SIAM™ (Satellite Image Automatic Mapper™) Process and Product Description

Problem background: Vision

Vision is an inherently ill-posed cognitive (*information-as-data-interpretation*) problem, synonym for scene-from-image reconstruction and understanding. Encompassing both biological vision and computer vision (CV), where CV is *superset-of* Earth observation (EO) image understanding (EO-IU), i.e., relationship 'CV ⊃ EO-IU' holds, *vision* is very difficult to solve because: (i) non-deterministic polynomial (NP)-hard in computational complexity, (ii) inherently ill-posed in the Hadamard sense, because affected by: (I) a 4D-to-2D data dimensionality reduction, from the 4D geospatial-temporal scene-domain to the (2D, planar) image-domain, and (II) a semantic information gap, from ever-varying sub-symbolic sensory data (sensations) in the image-domain to stable symbolic percepts in the mental model of the physical world (modeled world, world ontology, real-world model). Since it is inherently ill-posed, *vision* requires *a priori* knowledge in addition to sensory data to become better posed for numerical solution.

Satellite Image Automatic Mapper™ software process and output products

The Satellite Image Automatic Mapper™ (SIAM™) software executable is a lightweight computer program which is fully automatic, requiring neither human-machine interaction nor training data to run, and suitable for: (i) prior knowledge-based multi-sensor multi-spectral (MS) reflectance space hyperpolyhedralization (discretization, quantization, see Fig. 1) into static (non-adaptive to data) discrete and finite vocabularies of MS color names, where four color name vocabularies featuring coarse, intermediate, "shared" (inter-sensor) and fine granularities are interrelated, featuring inter-level parent-child relationships, refer to Table 1 to Table 4, (ii) connected-component (superpixel, image-object, segment) detection in the multi-level map of color names, see Fig. 2, and (iii) vector quantization (VQ) quality assessment, specifically, root-mean-square error (RMSE) estimation, in a piecewise-constant MS image approximation (reconstruction, object-mean view) [1], [2].

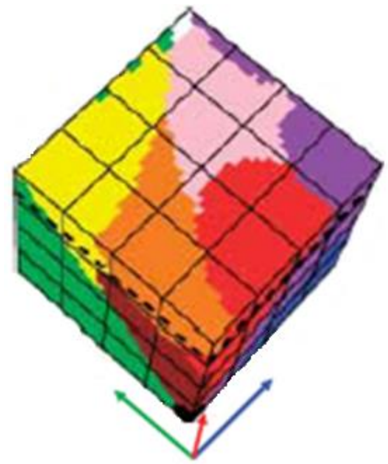

Fig. 1. Unlike a multi-spectral (MS) reflectance space hyperpolyhedralization, difficult to think of and impossible to visualize when the number of channels is superior to three, a monitor-typical Red-Green-Blue (RGB) data cube polyhedralization is intuitive to think of and straightforward to display. For example, based on psychophysical evidence, human basic color (BC) names can be mapped onto a monitor-typical RGB data cube. Central to this consideration is Berlin and Kay's landmark study in linguistics of a "universal" inventory of eleven BC words in twenty human languages: black, white, gray, red, orange, yellow, green, blue, purple, pink and brown. In the RGB data cube, the vocabulary of eleven BC names in human languages is equivalent to a mutually exclusive and totally exhaustive set of polyhedra, neither necessarily convex nor connected.

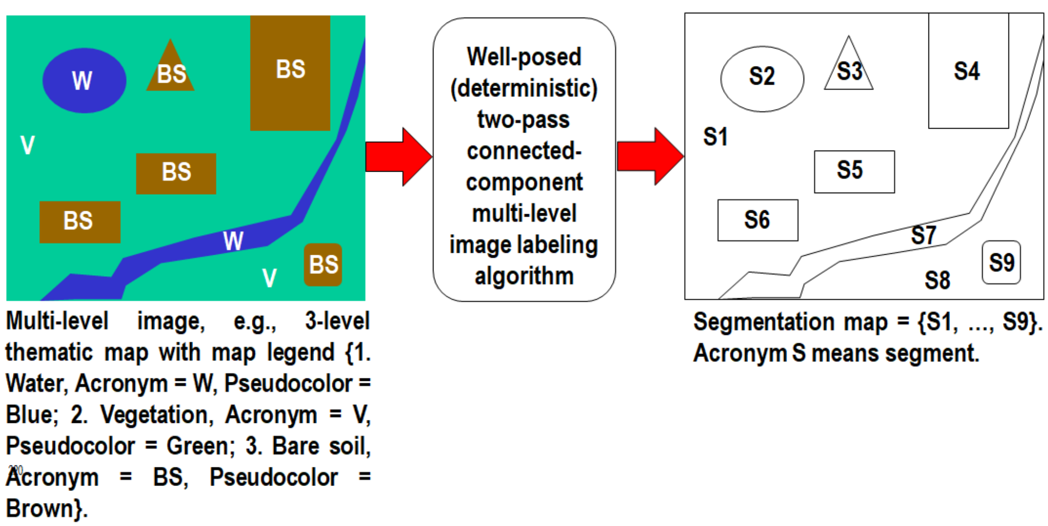

Fig. 2. One segmentation map is deterministically generated from one multi-level (e.g., binary) image, such as a thematic map, but the vice versa does not hold, i.e., many multi-level images can generate the same segmentation map. To accomplish the deterministic (unequivocal, well-posed) task of segmentation map generation from a multi-level image, the well-posed (deterministic) two-pass connected-component multi-level image labeling algorithm requires two raster scans of the input data set. In the figure above, as an example, nine image-objects/segments S1 to S9 can be detected in the 3-level thematic map shown at left. Each segment (image-object, connected-component) consists of a connected set of pixels sharing the same multi-level map label. An image-object is either (0D) pixel, (1) line or (2D) polygon. Each stratum/layer/level consists of one or more segments. For example, stratum *Vegetation* (V) consists of two disjoint segments, S1 and S8. In general, a stratum is a multi-part polygon. Hence, in any multi-level

