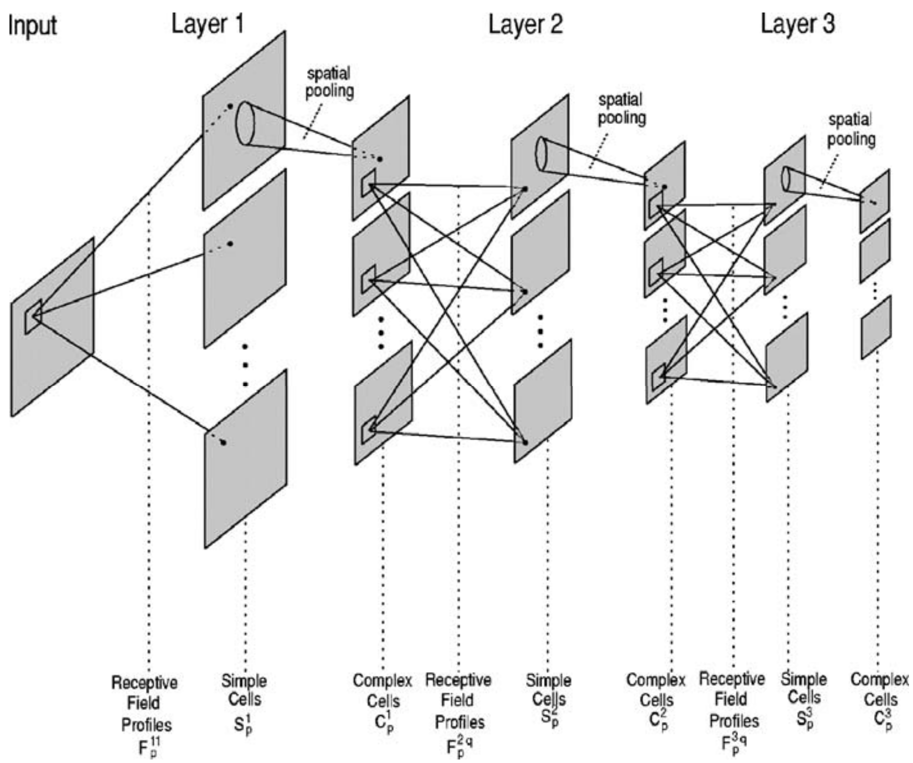


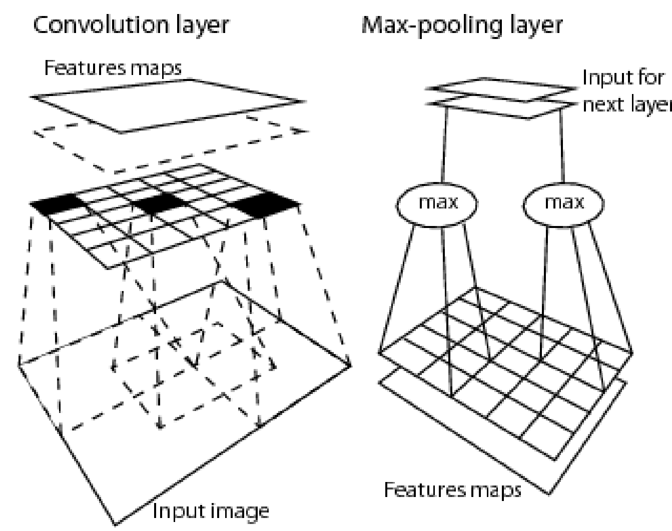


1D image analysis consistent with the context-sensitive OBIA paradigm = 1D sequence of image-objects = context-sensitive = sensitive to non-topological spatial info, insensitive to spatial topological info.
This is WHAT an image-object-based inductive data learning classifier looks at!!!!!

- **Within context, e.g., local window, spatial non-topological info is investigated, e.g., local histogram of gray values.**
- **Spatial non-topological info (e.g., angle measures, distance measures) is preserved within image-object.**
- **Inter-object spatial non-topological relationships (e.g., angle measures, distance measures) are LOST.**
- **Inter-object spatial topological relationships (e.g., adjacency, inclusion, etc.) are LOST.**

Intro - (2D) image analysis (spatial topological and non-topological info are preserved) = Retinotopic maps = Deep convolutional neural networks (DCNNs), alternative to traditional 1D image analysis (spatial topological and/or non-topological info is lost) ⊃ Pixel-based analysis (spatial topological and non-topological info is lost)

