

Object-Based Similarity Assessment Using Land Cover Meta-Language (LCML): Concept, Challenges, and Implementation

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Abstract—Land cover (LC) is an essential variable for environmental monitoring in many application domains. The detection of changes in LC can support the understanding of environmental dynamics. However, LC legends present a high degree of inconsistencies that significantly reduce their usability. This study investigates the effectiveness of ISO standard 19144-2, better known as Land Cover Meta-Language (LCML), to improve the standardization and harmonization of different LC taxonomies and maps. LCML vocabulary and syntactic rules facilitate the integration of natural resources information. LC classes are represented by a sequence of “Basic Elements” and attributes defined as “Properties” and “Characteristics.” Such elements are formalized in a Unified Modeling Language class diagram. This study presents first, a method to evaluate and score the “similarity” of different LCML legends, second, an application of the similarity assessment criteria to an area located in Bangladesh for translating its specific LCML legend into a different taxonomy, i.e., the System of Environmental Economic Accounting, and third, a Python implementation to be incorporated in new or already existing tools. The results obtained show that when class similarity assessment is carried out by Basic Elements only, the process performs well for simple classes. When classes are characterized by similar basic elements (e.g., biotic elements) structure, the introduction of class properties is needed to disambiguate complex situations. The findings indicate that the proposed methodology can exploit LCML land feature semantic representation. Moreover, it can be used for translating LCML classes into different taxonomies, for facilitating class comparison and change detection.

Index Terms—Interoperability, land cover meta-language (LCML), ontology integration, similarity assessment, taxonomy.

I. INTRODUCTION

ENVIRONMENTAL resources have never been so much degraded, putting at risk billions of people and undermining our efforts to end hunger and shift to greener and more

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sustainable development, as reported in [1]. There is an increasing and urgent need for monitoring natural resources to support sustainable and informed-based decision-making processes at local, subnational, national, and international levels. Information about land cover (LC) and its changes over time serve multiple purposes, from local to global levels, such as for agriculture, food security, ecosystem conservation, sustainable land management, humanitarian response programs, climate change mitigation, and adaptation [2]. Thus, LC mapping is a key source of baseline information to support multilateral environmental agreements and the implementation of the United Nations Sustainable Development Goals (UN SDGs indicators) [3]. Indeed, most of the SDGs indicators, such as 2.4, 6.6, 13.3, 14.4, and 15.3.1, are based on the use of updated LC maps and additional information layers. Several national, regional, and global datasets and LC maps have been produced for different purposes over the years, and the methods for representing and defining classes of land characteristics are as diverse as the land heterogeneity itself [4]. With recent developments in technologies, such as remote sensing (RS) and geographic information systems (GIS), available geographic data have increased exponentially [5]. Additionally, the increasing use of field mobile devices has greatly enlarged the number of field observations, which are collected using predefined legends. While the volume of available LC data increases, the compatibility and comparability of LC products become paramount, but inconsistencies persist [6]. Therefore, a methodology that can automatically measure semantic similarity between classification systems is very much needed to move forward the integration of the different LC products and development of consistent approaches. There are several semantic approaches to GIS interoperability, many guided by cognitive principles [7]–[11], and they use various representational approaches [12]. An attempt to measure the semantic similarity between categories in different land use/LC classification systems can be found in [13]. However, limited efforts have been made by the GIS and RS communities to develop a comprehensive methodology able to carry out a fully automatic LC harmonization using the advance of science in the use of the Standard Generalized Markup Language [14]. A critical factor in implementing such advanced harmonization activities has been the availability of a common LC classification system structure to be able to accommodate all possible LC categories created by map producers at local, national, regional, or global levels.