(categorical, nominal, qualitative) image/map domain, three labeled spatial primitives (spatial units) co-exist and are provided with parent-child relationships: (i) pixel with a level-label, e.g., V as *vegetation*, and a pixel-specific identifier (ID, e.g., the row-column coordinate pair), (ii) connected-component (segment), either 0D, 1D, or 2D, with a level-specific label e.g., V as *vegetation*, and a segment ID, e.g., S8, and (iii) stratum (multi-part polygon) with a level-specific label, equivalent to a stratum/layer/level ID, e.g., V as *vegetation*, whose multi-part polygons are S1 and S8.

Table 1. The SIAM™ system of six sub-systems. Summary of input bands and output spectral categories (color names in a multi-spectral reflectance space, MS). Acronyms: Landsat/ SPOT/ AVHRR/ AATRS/ QuickBird/ DMC-like SIAM™ = L/ S/ AV/ AA/ Q/ D-SIAM™. Bands: B = Blue, G = Green, R = Red, NIR = Near Infrared, MIR = Medium Infrared, TIR = Thermal Infrared. (*) Employed in sensor-independent bi-temporal post-classification land cover change/no-change detection.

SIAM™, r88v7	**Input Bands (B: Blue, G: Green, R: Red, NIR: Near Infra-Red, MIR: Medium IR, TIR: Thermal IR)**	**Preliminary Classification Map Output Products: Number of Output Spectral Categories.**			
		Fine Discretization Granularity	**Intermediate Discretization Granularity**	**Coarse Discretization Granularity**	**Inter-Sensor Discretization Granularity (*)**
L-SIAM™	7 bands – B, G, R, NIR, MIR1, MIR2, TIR	96	48	18	33
S-SIAM™	4 bands – G, R, NIR, MIR1	68	40	15	
AV-SIAM™	4 bands – R, NIR, MIR1, TIR	83	43	17	
AA-SIAM™	5 bands – G, R, NIR, MIR1, TIR	83	43	17	
Q-SIAM™	4 bands – B, G, R, NIR	61	28	12	
D-SIAM™	3 bands – G, R, NIR	61	28	12	

Table 2. Preliminary classification map's legend, adopted by the Landsat-like SIAM (L-SIAM)™ at fine discretization, consisting of 96 spectral categories (refer to Table 1). Pseudo-colors of the spectral categories are grouped on the basis of their spectral end-member, e.g., "*bare soil or built-up*", or parent spectral category, e.g., "high" leaf area index (LAI) vegetation types. The pseudo-color of a spectral category is chosen so as to mimic natural colors of pixels belonging to that spectral category.

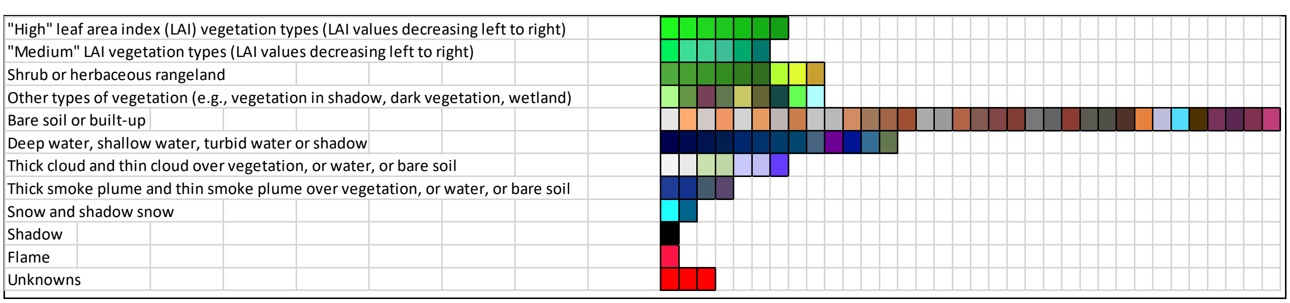

Table 3. Preliminary classification map's legend, adopted by the AVHRR-like SIAM (AV-SIAM)™ at fine discretization, consisting of 83 spectral categories (refer to Table 1). Pseudo-colors of the spectral categories are grouped on the basis of their spectral end-member, e.g., "*bare soil or built-up*", or parent spectral category, e.g., "high" leaf area index (LAI) vegetation types. The pseudo-color of a spectral category is chosen so as to mimic natural colors of pixels belonging to that spectral category.

"High" leaf area index (LAI) vegetation types (LAI values decreasing left to right)
"Medium" LAI vegetation types (LAI values decreasing left to right)
Shrub or herbaceous rangeland
Other types of vegetation (e.g., vegetation in shadow, dark vegetation, wetland)
Bare soil or built-up
Deep water, shallow water, turbid water or shadow
Thick cloud and thin cloud over vegetation, or water, or bare soil
Snow and shadow snow
Shadow
Flame
Unknowns

Table 4. Preliminary classification map's legend, adopted by the Quickbird-like (Q-SIAM)™ at fine discretization granularity, consisting of 61 spectral categories (refer to Table 1). Pseudo-colors of the spectral categories are grouped on the basis of their spectral end-member, e.g., "*bare soil or built-up*", or parent spectral category, e.g., "high" leaf area index (LAI) vegetation types. The pseudo-color of a spectral category is chosen so as to mimic natural colors of pixels belonging to that spectral category.