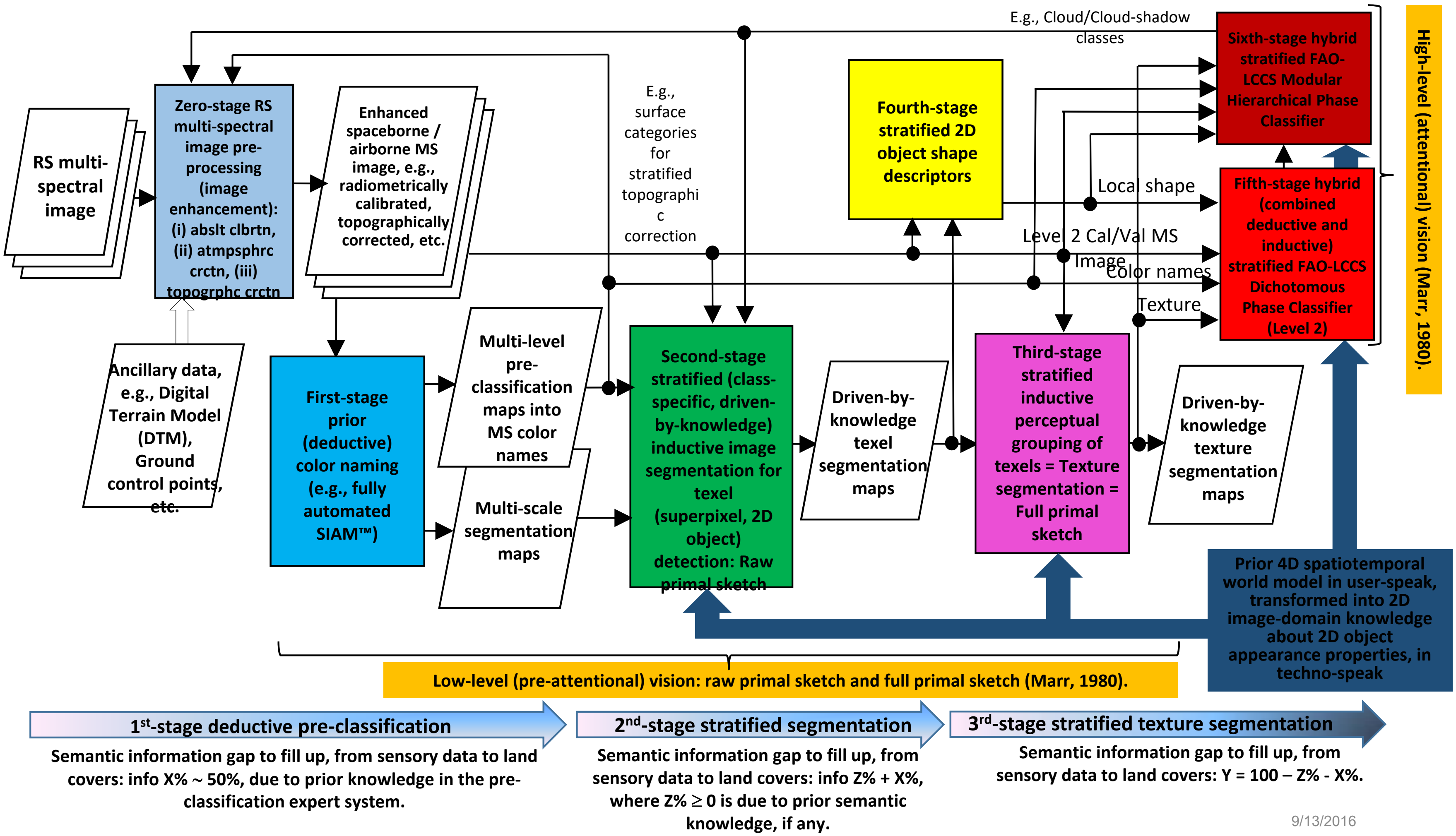




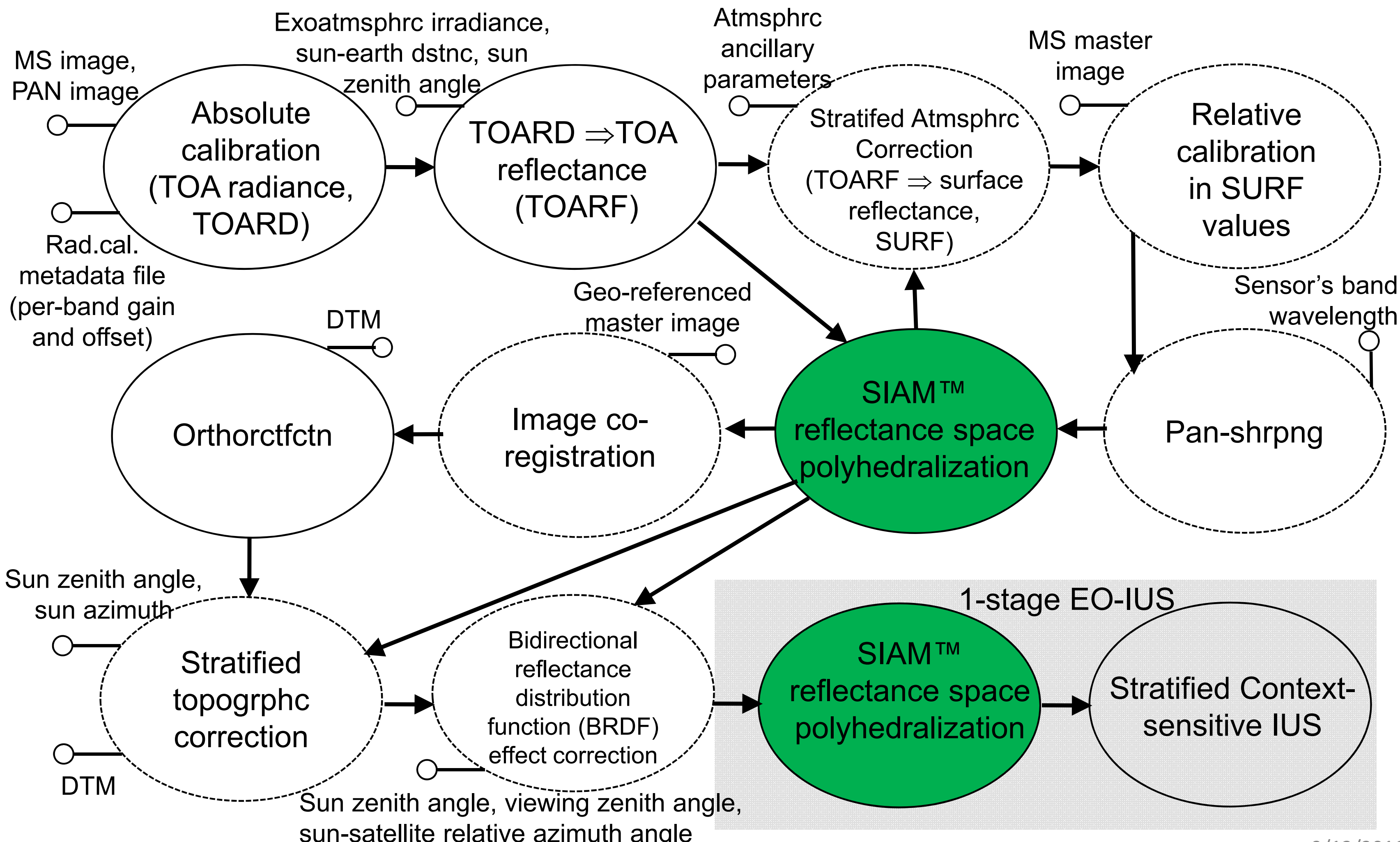
Problem 1: DCNN design (meta)parameters (no. layers, no. features per layer, spatial filter size, spatial stride, spatial pooling size, spatial pooling stride) are user-defined based on heuristics!!

Problem 2: no foveated! All filters span the same visual field.

Novel 6-stage hybrid feedback EO-IU subsystem of the EO-IU4SQ system



Automated hybrid feedback EO Level 2 image pre-processing $\subseteq$ QA4EO *Cal*



Radiometric calibration of DNs into TOARF or SURF values: Triple advantage

1) Mandatory to guarantee **inter-image harmonization and inter-sensor operability** by providing dimensionless DNs with a community-agreed physical unit of measure.

2) Beneficial because DNs provided with a physical unit of measure can be **input to physical data models as well as to statistical data models.** On the contrary, DNs provided with no physical unit of measure can be input to statistical data models exclusively.

3) Beneficial because images radiometrically calibrated into TOARF or SURF values in range [0, 1] and coded as a **4-byte data float can be compressed by a factor of 4 into a 1-byte char** in range {0, 255} **with a negligible quantization error** = 0.2%.

If a 4-byte data float in range [0, 1] is quantized into a 1-byte integer in range {0, 255}, the float-to-byte quantization error is (input value max - input value min) / number of quantization levels / 2 (because of the rounding error to the closest integer, either above or below = (1 - 0) / 256 / 2 = 0.00195 = 0.2%

Zoom-in-in Zero-stage for Level-2 image pre-processing: Example

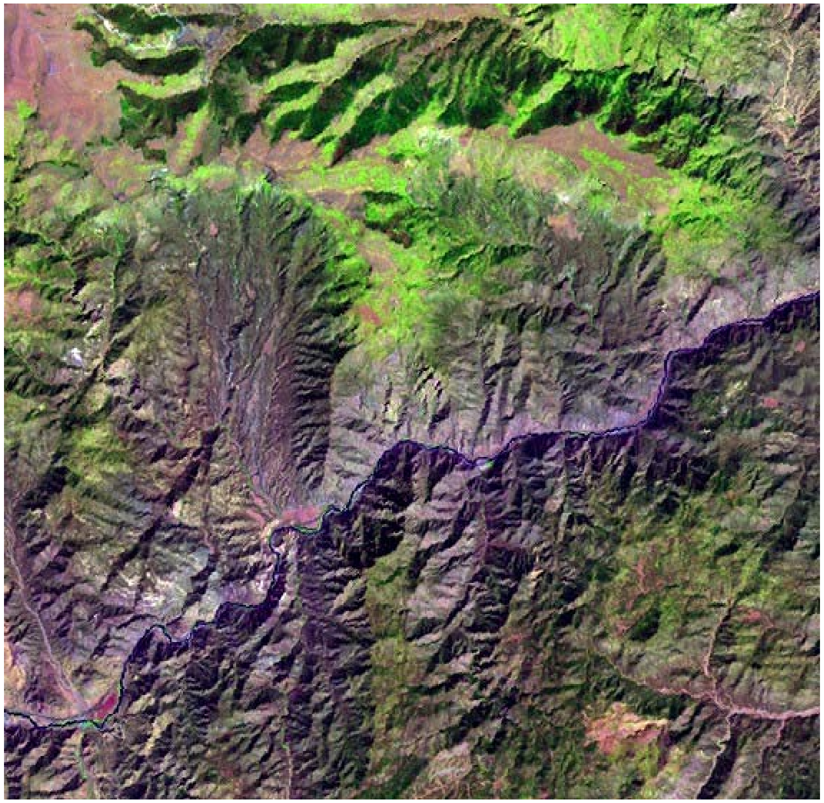


Fig. A. Zoomed area of a Landsat 7 ETM+ image of Colorado, USA (path: 128, row: 021, acquisition date: 2000-08-09), depicted in false colors (R: band ETM5, G: band ETM4, B: band ETM1), 30m resolution, radiometrically calibrated into TOA reflectance.

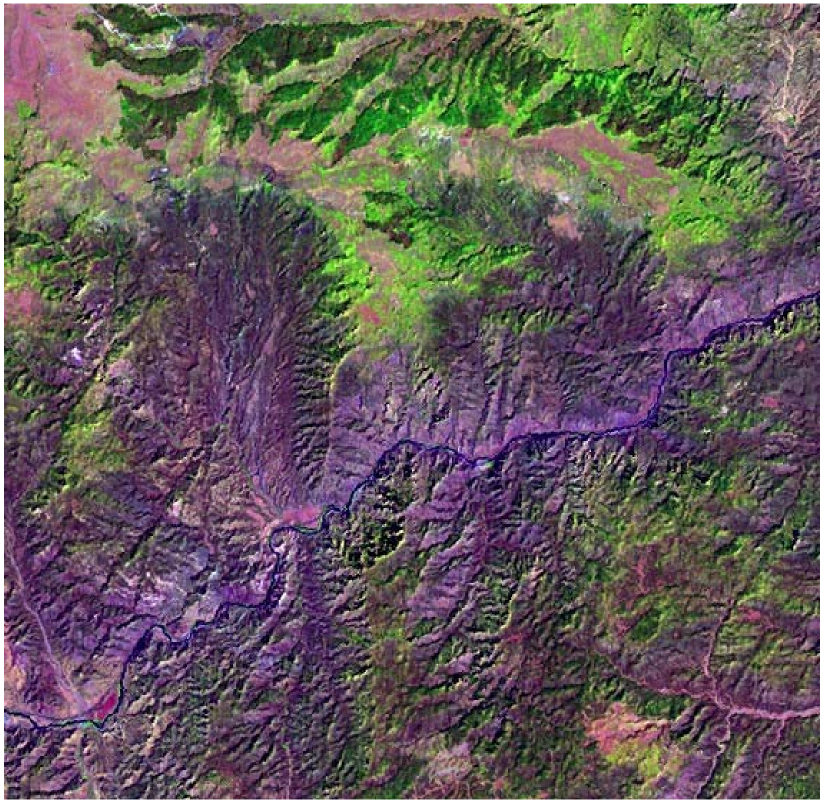
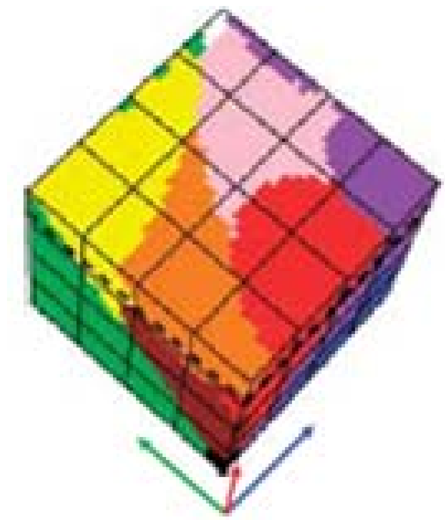


Fig. B. Stratified topographic correction of Fig. A, based on a 16-class preliminary spectral map and the SRTM DEM.