A possible approach is the use of a shared vocabulary with which to construct derived legends/nomenclatures. In this case, the measure of similarity relies on the likeness of the different shared terms with which a legend class is built. This has been the case of a similarity measure tool embedded in the FAO LCCS v.1 and LCCS v.2 software [2], [15]. Specifically, LCCS v.2 was proven useful to harmonize different LC taxonomies, as recognized by the panel of the Global Observation of Forest and Land Cover Dynamics [16], [17]. In addition, based on the criteria introduced by Salafsky *et al.* [18], [19], LCCS v.2 classification system was also proven adequate to translate LC classes, obtained from satellite data classifications, into habitat classes [20]–[24]. In the meanwhile, in order to improve standardization and increase the harmonization process, FAO developed the Land Cover Meta-Language (LCML) that in 2012 became an international standard (ISO 19144-2) [25]. LCML provides a reliable basis for the interaction without replacing the increasing number of national, regional, and global LC mapping criteria and monitoring activities. In its operational mode, LCML enables the breakdown of LC classes into basic standardized atomic elements (LCML basic elements) further enriched by a series of attributes (i.e., LCML Properties, LCML Element and Class Characteristics) regardless of mapping scale, LC type, data collection method, or geographic location [26]. This ISO standard provides a meta-language expressed as a Unified Modeling Language (UML) class diagram, where all the rules and syntax are clearly instantiated. Such a rich and complex description can be exploited in several ways. For example, it could be used by an automatic or semiautomatic tool devised to compare different classes and report on their similarity, giving a granular score ranging from 1 to 100 (higher similarity). Taking into consideration the need to improve consistency and harmonization of LC information for different purposes, this study provides a methodological approach for measuring LC semantic similarity by creating compatible object-oriented land cover databases and applying the LCML rules and conditions to assess the “Object Based” similarity between LC databases. This article is organized as follows. Section II provides an overview of the LCML fundamentals; Section III describes the semantic assessment methodological approach proposed in this article; Section IV provides the results obtained in an application to the Cox’s Bazar study area located in Bangladesh. Such country has extensively used LCML for the LC mapping [27], and a preliminary version of the similar assessment approach was already implemented under the geoportal of the Bangladesh Forest Information System [28]. In this article, the similarity measure has been improved and used to translate FAO LCML map in a different standard, i.e., the System of Environmental Economic Accounting (SEEA) and to validate the effectiveness of the proposed taxonomy harmonization process. Conclusions and future work are discussed in Section V. Last but not least, in the appendix, a step-by-step example for applying similarity assessment between two LC classes is reported, as well as an overview of a Python-based standalone package implementation of the similarity assessment is proposed, along with other ancillary functionalities.

II. METHODS

A. LCML Concepts

A brief overview of the LCML concepts is provided here. According to the LCML model, LC can be represented using simple atomic elements, using physiognomic criteria rather than categories [2], [29]. Such elements (e.g., tree, shrub, herb, building, etc.) can be enriched by extra attributes and can be recombined into complex categories, as represented in different classical ontologies. LC classes are then represented in a database by a sequence of basic objects and extra attributes defined as “Properties” and “Characteristics.” The LCML Basic Elements (basic objects), their relationships, inheritance and properties and characteristics associated with them are formalized in a UML class diagram, also part of the standard. Any user, applying LCML rules and conditions, should be able to create compatible legends that will result in object-oriented land cover databases [30]. As a result, different datasets obtained from local to global levels can be integrated, and the semantic interoperability can be performed without referring to any particular predefined list of classes. At the core of LCML, there is a clear and well-defined syntax enabling the combination of the different LCML objects. This approach allows the creation of specific rules to calculate similarity between different categories [31]. Each class always includes and begins with one or more basic elements that capture the physiognomic structure of real-world objects, such as trees, shrubs, or buildings. To each one of them, extra attributes in form of “Properties” and/or “Characteristics” can be added. The former provides a way to annotate extra qualities enhancing the physiognomic structural aspect of a basic element, such as “height,” “cover,” and “leaf type.” The latter can be used to describe any extra information enhancing other qualitative attributes of a specific object, such as “floristic aspect,” “management practices,” and “irrigation types” in case of cultivated crops.