"High" leaf area index (LAI) vegetation types (LAI values decreasing left to right)
"Medium" LAI vegetation types (LAI values decreasing left to right)
Shrub or herbaceous rangeland
Other types of vegetation (e.g., vegetation in shadow, dark vegetation, wetland)
Bare soil or built-up
Deep water or turbid water or shadow
Smoke plume over water, over vegetation or over bare soil
Snow or cloud or bright bare soil or bright built-up
Unknowns

Since it is physical model-based, the SIAM expert system for MS color naming requires as input a spaceborne/airborne MS image provided with a physical meaning, namely, with a physical unit of radiometric measure. In more detail, SIAM requires as input a MS image radiometrically calibrated into top-of-atmosphere (TOA) reflectance (TOARF), surface reflectance (SURF) or surface albedo values, where SURF is a special case of TOARF in clear sky and flat terrain conditions, i.e., TOARF $\supseteq$ SURF, in fact, TOARF $\approx$ SURF + atmospheric "noise" + topographic "noise".

It is worth mentioning that, in EO-IU $\subset$ CV tasks, MS color names in the (2D) image-domain should never ever be confused with target land cover (LC) classes pertaining to the 4D spatial-temporal scene-domain, refer to Table 5. *Vision*, in general, encompassing CV as a special case, is inherently ill-posed and requires *a priori* knowledge in addition to sensory data to become better posed for numerical solution. An important source of *a priori* knowledge considered necessary-but-not-sufficient to accomplish CV tasks in operating mode is the binary relationship R: A $\Rightarrow$ B $\subseteq$ A $\times$ B from set A = VocabularyOfColorNames to set B = LegendOfObjectClassNames, where A $\times$ B is the 2-fold Cartesian product between sets A and B, refer to Table 5 [1], [2].

Table 5. Example of a binary relationship R: $A \Rightarrow B \subseteq A \times B$ from set A = VocabularyOfColorNames, with cardinality $|A|$ = a = ColorVocabularyCardinality = 11, and the set B = LegendOfObjectClassNames, with cardinality $|B|$ = b = ObjectClassLegendCardinality = 3, where $A \times B$ is the 2-fold Cartesian product between sets A and B. The Cartesian product of two sets $A \times B$ is a set whose elements are ordered pairs. The size of $A \times B$ is rows $\times$ columns = $a \times b$. The dictionary LegendOfObjectClassNames is a superset of the typical taxonomy of land cover (LC) classes adopted by the remote sensing (RS) community. "Correct" entry-pairs (marked with √) must be: (i) selected by domain experts, based on a *hybrid* combination of deductive prior beliefs with inductive evidence from data, and (ii) community-agreed upon, to be used by members of the community.

		Target classes of individuals (entities in a conceptual model for knowledge representation built upon an ontology language)		
		Class 1, Water body	Class 2, Tulip flower	Class 3, Italian tile roof
Basic color (BC) names	black		√	
	blue	√	√	
	brown	√	√	√
	grey			
	green	√	√	
	orange		√	
	pink		√	
	purple		√	
	red		√	√
	white		√	
	yellow		√	

Largely oversighted by the RS and CV literature, an undisputable observation (true-fact) is that, in general, spatial information dominates color information in *vision* [1], [2]. This commonsense knowledge is obvious, but not trivial. On the one hand, it may sound awkward to many readers, including RS experts and CV practitioners. On the other hand, it is acknowledged implicitly by all human beings wearing sunglasses: human panchromatic vision is nearly as effective as chromatic vision in scene-from-image reconstruction and understanding. This true fact means that spatial information dominates both the 4D geospatial-temporal scene-domain and the (2D) image-domain involved with the cognitive task of *vision.*

By discretizing (numerical) color values, specifically, MS reflectance values, into (categorical) color names, equivalent to hyperpolyhedra in a MS reflectance hypercube, SIAM copes with secondary colorimetric information exclusively, i.e., it ignores spatial information components, either topological or non-topological, typically dominating color information in both the scene-domain and the image-domain.

It means that, in the remote sensing (RS) common practice, the prior knowledge-based SIAM decision tree for MS color naming contributes towards filling the semantic information gap from sub-symbolic pixels to semantic image-objects (either 0D point, 1D line or 2D polygon) by means of semi-symbolic color names, equivalent to a hidden, non-observable categorical variable [1], [2]. On a standalone basis, SIAM is suitable for (independent, third-party) validation of MS sensory data, acquired by any past, present or future MS imaging sensor and radiometrically calibrated into TOARF, SURF or surface albedo values. In a multi-stage EO-IU system, capable of colorimetric and spatial analytics based on a hybrid (combined deductive/ top-down/ physical model-based and inductive/ bottom-up/ statistical model-based) convergence-of-evidence approach to scene-from-image reconstruction and understanding, the SIAM deductive color naming works as first-stage CV subsystem, suitable for secondary color analysis preliminary to dominant spatial analytics.

Legend of fuzzy sets of a quantitative variable.