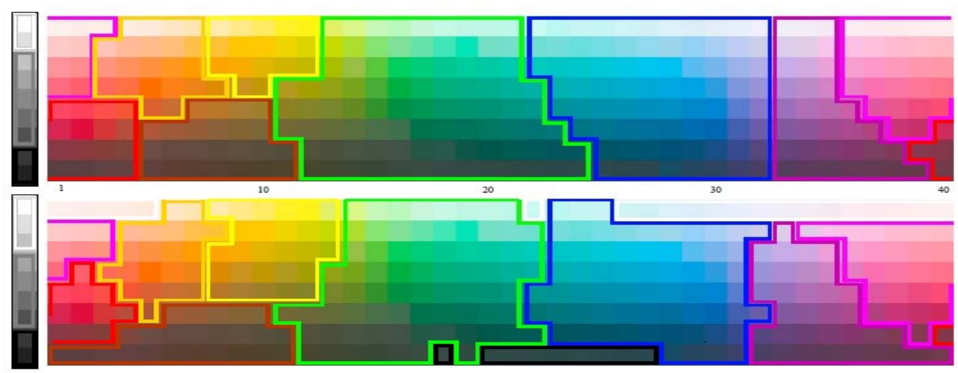
Perceptual continuous color space discretization (quantization) ⇔ Prior knowledge-based (deductive, top-down) color naming

RGB cube polyhedralization: prior polyhedra, corresponding to RGB color names, can be either convex or not, either connected or not.



L. D. Griffin, "Optimality of the basic color categories for classification", J. R. Soc. Interface, vol. 3, pp. 71–85, 2006 [43]

Alternative color name categories on the Munsell color array. The colored lines indicate the boundaries of the eleven basic colors (BCs) in human languages: black, blue, brown, grey, green, orange, pink, purple, red, white, and yellow.



Color naming ⇔ Continuous color-space discretization

- **(Discrete and finite) color names can be employed in a class-specific feature library suitable for use in prior knowledge-based classification systems** (S. Lang et al., Multiscale object feature library for habitat quality monitoring in Riparian forests, IEEE TGRS, vol. 11, no. 2, pp. 559-563, 2014).
- **<u>Any mapping between color names and target classes of individuals, represented as a cross-tabulation matrix (either non-square or square) where correct entries are marked as √, must be community agreed upon</u>**.

SIAM™

			Target classes of individuals (entities in a conceptual model for knowledge representation [59] built upon an ontology language [60])		
			Class 1, Water body	Class 2, Tulip flower	Class 3, Italian tile roof
Col[illegible]s	black			√	
	blue		√	√	
	brown		√	√	√
	grey				
	green		√	√	
	orange			√	
	pink			√	
	purple			√	
	red			√	√
	white			√	
	yellow			√	

Mapping between color names and target classes of individuals. Correct entries (marked as √) must be community agreed upon.

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Run RGBIAM™ on a non-calibrated RGB image: multi-level color mapping

Fig. A. Top row. Quick-look RGB image and its RGBIAM color quantization maps at 50 and 12 color levels respectively.

Fig. B. Bottom row. 8-adjacency cross-aura contour maps generated from the two pre-classification maps, plus their sum (at the bottom left).

Run RGBIAM™ on a non-calibrated RGB image : piecewise-constant image approximation

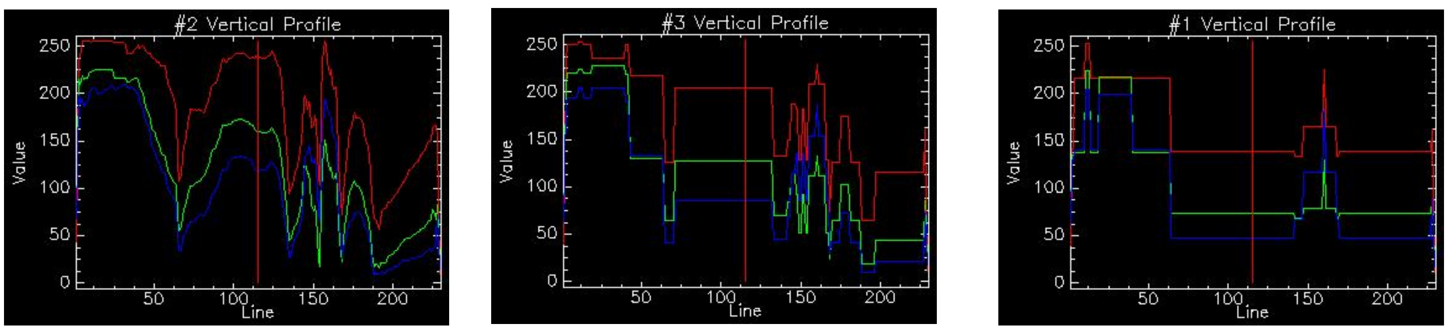


Fig. A. Top line. Quick-look RGB (3-band, in the .jpg file format) image and its piecewise constant approximations, based on the RGBIAM maps at 50 and 12 color levels respectively.

Fig. B. Bottom line. Vertical image profiles.

50 color levels, image-wide Root Mean Square Qntztn Error.
Band: 1, Root Mean Square Qntztn Error: 15.261817
Band: 2, Root Mean Square Qntztn Error: 16.468367
Band: 3, Root Mean Square Qntztn Error: 17.292217

12 color levels, , image-wide Root Mean Square Qntztn Error.
Band: 1, Root Mean Square Qntztn Error: 34.113970
Band: 2, Root Mean Square Qntztn Error: 36.990855
Band: 3, Root Mean Square Qntztn Error: 40.166423

Run RGBIAM™ on a non-calibrated RGB image : vector quantization error estimation

Fig. A. Top line, center and left. Per-pixel square quantization error sum across bands, when the reconstructed image, generated from the fine (center) and coarse quantization levels (right), is compared with the input image, shown at the left side.

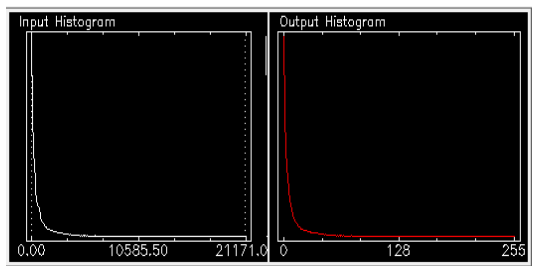


Fig. B. Square Error Sum, Basic Stats: Min = 0.0, Max = 21171.0, Mean = 803.150923, Stdev = 1230.231361.

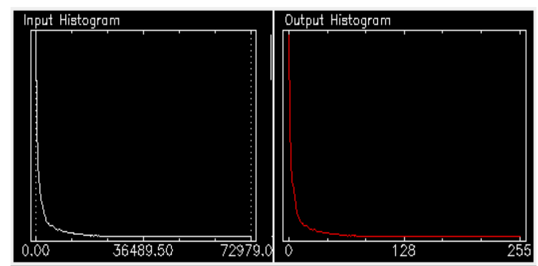


Fig. B. Square Error Sum, Basic Stats: Min = 0.0, Max = 72979.0, Mean = 4145.427894, Stdev = 7967.770808.

- Inductive k-means vector quantization of a non-calibrated RGB image
- RGBIAM initialization of an inductive k-means vector quantizer (hybrid inference system)

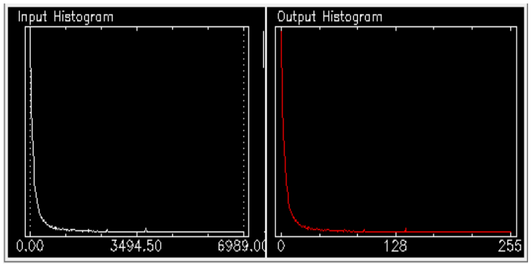


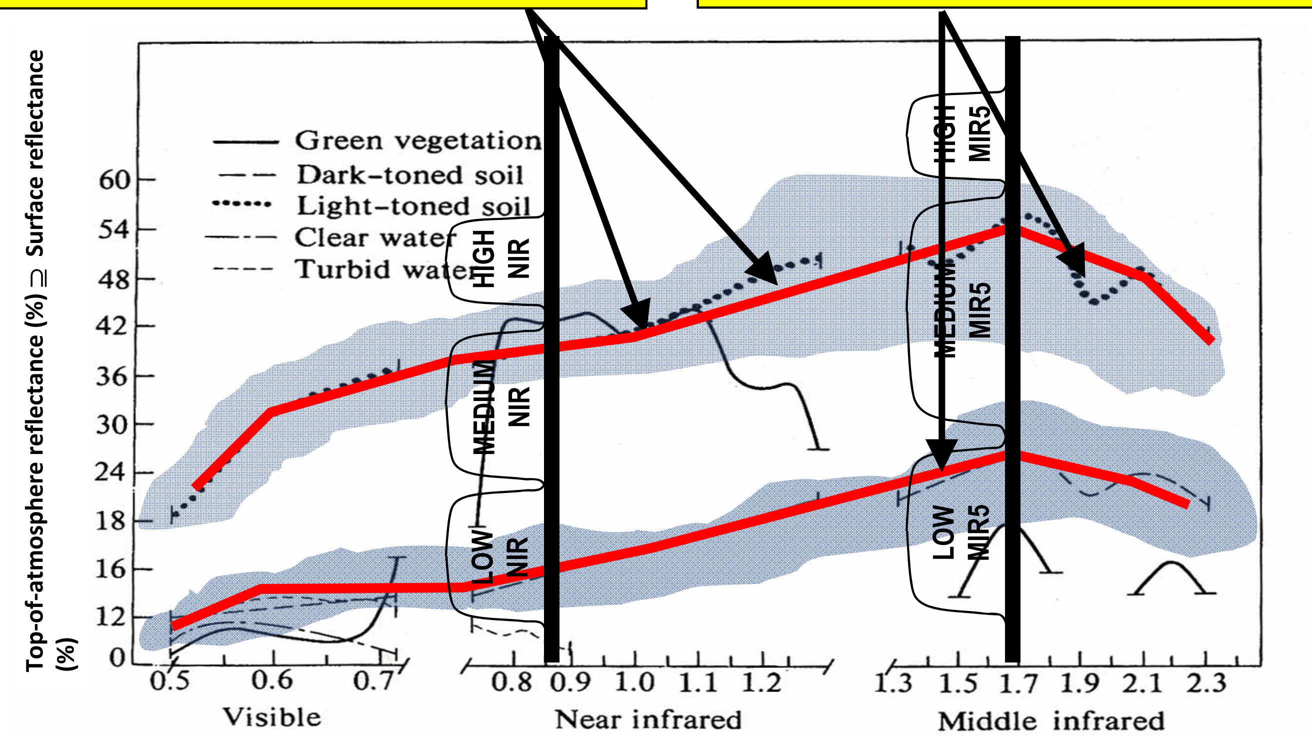
Fig. B. Square Error Sum, Basic Stats: Min = 0.0, Max = 6989.0, Mean = 306.877626, Stdev = 544.575772.