Two examples of class structure defined using LCML are reported in Figs. 1 and 2. The LCML “Basic Elements” are fixed and can be changed only applying the ISO rules governing the “Joint Standard and Register.” Basically, the meta-language Basic Elements are the indispensable vocabulary for describing any LC features. The fact that the vocabulary is fixed (or can be upgraded/modified only after a specific ISO route) gives to the whole system the necessary stability to substantiate its role of reference language to harmonize different legends/nomenclatures. The UML diagram rules are instantiated in a specific software (LCCS v.3) that allows the application of the model in an easy and user-friendly way. The outputs (legends) are automatically validated against an XML Schema Definition document to automatically transfer the coded information into a “machine readable language.” This procedure enables a fully automated “machine understanding” of the LCML class structure, and thus all the basic elements, properties, and characteristics are expressed in the validator. The combination of a clear definition of class structure and its standardized computer-friendly description make possible both transparent and automatic assessment of class similarity.

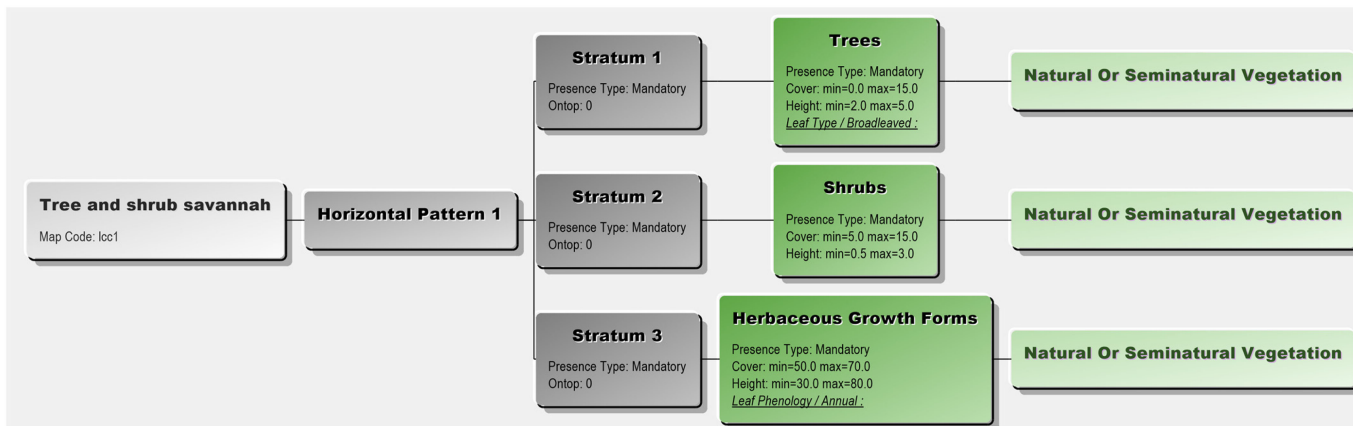


Fig. 1. Description of an LC class for a tree and shrub savannah using LCML. Three basic elements are identified, namely trees, shrubs, and herbaceous growth forms, along with their relationships. Properties attached to the basic elements further specify other requirements for cover and height, among other details.