LOW
MEDIUM
HIGH

Suitability [12] = Process (P) Q^2Is and Outcome (O) Q^2Is $\pm\delta \subseteq$ QA4EO *Val*	Example: System 1
Availability (Findability, according to the standard set of engineering principles known as FAIR applied to input/output data, products and processes [113]) **(O, P).**	HIGH
Accessibility (included in the FAIR criteria [113] applied to input/output data, output products and processes) **(O, P).**	MEDIUM
Degree of automation (P) = Human-machine interaction: (a) number, physical meaning and range of variation of hyperparameters to be user-defined, (b) collection of the required training data set, if any. If hyperparameters increase in number, i.e., the model complexity (degrees-of-freedom) increases, then also variance increases in the bias-variance trade-off.	HIGH
Model complexity (P) = number of degrees-of-freedom = (i) number of hyperparameters to be user-defined, equivalent to a priori knowledge encoded by design **+ (ii) number of parameters** to be learned-from-data. **If model complexity increases, then variance (dependency on data) increases.**	LOW
Computational complexity (P) = number of elementary operations, e.g., linear/polynomial/exponential complexity in image size.	LOW
Effectiveness/Accuracy (O), related to the **bias (error) term in the bias-variance cost function**: for example, (a) thematic QIs (TQIs) and (b) spatial QIs (SQIs), provided with a degree of uncertainty in measurement $\pm\delta$.	HIGH
Efficiency (P): e.g., (a) computation time and (b) run-time memory occupation.	HIGH
Robustness/Reliability (vice versa**, Sensitivity) to changes in input images (P)**, e.g., large spatial extent (no toy problem). Related to concepts such as **interoperability** and **transferability, e.g., Artificial General Intelligence (AGI) aims at low-bias together with low-variance.**	HIGH
Robustness/Reliability (vice versa**, Sensitivity) to changes in input parameters (P)**.	HIGH
Scalability to changes in sensor specifications and/or user requirements = Re-usability = Maintainability = Transferability (P), e.g., panchromtc/chrmtc computer vision system.	HIGH
Interpretability/traceability of the model/solution (P). E.g., "the black box problem" affecting ANNs [120].	HIGH
Timeliness (P), from data acquisition to high-level product generation, increases with man power and computing power.	HIGH
Costs (O, P), increasing with man power and computing power.	LOW
Value (O, P): e.g., semantic information level of outcome, economic value of output products or services, etc.	MEDIUM (in semantics)

Fig. 3. Proposed minimally dependent and maximally informative (mDMI) set of outcome and process (OP) quantitative quality indicators (OP-Q^2Is). The SIAM software toolbox for MS color naming, superpixel detection and vector quantization (VQ) quality assessment can be considered in "operating mode" because it scores "high" (or medium) in every index of the mDMI set of OP-Q^2Is.

SIAM outcome and process quantitative quality indicators

By scoring "high" in a minimally dependent and maximally informative (mDMI) set of outcome and process (OP) quantitative quality indicators (OP-Q^2Is), the SIAM lightweight computer program can be considered suitable for CV applications in "operating mode", see Fig. 3.

In terms of degree of automation, SIAM is "fully automatic", i.e., it requires neither user-defined parameters nor training data samples to run.

In terms of computational complexity, SIAM is near real-time. In more detail, its computational complexity increasing linearly with image size. For example, on a standard laptop computer, it requires four minutes to map a Landsat scene onto four color maps (at coarse, intermediate, shared and fine granularities, see Table 1) plus segmentation maps plus VQ error maps.

In terms of scalability/interoperability, SIAM is eligible for use with any past, existing or future planned spaceborne/airborne MS imaging sensor, irrespective of its spatial resolution, as far as a MS image file is provided with a calibration metadata file.

In terms of robustness to changes in input data, SIAM was validated by independent means at continental scale. In particular, the degree of match of the SIAM pre-classification maps, automatically generated from a 30 m resolution 2006 Landsat image mosaic of the conterminous Unites States (CONUS), with the U.S. Geological Survey (USGS) 30 m resolution 2006 National Land Cover Data (NLCD) map, is 95.41 ± 0%, with a Categorical Variable Pair Similarity Index (CVPSI) value of 44.37%. This metrological CVPSI value means that the information gap from sensory data to LC classes is filled up to 44.37%, based on prior knowledge exclusively, in near real-time and without user interactions, at the first stage of a hybrid (combined deductive and inductive) EO-IU system architecture, refer to Fig. 4 [1], [2].