Top row. Left: Quick-look RGB image. Center: inductive k-means color quantization map, k = 49, Iterations = 3, random centroid initialization. Right: Piecewise constant image reconstruction. Bottom left: Piecewise constant image reconstruction when the inductive k-means color quantization algorithm is initialized by the RGBIAM's 50 centers of color categories. The Root Mean Square Quantization Error decreases with the same number of vector quantization levels k!!! Bottom right: Per-pixel square quantization error sum across bands, when the reconstructed image is compared with the input image.

Prior knowledge-based SIAM™ decision-tree modeling of spectral envelopes

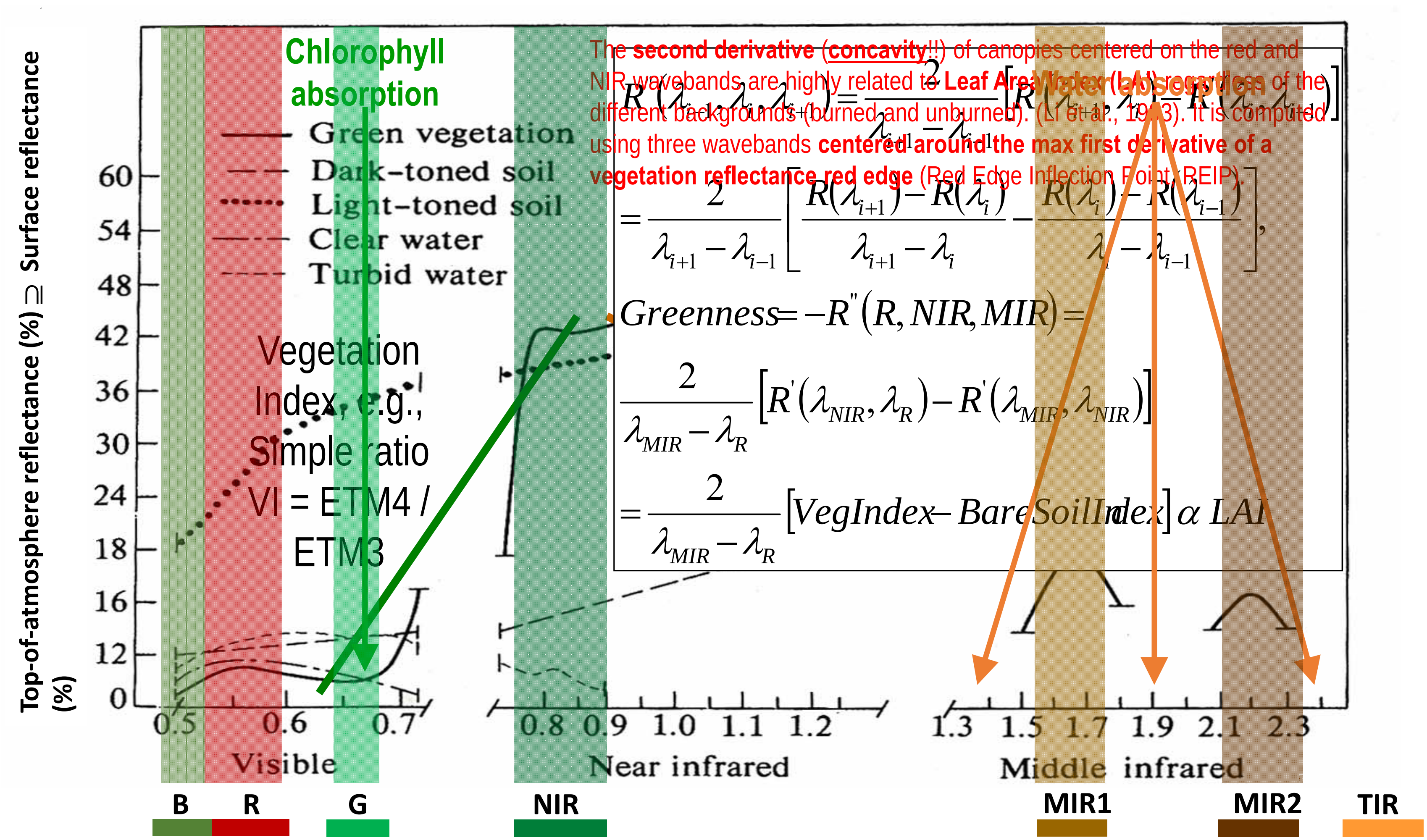
1st LEVEL OF ANALYSIS: SHAPE MODELING.
For a given spectral signature (e.g., Barren land), model inter-band fuzzy relationships, e.g., *TM5 > (TM4* ± 10%).

2nd LEVEL OF ANALYSIS: INTENSITY MODELING.
Spectral signature quantization through fuzzy sets, e.g., *Bright Barren Land* and *Dark Barren land* .



28

3-band Greenness Index(R, NIR, MIR) ∝ Leaf Area Index (LAI)



$$R''(\lambda_{i-1},\lambda_i,\lambda_{i+1}) = \frac{2}{\lambda_{i+1}-\lambda_{i-1}}\left[R'(\lambda_{i+1},\lambda_i) - R'(\lambda_i,\lambda_{i-1})\right]$$

$$= \frac{2}{\lambda_{i+1}-\lambda_{i-1}}\left[\frac{R(\lambda_{i+1})-R(\lambda_i)}{\lambda_{i+1}-\lambda_i} - \frac{R(\lambda_i)-R(\lambda_{i-1})}{\lambda_i-\lambda_{i-1}}\right],$$

$$Greenness = -R''(R, NIR, MIR) = \frac{2}{\lambda_{MIR}-\lambda_R}\left[R'(\lambda_{NIR},\lambda_R) - R'(\lambda_{MIR},\lambda_{NIR})\right]$$

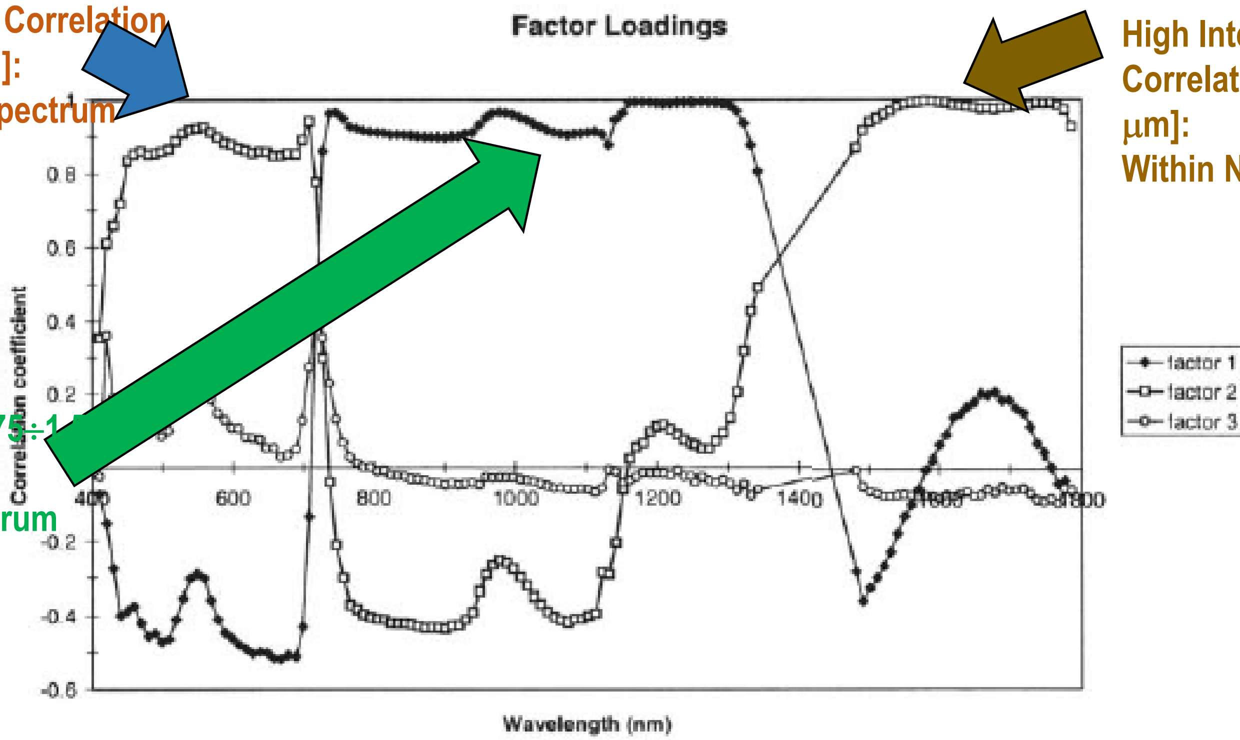
$$= \frac{2}{\lambda_{MIR}-\lambda_R}\left[VegIndex - BareSoilIndex\right] \alpha \; LAI$$

29

Intro: Inter-band correlation of continuous spectral (hyperspectral) imaging sensors (F. van der Meer and S.M. De John, Eds., Imaging Spectrometry, 2000)

High Inter-band Correlation 1 [0.35÷0.75 μm]:
Within Visible spectrum

High Inter-band Correlation 2 [0.75÷1.5 μm]:
Within NIR spectrum



High Inter-band Correlation 2 [0.75÷1.5 μm]:
Within NIR spectrum

Correlation coefficients for the main factors resulting from a principal component analysis and factor rotation for an agricultural data set based on spectral bands of AVIRIS spectrometers 1, 2 and 3. Flevoland test site, July 5th 1991.