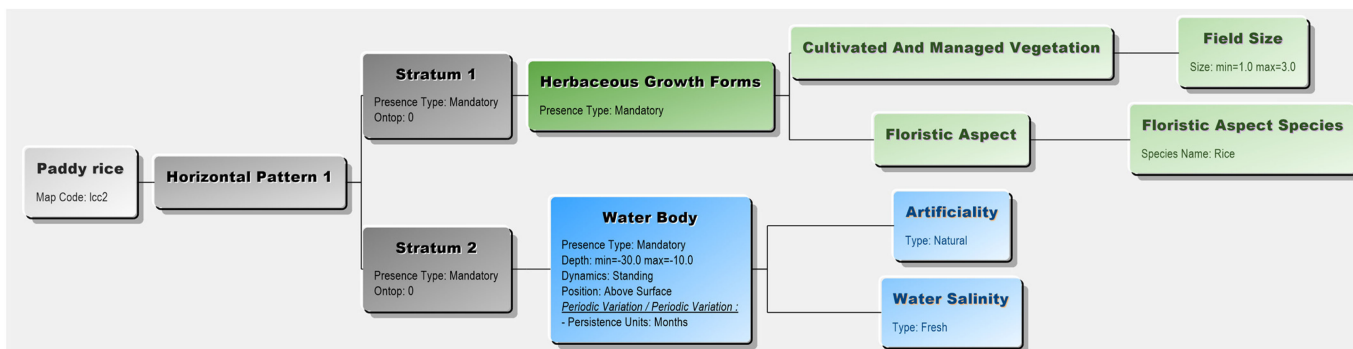


Fig. 2. A second example of an LC class in LCML describing a paddy rice. In this case, there is the combination of two LCML objects, an “herbaceous” growth form (the rice) and a layer of water. Extra attributes linked to the basic objects further define the overall class semantic meaning.

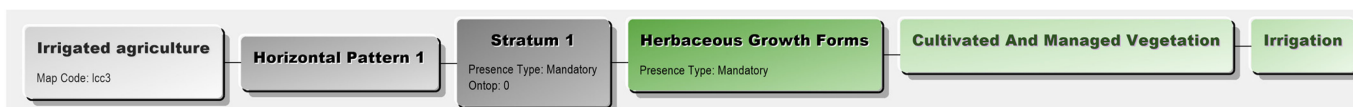


Fig. 3. A class describing irrigated agriculture. Only a single basic element is used to describe the class, and naturally, its presence is mandatory. Characteristics and subcharacteristics are defined related to its cultivated and irrigated requirements.

B. Similarity Assessment Methodology

The standardized schemas describing LC classes in LCML can be exploited to define an automatic similarity assessment that can identify how much two (and by extension, more) classes are similar to each other. This can be done by defining a way to compare basic elements, properties, and characteristics between classes. In order to keep the scope size and complexity under control, the automatic similarity assessment proposed in this article uses basic elements and only the attribute “properties,” whereas the attributes “characteristics” will be the focus of a future work. As mentioned earlier, class similarity is performed through the following steps:

- 1) correspondence;
- 2) extensiveness;
- 3) computation.

C. Basic LCML Element Similarity

Any class generated in LCML always follows a standard logic composition rule path starting from the selection of one or more “Basic LCML Elements.” For e.g., to describe an irrigated agriculture feature, the user starts identifying the LCML element “herbaceous vegetation” to which two different attributes are attached: “cultivated” and “irrigated,” as reported in Fig. 3. This example shows the key importance in the LCML syntax of the “Basic LCML Elements.” Practically, they are the bone structure around which a class is created; therefore, the calculation of class similarity based on their presence/absence/degree of correspondence (Likeness value) is the first and most important value of the “multiphase” computation.

The need for both accounting basic element likeliness and the number of matched elements between two classes requires to