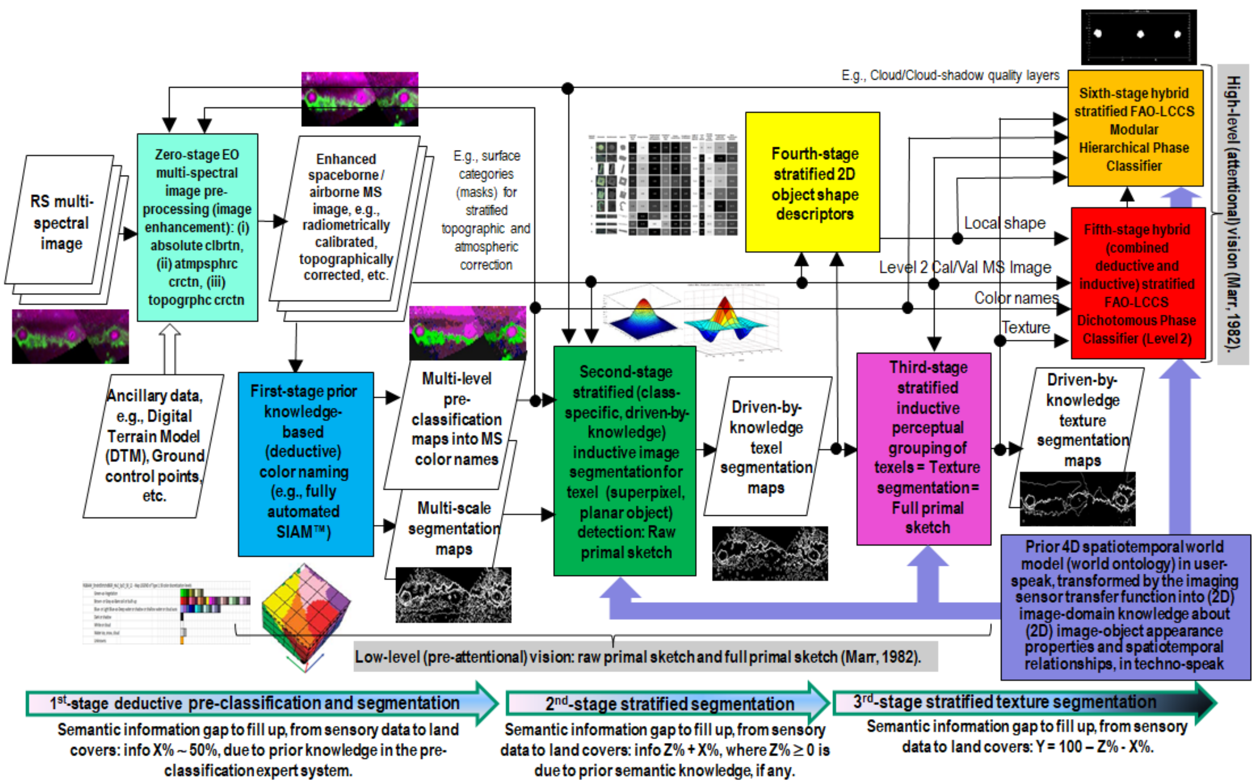

Fig. 4. Six-stage hybrid (combined deductive and inductive) feedback EO image understanding (EO-IU) system design, identified as QuickMap™ technology, where acronym SIAM stays for Satellite Image Automatic Mapper (SIAM), a lightweight computer program for MS reflectance space hyperpolyhedralization into a static vocabulary of MS color names, connected-component (superpixel) detection and vector quantization (VQ) quality assessment. The proposed six-stage hybrid EO-IU system architecture is based on a convergence-of-evidence approach to vision, consistent with Bayesian naïve classification [1], [2]. Alternative to inductive feedforward EO-IU system architectures adopted by the RS mainstream, such as Deep Convolutional Neural Networks (DCNNs) trained from data end-to-end, the proposed six-stage hybrid EO-IU system design complies with the engineering principles of modularity, hierarchy and regularity considered necessary for scalability in structured system design. Its hierarchy comprises a first-stage general-purpose, sensor-, application- and user-independent EO image understanding (classification) subsystem,

followed by a second-stage sensor-, application- and user-specific EO image understanding subsystem. This two-stage EO-IU system design is fully consistent with the standard two-stage fully-nested Land Cover Classification System (LCCS) taxonomy promoted by the Food and Agriculture Organization (FAO) of the United Nations, where a first-stage 3-level 8-class Dichotomous Phase (DP) is preliminary to a second-stage Modular Hierarchical Phase (MHP) [9]. For the sake of visualization, each of the six EO data processing stages plus stage-zero for EO data pre-processing (enhancement) is depicted as a rectangle with a different color fill. Visual evidence stems from multiple information sources, specifically, numeric color values quantized into categorical color names, local shape, texture and inter-object spatial relationships, either topological or non-topological. An example of first-stage general-purpose, user- and application-independent EO image classification taxonomy required by an ESA EO Level 2 Scene Classification Map (SCM) product [8] is the 3-level 8-class FAO LCCS-DP legend, in addition to quality layers cloud and cloud–shadow. Second-stage EO image classification is user- and application-specific, where an SCM product of Level 3 or superior is provided with a map legend consistent with the FAO LCCS-MHP taxonomy [9].

Application domains

Rather than as a standalone EO-IU system, suitable for (independent, third-party) validation of MS sensory data acquired by any past, present or future MS imaging sensor and radiometrically calibrated into TOARF, SURF or surface albedo values, the SIAM expert system for MS color naming is conceived as a symbolic syntactic pre-attentive vision first stage of a novel hybrid (combined deductive/ top-down/ physical model-based and inductive/ bottom-up/ statistical model-based) EO-IU system design, see Fig. 4. In this hybrid multi-stage EO-IU system architecture, the SIAM color space discretization first stage provides prior knowledge-based (deductive) initial conditions to a high-level hybrid MS image classifier.

In addition to classification purposes, the first-stage SIAM semi-symbolic output maps in MS color names, automatically generated from an input EO image, can be adopted as input by inherently ill-posed EO image pre-processing (enhancement) tasks, see Fig. 4, such as atmospheric correction, topographic correction, bidirectional reflectance distribution function (BRDF) effect correction, image mosaicking and image pair co-registration, to become better posed (class-conditioned, driven-by-prior-knowledge, stratified, masked) for numerical treatment [1], [2], [3], [4], [5], see Fig. 5.