First-stage SIAM™ cross-platform capabilities. Config.: Q-SIAM™. WorldView-2, 8-band, 2 m resolution, Brazilia, 2010-02-04, Zoomed area.

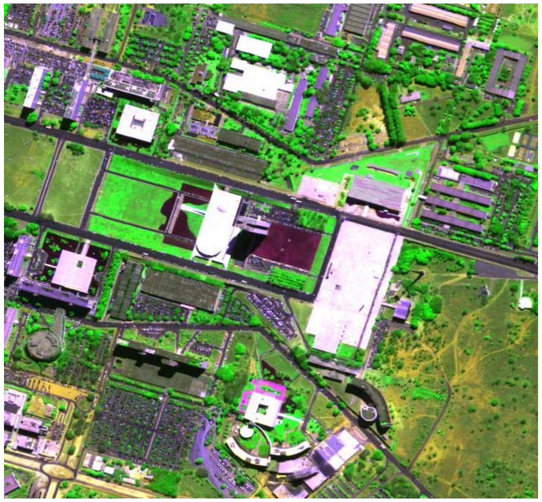
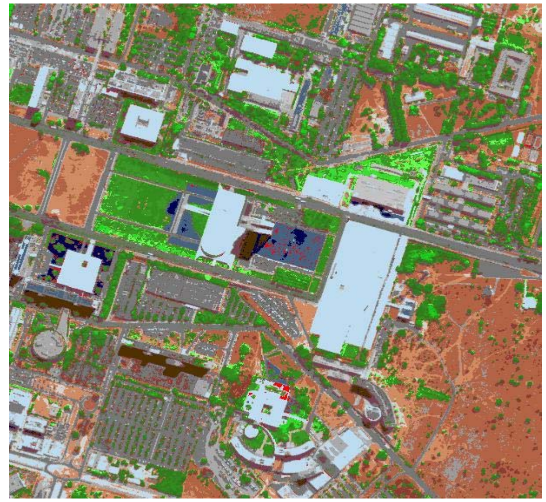


Fig. A. WV-2 image, detail, false colors, histogram stretching.



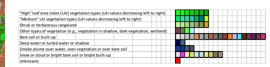


Fig. B. SIAM™ preliminary classification map, detail.

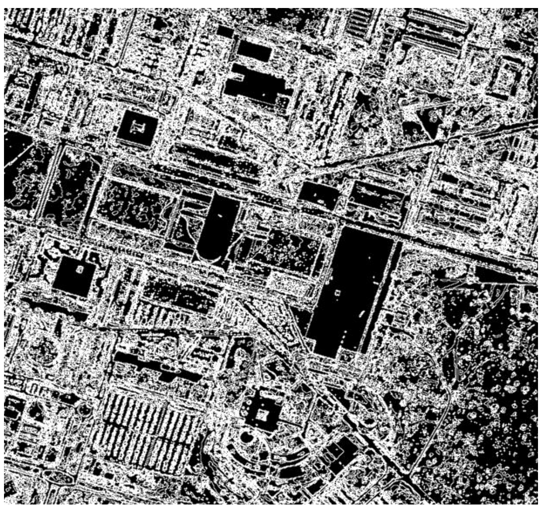


Fig. C. SIAM™ contour map, detail.

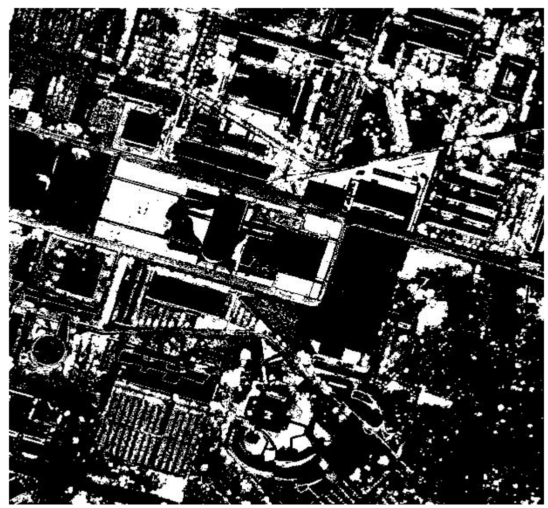
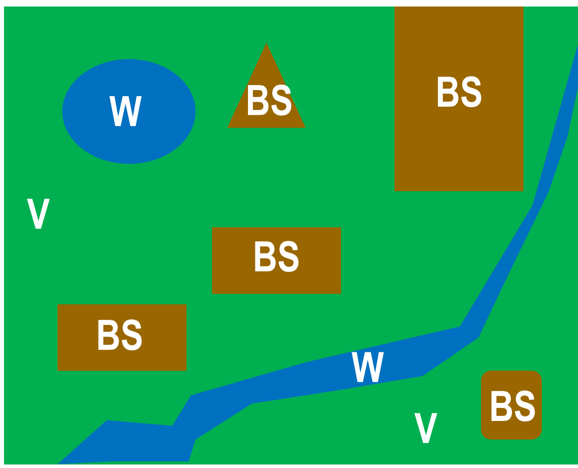


Fig. D. SIAM™ binary vegetation map, detail.

First-stage well-posed two-pass connected-component multi-level image labeling algorithm (Sonka et al., 2008)

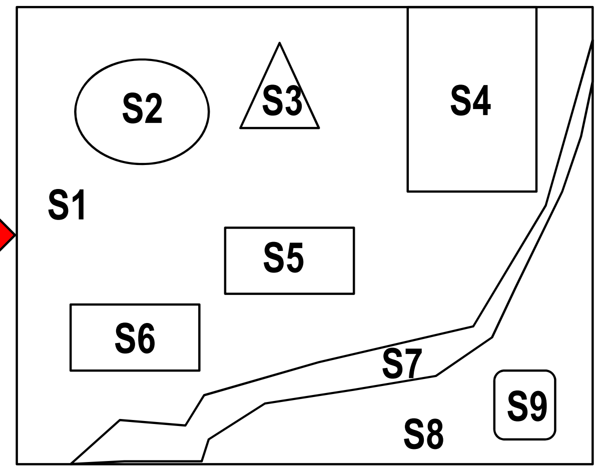
In series with SIAM. It is not SIAM!



Multi-level image, e.g., 3-level thematic map with map legend {1. Water, Acronym = W, Pseudocolor = Blue; 2. Vegetation, Acronym = V, Pseudocolor = Green; 3. Bare soil, Acronym = BS, Pseudocolor = Brown}.

Well-posed (deterministic) two-pass connected-component multi-level image labeling algorithm

≠ Quantitative/ numeric image segmentation algorithms



Segmentation map = {S1, …, S9}. Acronym S means segment.

Cloud/Cloud-shadow quality layers

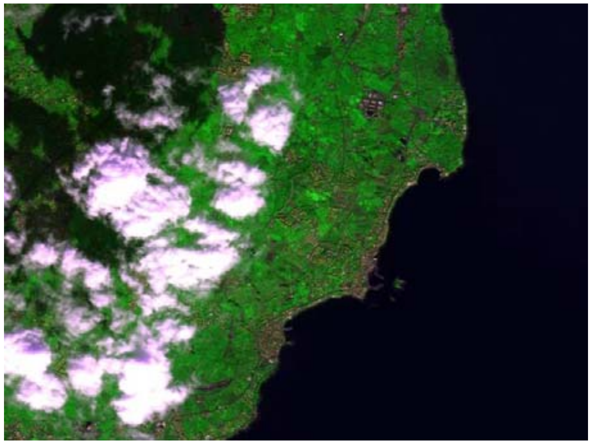


Fig. A. AVNIR-2 ALAV2A041622840 image of Sicily in false colors (R: band 2, G: band 4, B: band 1). Path: …, Row: …, acquisition date: YYYY-MMDD, spatial resolution: 10 m.