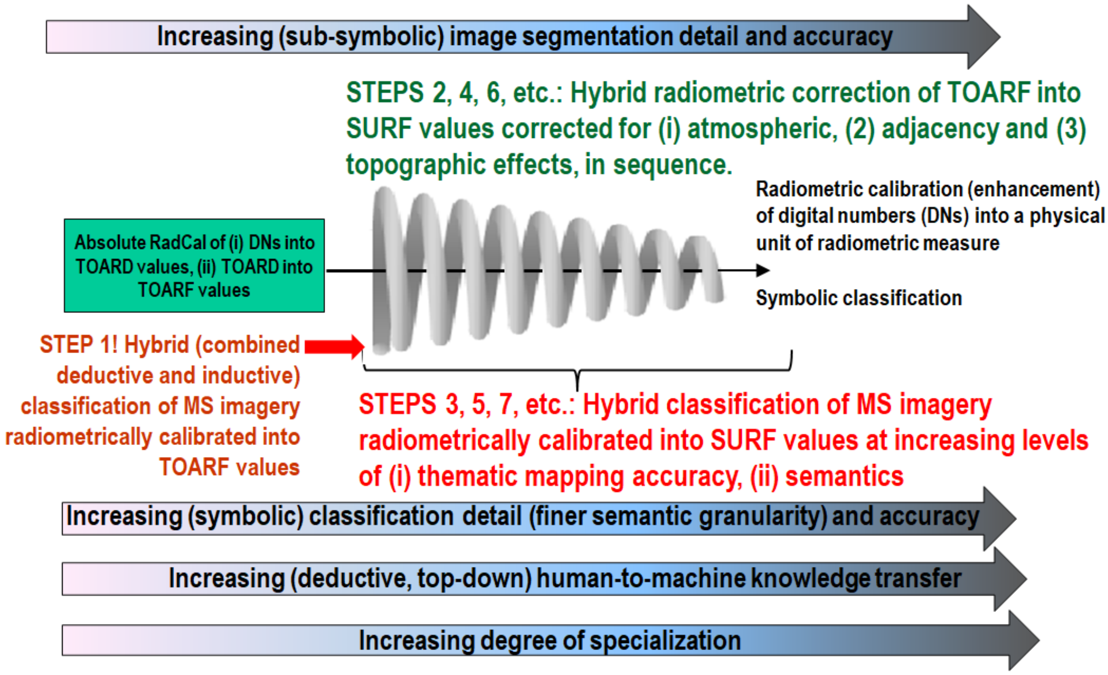

Fig. 5. Ideal ESA EO Level 2 product generation design [8] as a hierarchical alternating sequence of: (A) hybrid (combined deductive and inductive) radiometric enhancement of multi-spectral (MS) dimensionless digital numbers (DNs) into top-of-atmosphere reflectance (TOARF), surface reflectance (SURF) values and spectral albedo values corrected in sequence for (1) atmospheric, (2) adjacency, (3) topographic and (4) BRDF effects, and (B) hybrid (combined deductive and inductive) classification of TOARF, SURF and spectral albedo values into a sequence of ESA EO Level 2 scene classification maps (SCMs), whose legend (taxonomy) of community-agreed land cover (LC) class names, in addition to quality layers cloud and cloud–shadow, increases hierarchically in semantics and mapping accuracy. An implementation in operating mode of this EO image pre-processing system design for stratified topographic correction (STRATCOR) is presented and discussed in [3]. In comparison with this desirable system design, let us consider that, for example, the existing Sen2Cor software toolbox, developed by ESA to support a Sentinel-2 sensor-specific Level 2 product generation on the user side [8], adopts no hierarchical alternating approach between MS image classification and MS image radiometric enhancement. Rather, ESA Sen2Cor accomplishes, first, one SCM generation from TOARF values based on a per-pixel (spatial context-insensitive) prior spectral knowledge-based decision tree. Next, a class-conditional MS image radiometric enhancement of TOARF into SURF values corrected for atmospheric, adjacency and topographic effects is accomplished in sequence, stratified by the same SCM product generated at first stage from TOARF values.

Technological innovations

To the best of these authors' knowledge, the SIAM lightweight computer program is the sole expert system of systems for MS color naming proposed in the RS literature and/or in EO image processing commercial software toolboxes to be considered in operating mode, see Fig. 3, capable of guaranteeing interoperability (transferability) across past, present and future MS imaging sensors, whose sole requirement is to deliver MS imagery provided with a metadata calibration file, in compliance with the intergovernmental Group on Earth Observations (GEO)-Committee on Earth Observation Satellites (CEOS) Quality Accuracy Framework for Earth Observation (QA4EO) Calibration/Validation (Cal/Val) requirements [6].

Research and development (R&D) of a CV ⊃ EO-IU system in operating mode is necessary-but-not-sufficient pre-condition for multi-sensor multi-temporal and multi-angular EO *big data cube* analytics as *part-of* the GEO's visionary goal of a Global EO System of Systems (GEOSS) [6], never accomplished to date by the RS community. The general notion of GEOSS encompasses open sub-problems, such as semantic content-based image retrieval (SCBIR) + semantics-enabled information/knowledge discovery (SEIKD) = artificial general intelligence (AI) for Data and Information Access Services (AI4DIAS) at the ground segment. Dependence relationship CV in operating mode ⊃ EO-IU as *part-of* GEOSS, i.e., 'CV ⊃ EO-IU in operating mode → [EO-SCBIR + SEIKD = AI4DIAS] → GEO-GEOSS', means that the GEOSS open problem, together with its still-unsolved (open) sub-problems of SCBIR and SEIKD, cannot be accomplished until the necessary-but-not-sufficient pre-condition of CV ⊃ EO-IU in operating mode is fulfilled in advance, see Fig. 6.

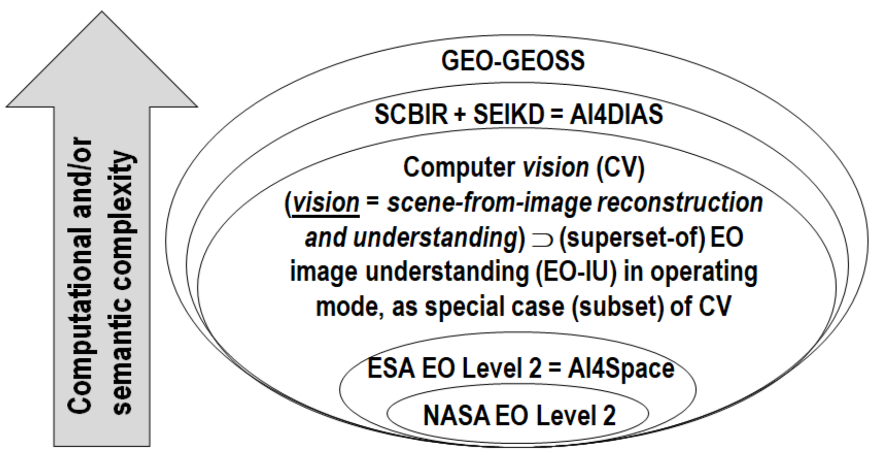

Fig. 6. In agreement with the standard Unified Modeling Language (UML) for graphical modeling of object-oriented software, relationship *part-of*, denoted with symbol '→' pointing from the supplier to the client, should not to be confused with relationship *subset-of*, '⊃', meaning specialization with inheritance from the superset to the subset. A National Aeronautics and Space Administration (NASA) EO Level 2 product is defined as "a data-derived geophysical variable at the same resolution and location as Level 1 source data". Herein, it is considered *part-of* an ESA EO Level 2 product defined as: (a) a single-date multi-spectral (MS) image whose digital numbers (DNs) are radiometrically corrected into surface reflectance (SURF) values for atmospheric, adjacency and topographic effects, stacked with (b) its data-derived general-purpose, user- and application-independent scene classification map (SCM), whose thematic map legend includes quality layers cloud and cloud–shadow. In this paper, ESA EO Level 2 product [8] is regarded as an information primitive to be accomplished by Artificial Intelligence for the Space segment (AI4Space), such as in future intelligent small satellite constellations, rather than at the ground segment in an AI for Data and Information Access Services (AI4DIAS) framework. In this graphical representation, additional acronyms of interest are computer vision (CV), whose special case is EO image understanding (EO-IU) in operating mode, semantic content-based image retrieval (SCBIR), semantics-enabled information/knowledge discovery (SEIKD), where SCIR + SEIKD is considered synonym for AI4DIAS, and Global Earth Observation System of Systems (GEOSS), defined by the Group on Earth Observations (GEO). Our working hypothesis postulates that the following dependence relationship holds true:

'NASA EO Level 2 product → ESA EO Level 2 product = AI4Space ⊂ EO-IU in operating mode ⊂ CV → [EO-SCBIR + SEIKD = AI4DIAS] → GEO-GEOSS'.

This equation means that GEOSS, whose *part-of* are the still-unsolved (open) problems of SCBIR and SEIKD, cannot be achieved until the necessary-but-not-sufficient pre-condition of CV in operating mode, specifically, systematic ESA EO Level 2 product generation, is accomplished in advance. Since it is inherently ill-posed, vision requires *a priori* knowledge in addition to sensory data to become better posed for numerical solution. If the aforementioned working hypothesis holds true, then the complexity of SCBIR + SEIKD is not inferior to the complexity of *vision*, acknowledged to be inherently ill-posed and non-deterministic polynomial (NP)-hard. To make the inherently-ill-posed CV problem better conditioned for numerical solution, a CV system is required to comply with human visual perception. In other words, a CV system is constrained to include a computational model of human vision, i.e., 'Human vision → CV'. Hence, dependence relationship:

'Human vision → CV ⊃ EO-IU in operating mode ⊃ NASA EO Level 2 product → ESA EO Level 2 product → [EO-SCBIR + SEIKD = AI4DIAS] → GEO-GEOSS'

becomes our working hypothesis. Equivalent to a first principle (axiom, postulate), this equation can be considered the first original contribution, conceptual in nature, to the new notion of DIAS 2.0 = AI4DIAS.

In a future DIAS 2.0 = AI4DIAS = EO-SCBIR + SEIKD DIAS 2nd-generation, see Fig. 6, an EO-IU ⊂ CV ⊂ AI module in operating mode, capable of qualitative/equivocal *information-as-data-interpretation*, must be encapsulated into the traditional DIAS 1.0 platform, typically dealing with the quantitative/unequivocal notion of *information-as-thing*, such as data communication/transmission tasks, to provide the EO big data cube, characterized by the five Vs of volume, velocity, variety, veracity and value [7], with an AI eligible for transforming sensory EO *big data* into value-adding information products and services (VAPS). In practice, AI4DIAS = DIAS 2.0 is expected to recover from the data-rich information-poor (DRIP) syndrome affecting the current DIAS 1.0 generation, where no CV system in operating mode provides each EO image stored in the database with meanings (semantics), such as an EO data-derived Level 2 Scene Classification Map (SCM) in compliance with the ESA EO data-derived Level 2 information product definition [8]. Once provided with an EO-IU subsystem in operating mode, an AI4DIAS 2.0 is expected to be provided with a graphic user interface (GUI) completely different from GUIs implemented in DIAS 1.0. The former must bring to surface, i.e., up to the user attention, information in general and semantics in particular, which is available by default in the AI4DIAS 2.0 cube, starting from EO data-derived Level 2 SCMs [8]. Availability of semantics at the GUI level supports symbolic human reasoning, such as "intelligent" semantic content-based data retrieval, namely, EO-SCBIR, in addition to SEIKD activities, synonym for DIAS 2.0 capable of incremental learning, a.k.a. ever-increasing "intelligence". For example, multi-source single-date EO data-derived Level 2 SCMs can be adopted as input to infer higher-level multi-temporal semantic information/knowledge, such as post-classification change/no-change LC class detection in EO data-derived Level 2 SCM time-series.

User cases

Z-GIS created a WebMap service on an ONDA Virtual Machine (VM) showing use cases of the Landsat-like SIAM (L-SIAM) map at fine color discretization, consisting of 96 color names, see Table 1.