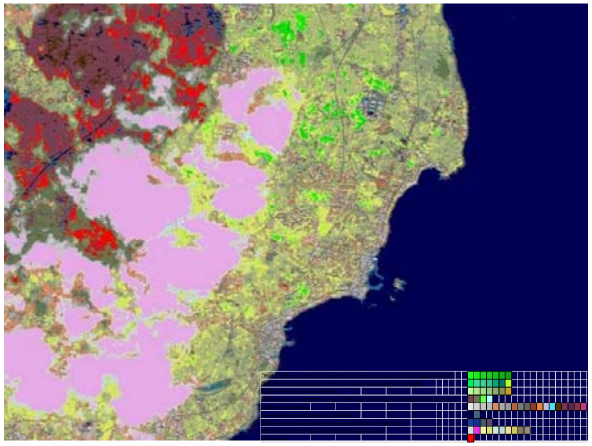
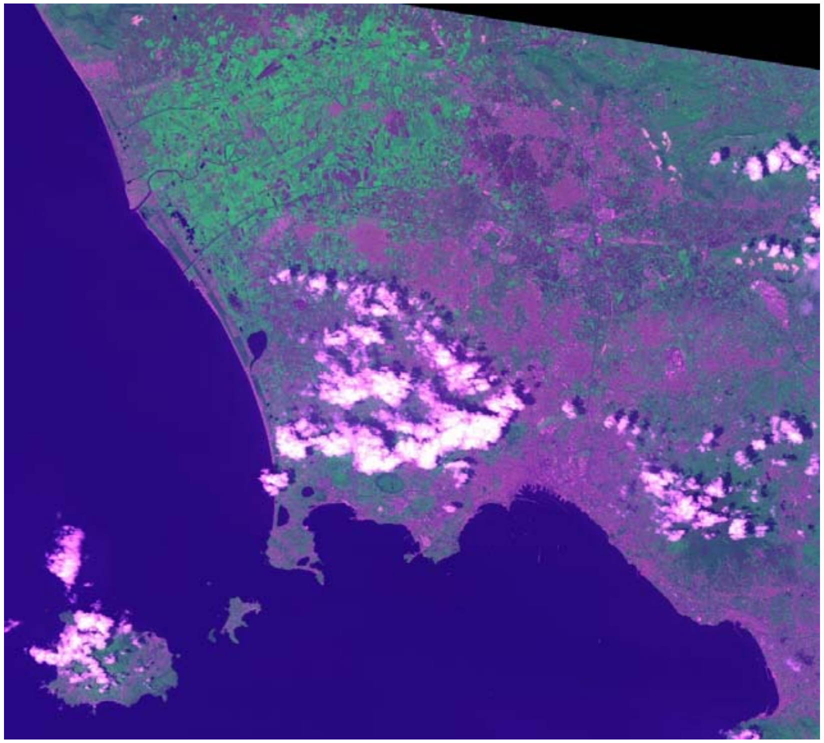


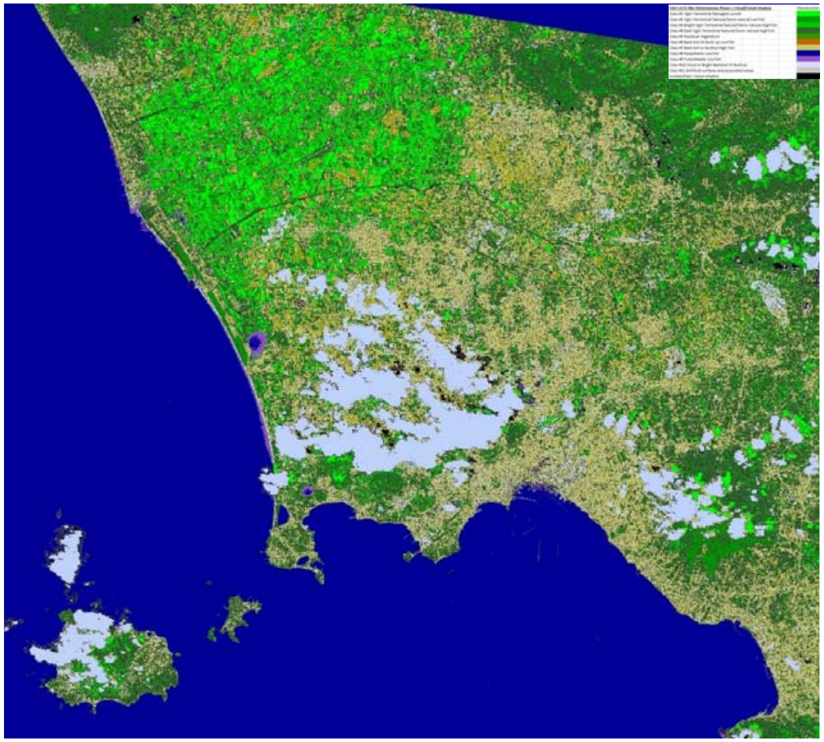
Fig. B. Preliminary classification map generated from Fig. A, consisting of 52 spectral categories.

Fig. C. Binary cloud mask generated from Fig. B, based on segment-based color and geometric properties plus spatial topological relationships (e.g., adjacency, inclusion).

EO-IU4SQ's example: Level-2 FAO-LCCS thematic map, Sensor 1



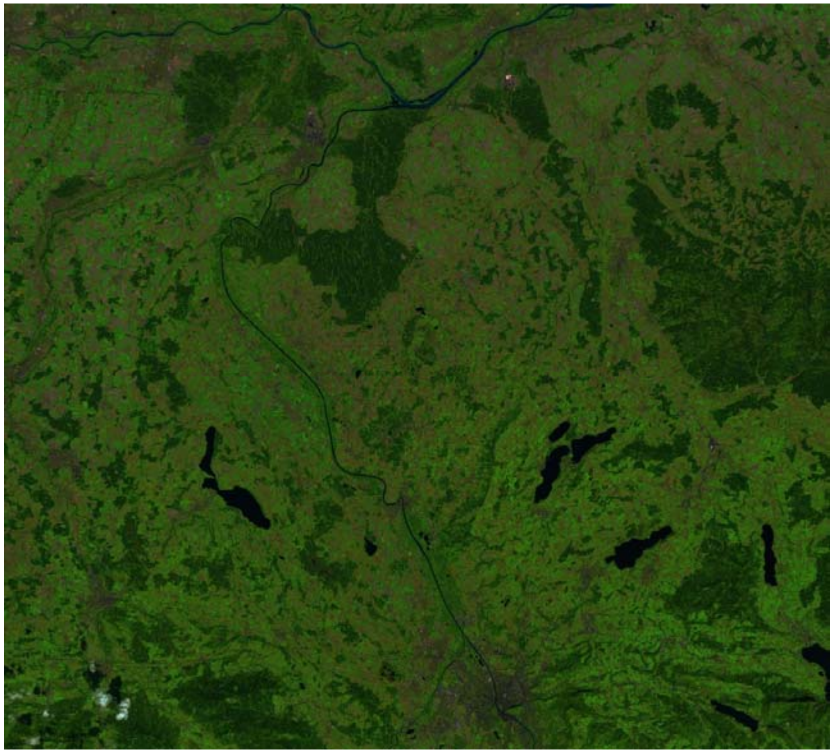
1(a). 4-band (B, G, R, NIR) ALOS AVNIR-2 image of Campania, Italy, radiometrically calibrated into TOARF values and depicted in false colors (R = MIR, G = NIR, B = Visible Blue), 10 m resolution.



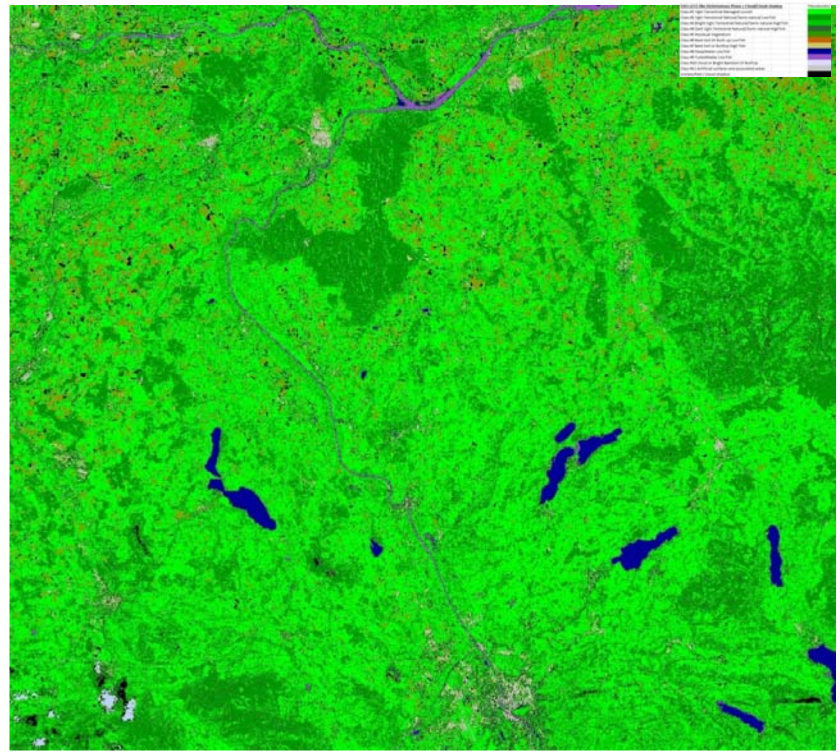
1(g). 10-class classification map based on a convergence-of-evidence approach, in compliance with the FAO-LCCS 3-level Dichotomous Phase [49], plus Cloud/Cloud-shadow detection. Map legend:

Sources of evidence are: image segments, color names, texture from segment contours. Noteworthy, neither geometric (shape and size) properties of segments nor inter-segment spatial relationships have been investigated, yet.

EO-IU4SQ's example: Level-2 FAO-LCCS thematic map, Sensor 2



1(a). Sentinel-2A image of Austria radiometrically calibrated into TOARF values, depicted in false colors (R = MIR, G = NIR, B = Visible Blue), 10 m resolution. No histogram stretching for visualization purposes.