This WebMap service shows:

- An area of interest (AOI) identified in Europe where to select multi-temporal multi-source EO image acquisitions.

- The multi-source SIAM capabilities (in a dockerized software solution) constrained by full automation and fast processing, in linear computational complexity with image size, where the data mapping problem can be scaled up easily to cope with changes in sensor specifications. On the ONDA VM platform, SIAM required 7 minutes on average to map a Sentinel-2 tile into 4 color maps + 4 segmentation maps + 1 VQ error estimates, without running SIAM in parallel. Using more CPUs, the processing time per Sentinel-2 tile can be reduce to around 2 minutes.
- Convincing SIAM results for multi-source single-date EO imagery and for post-classification change/no-change detection between two single-sensor or multi-sensor image time-series.
- Convincing SIAM mapping of cloud/cloud-shadow into candidate areas, compared to the ESA Sentinel-2 Level-1C Cloud masks and ESA EO Level 2 Sentinel 2 (atmospheric, topographic and adjacency) Correction Prototype Processor (Sen2Cor) [8].
- … and much more, depending on the application case, e.g., “intelligent” (driven-by-knowledge, stratified, class-conditional) vegetation (greenness) index detection, class-conditional biophysical variable (e.g., leaf area index, LAI) estimation, etc.

The list of input EO data sets and EO data-derived information products adopted by the WebPam service for comparison with SIAM is the following.

- Sentinel-2 MSI
  - 58 Sentinel-2 tiles at 10 m resolution: 29 for an overpass from Northern Germany to Italy on 30/03/2019 and the same area acquired on 19/04/2019.
- Landsat-8 OLI.
  - 3 Landsat-8 images acquired on 21/04/2019.
- For comparison purposes with the SIAM output map of semi-symbolic color names, mosaic of 29 ESA Sen2Cor Level 2 SCMs, 20m spatial resolution, Sentinel-2 data-derived on 19/04/2019. The Sen2Cor SCM legend consists of four different classes for clouds, including cirrus, and six different LC classes, namely, shadows, cloud shadows, vegetation, soils/deserts, water and snow.
- For comparison purposes with the SIAM output map of semi-symbolic color names, mosaic of 29 ESA Sentinel-2 Level 1C Cloud Masks, Sentinel-2 data-derived on 19/04/2019. The legend of the Sentinel-2 Level 1C Cloud Masks includes opaque clouds and cirrus.

References

[1] Baraldi, A.; Humber, M.L.; Tiede, D.; Lang, S. GEO-CEOS stage 4 validation of the Satellite Image Automatic Mapper lightweight computer program for ESA Earth observation Level 2 product generation – Part 1: Theory. Cogent Geosci. 2018, 1467357, doi:10.1080/23312041.2018.1467357.

[2] Baraldi, A.; Humber, M.L.; Tiede, D.; Lang, S. GEO-CEOS stage 4 validation of the Satellite Image Automatic Mapper lightweight computer program for ESA Earth observation Level 2 product generation– Part 2: Validation. Cogent Geosci. 2018, 1467254, doi:10.1080/23312041.2018.1467254.

[3] Baraldi, A.; Gironda, M.; Simonetti, D. Operational two-stage stratified topographic correction of spaceborne multi-spectral imagery employing an automatic spectral rule-based decision-tree preliminary classifier. IEEE Trans. Geosci. Remote Sens. 2010, 48, 112–146.

[4] A. Baraldi and D. Tiede, “AutoCloud+, a “universal” physical and statistical model-based 2D spatial topology-preserving software for cloud/cloud–shadow detection in multi-sensor single-date Earth observation multi-spectral imagery – Part 1: Systematic ESA EO Level 2 product generation at the ground segment as broad context”, ISPRS Int. J. Geo-Inf., vol. 7, no. 12, 457, 2018. DOI: https://doi.org/10.3390/ijgi7120457. [Online] Available: http://www.mdpi.com/2220-9964/7/12/457/pdf

[5] A. Baraldi and D. Tiede, “AutoCloud+, a “universal” physical and statistical model-based 2D spatial topology-preserving software for cloud/cloud–shadow detection in multi-sensor single-date Earth observation multi-spectral imagery – Part 2: Outcome and process requirements specification, information/knowledge representation, system design, algorithm, implementation and preliminary experimental results”, ISPRS Int. J. Geo-Inf., vol. 7, no. 12, 457, 2018. DOI: https://doi.org/10.3390/ijgi7120457. [Online] Available: https://www.mdpi.com/2220-9964/7/12/457#supplementary

[6] Group on Earth Observation/Committee on Earth Observation Satellites (GEO-CEOS). A Quality Assurance Framework for Earth Observation, Version 4.0. 2010. Available online: http://qa4eo.org/docs/QA4EO_Principles_v4.0.pdf (accessed on 17 November 2018).

[7] Yang, C.; Huang, Q.; Li, Z.; Liu K.; Hu, F. Big Data and cloud computing: Innovation opportunities and challenges. Int. J. Digit. Earth 2017, 10, 13–53, doi:10.1080/17538947.2016.1239771.

[8] Deutsches Zentrum für Luft-und Raumfahrt e.V. (DLR); VEGA Technologies. Sentinel-2 MSI–Level 2A Products Algorithm Theoretical Basis Document; Document S2PAD-ATBD-0001; European Space Agency: Paris, France, 2011.

[9] Di Gregorio, A.; Jansen, L. Land Cover Classification System (LCCS): Classification Concepts and User Manual; FAO Corporate Document Repository; FAO: Rome, Italy, 2000. http://www.fao.org/DOCREP/003/X0596E/X0596e00.htm (accessed on 10 February 2015).