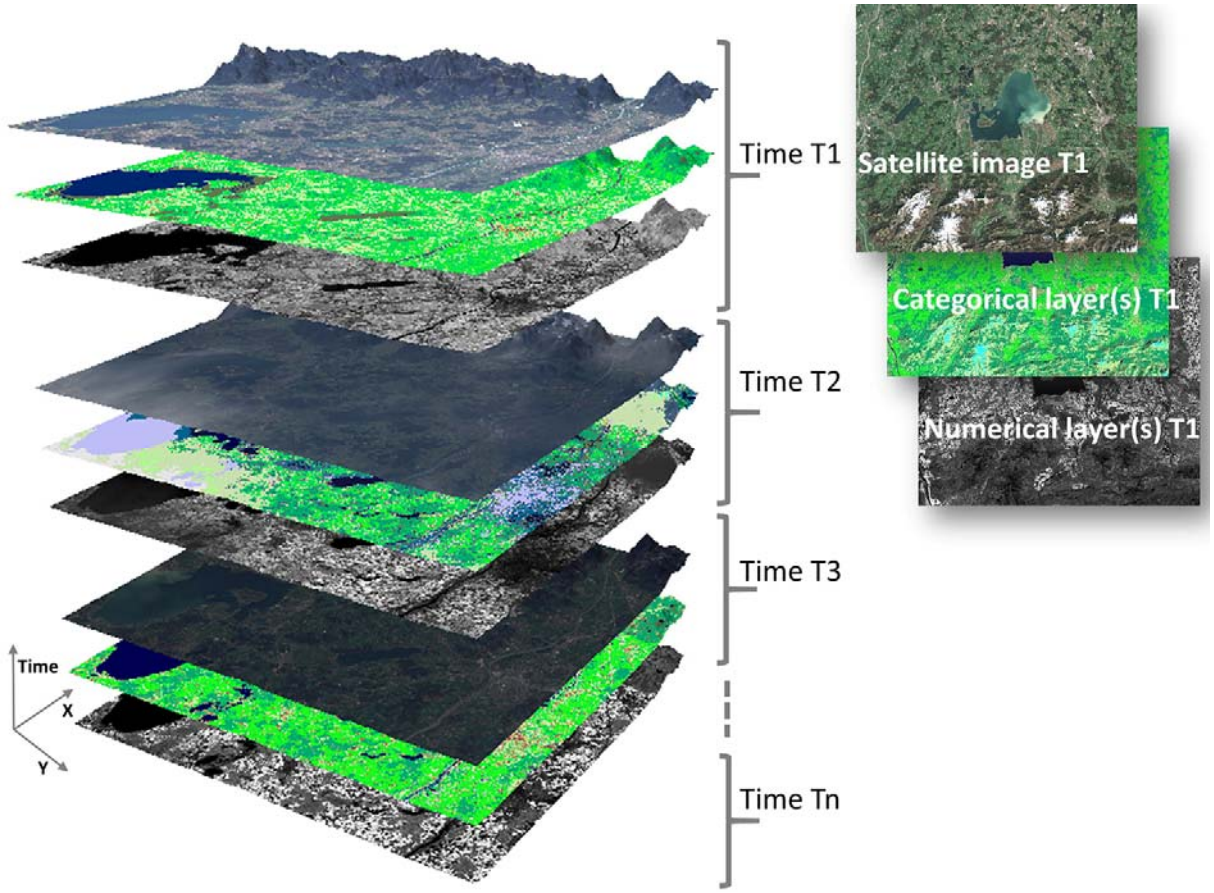


1(g). 10-class classification map based on a convergence-of-evidence approach, in compliance with the FAO-LCCS 3-level Dichotomous Phase [49], plus Cloud/Cloud-shadow detection. Map legend:

Sources of evidence are: image segments, color names, texture from segment contours. Noteworthy, neither geometric (shape and size) properties of segments nor inter-segment spatial relationships have been investigated, yet.

EO-IU4SQ's spatiotemporal analytics: Novelty values

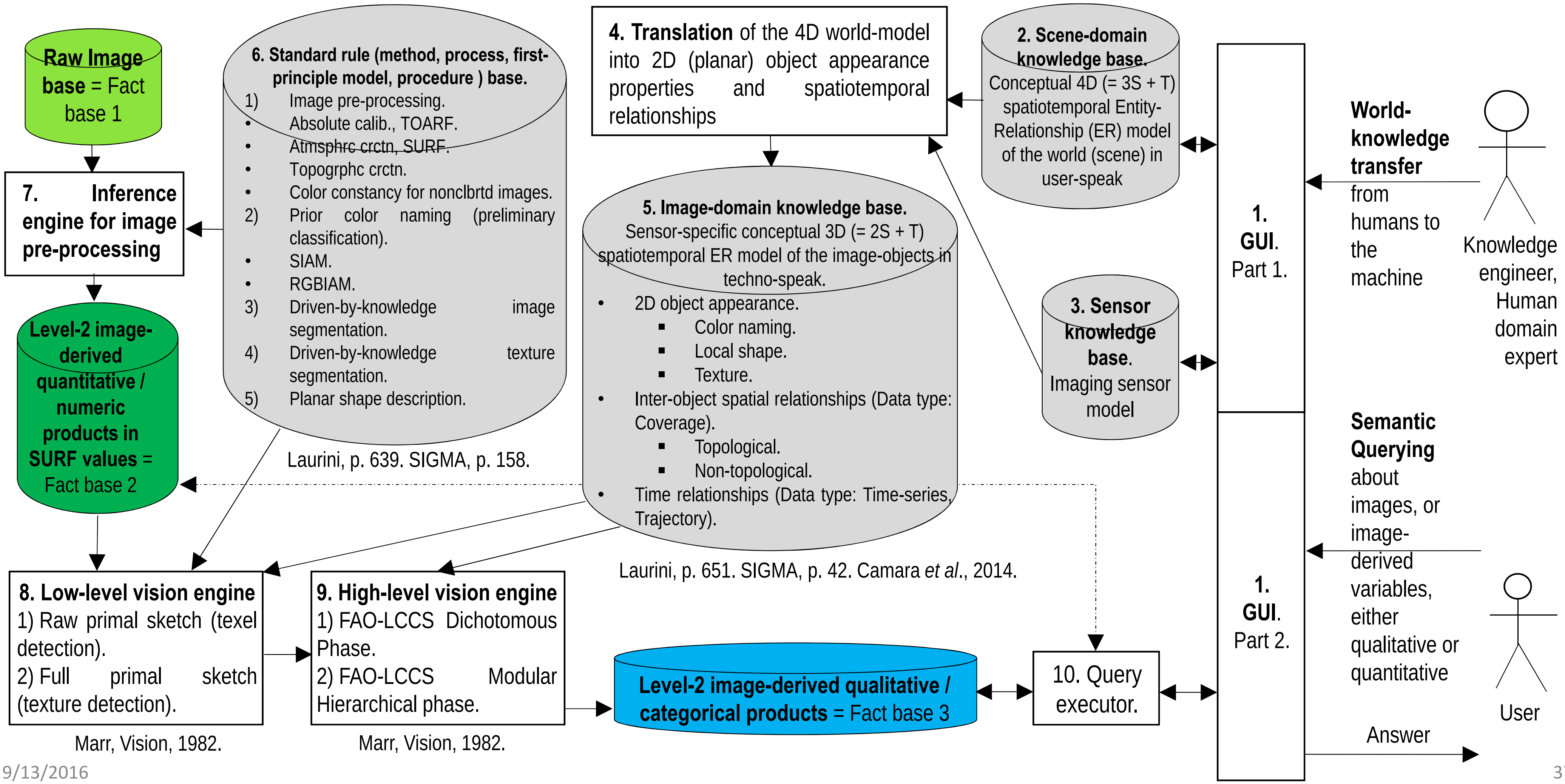
The EO-IU4SQ system for spatiotemporal analytics of multi-source EO big data. Each EO image is automatically provided with numeric/quantitative and categorical/qualitative information layers.



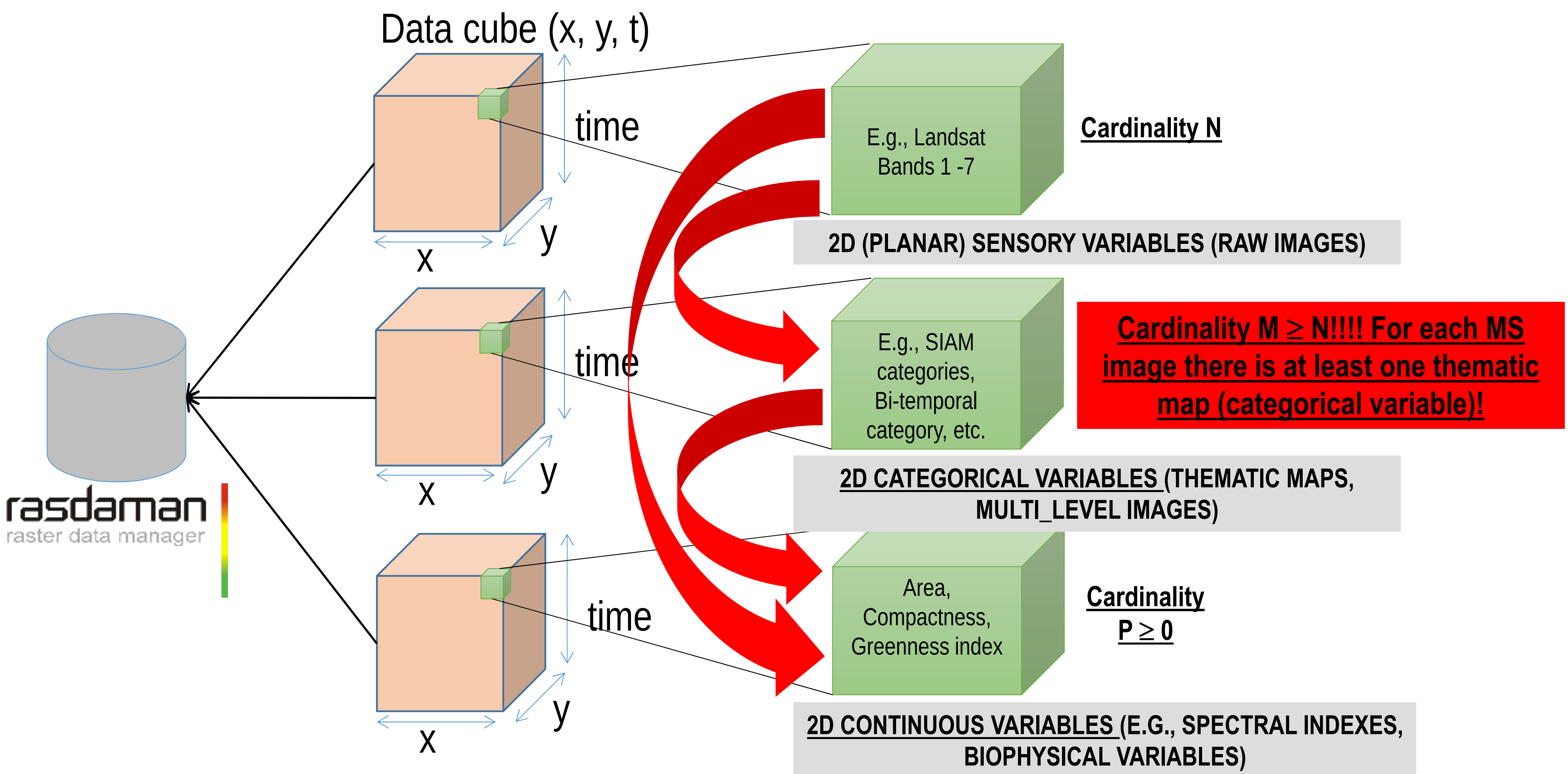
Contributors:

- Martin Sudmanns
- Dirk Tiede
- Andrea Baraldi
- Mariana Belgiu
- Stefan Lang

EO-IU4SQ System Architecture (Unina & Univ. Salzburg)



EO-IU4SQ's raster database set-up

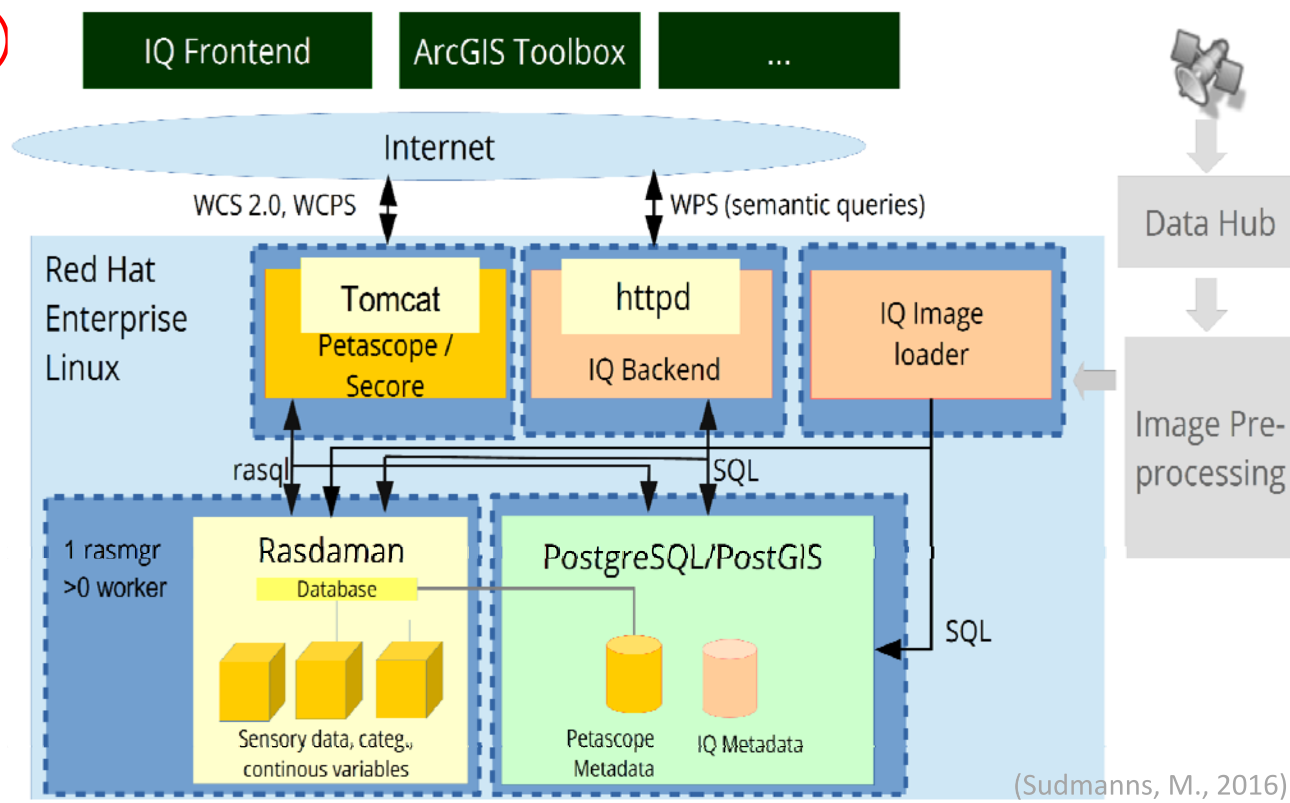


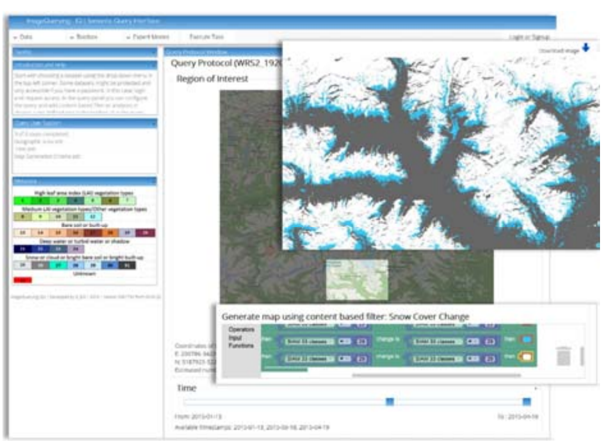
EO-IU4SQ prototype demo

Through the GUI (a graphics inference engine), image-derived information layers are made available to a user for SCBIR or geospatial data analysis. Expert queries are forming a growing knowledge base for managing and sharing.

Architecture in a client-server solution

3

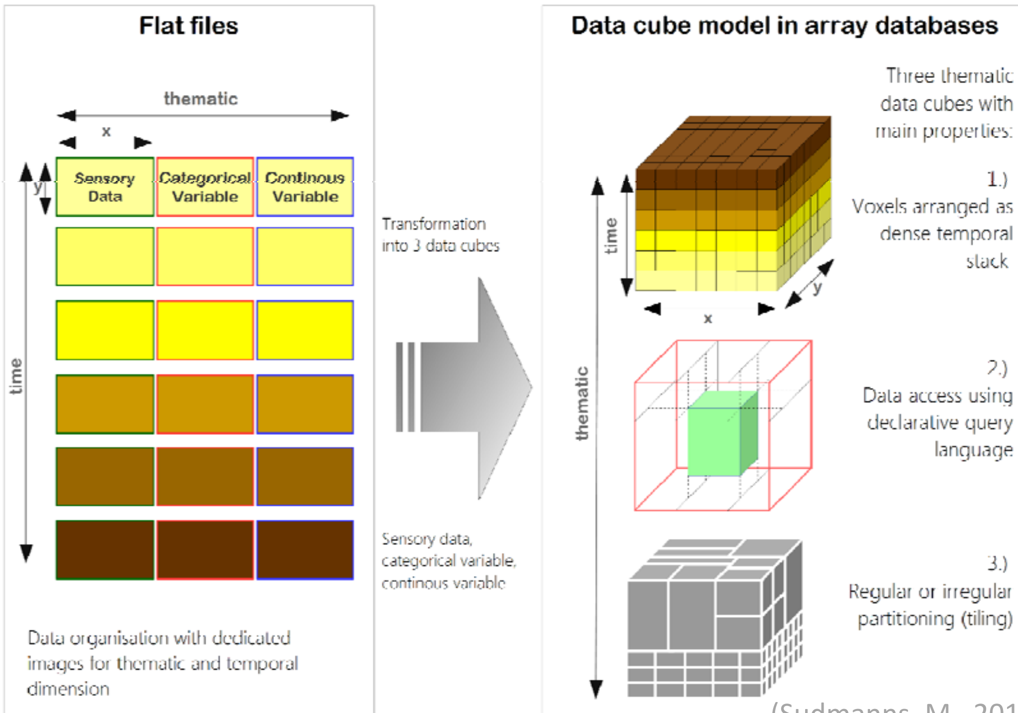




Web-based Image Querying (IQ) prototype. The term IQ is used for the prototypical implementation of the EO-SQ subsystem.

EO-IU4SQ prototype demo

2



(Sudmanns, M., 2016)

To accomplish efficient geospatial data analysis through time within a user-defined AOI and target time interval, the implementation adopts an array database system (specifically, RasDaMan) within a client-server solution.

Storage using flat files versus storage of images in an array database.

EO-IU4SQ prototype demo