TABLE I
SAMPLE TABLE COMPARING BIOTIC (VEGETATED) ELEMENTS, CONSIDERING THE “CORRESPONDENCE” BETWEEN BASIC ELEMENTS

	LC_GrowthForms (B)	LC_WoodyGrowthForms (C)	LC_Trees (D)	LC_Shshrubs (E)	LC_HerbaceousGrowthForms (F)	LC_Graminae (G)	LC_Forbs (H)	LC_LichenandMosses (I)	LC_Lichen (J)	LC_Mosses (K)	LC_Algae(L)
LC_GrowthForms (B)	10	9	9	9	9	9	9	9	9	9	9
LC_WoodyGrowthForms (C)	9	10	9	9	3	3	3	1	1	1	2
LC_Trees (D)	9	9	10	6	3	3	3	1	1	1	2
LC_Shshrubs (E)	9	9	6	10	4	4	4	1	1	1	2
LC_HerbaceousGrowthForms (F)	9	3	3	4	10	9	9	4	4	4	4
LC_Graminae (G)	9	3	3	4	9	10	9	4	4	4	4
LC_Forbs (H)	9	3	3	4	9	9	10	4	4	4	4
LC_LichenandMosses (I)	9	1	1	1	4	4	4	10	9	9	4
LC_Lichen (J)	9	1	1	1	4	4	4	9	10	9	4
LC_Mosses (K)	9	1	1	1	4	4	4	9	9	10	4
LC_Algae (L)	9	2	2	2	4	4	4	4	4	4	10

Note: When comparing elements of the same type, the maximum score is given. For instance, the element LC Tree indicates a maximum value 10 in the column D (because LC Tree is compared with the same element LC Tree). In the same way, a tree is more similar to a generic woody growth form (score 9) than to mosses (minimum score of 1).

use some composing function that can account for both. Hence, a bivariate approach as presented in [12] is used during the multiphase computation, considering two values: 1) correspondence (likeliness) and 2) extensiveness.

1) *Correspondence*: LCML UML meta-model has been shaped for accounting “real-world” LC relationships between different basic LCML elements. The similarity assessment approach described here exploits this concept by associating a degree of similarity for each different pair of basic elements, that is, as an example, it gives a better similarity score when comparing a tree with a shrub than when comparing a tree with a rock. The likeliness is therefore computed as a value ranging from 1 to 10, as shown in Table I for biotic elements. FAO LCML, being easily representable in a UML model, adapts very well to a network model [32].

Correspondence score between basic elements can hence be based on the path distance between basic elements in the UML schema. However, being UML a representation of a complex reality, in the tables, correspondences start from the evaluation results of path distance, and then they are individually tweaked for better capturing expert judgment.

When comparing two LC classes, known as input and reference, the correspondence algorithm computes a value in the following way: For each one of the “inputs Basic LCML Element,” the most likelihood of the reference Basic LCML Element will be selected and Correspondence value (from 1 to 10) will be assigned according to the corresponding Correspondence table. The “input Basic LCML Element” is the element(s) forming a query (or interrogation) class for which a similarity value is calculated in relation to one or more reference classes composed by one or more element (s) called “reference Basic LCML Element.”

The major computation rules postulate that the system automatically selects for each “input Basic LCML Element” the

TABLE II
SAMPLE OF BASIC LCML ELEMENT EXTENSIVENESS VALUE TABLE

	Input count							
	1	2	3	4	5	6	7	8
1	10	7	6	5	4	3	2	1
2	6	10	9	7	6	4	2	1
3	5	6	10	9	8	6	5	3
4	2	5	6	10	9	7	6	4
5	1	3	5	7	10	9	7	6
6	1	2	5	6	7	10	9	7
7	1	2	3	4	6	7	10	9
8	1	2	3	4	5	6	7	10

Note. Input corresponds to the class for which the calculation of similarity is done, reference is the reference class on which the comparison of the similarity is computed, and C is the extensiveness values from 1 to 10.

“reference Basic LCML Element” with the highest correspondence. This is done using the values listed in the Correspondence table. When two or more “input Basic LCML Elements” find two or more similar values of different “reference LCML Basic Elements,” the hierarchy established by LCML UML diagram can be used to disambiguate and automatically select the most convenient “reference LCML Basic Element.”

2) *Extensiveness (Step 2)*: The computation of “Extensiveness” compares the number of “Input Basic LCML Elements” against the number of the “Reference Basic LCML Elements.” The value is calculated according to the “LCML Extensiveness value” table as shown in Table II.

It is worth noting that basic elements that are not mandatory (hence required for an LC to be considered belonging to a specific class) can be challenging to handle. This is the case for elements that, according to LCML terminology, have an “optional” or “exclusive” presence type. Different ways can be used to address this situation. Two policies are investigated in

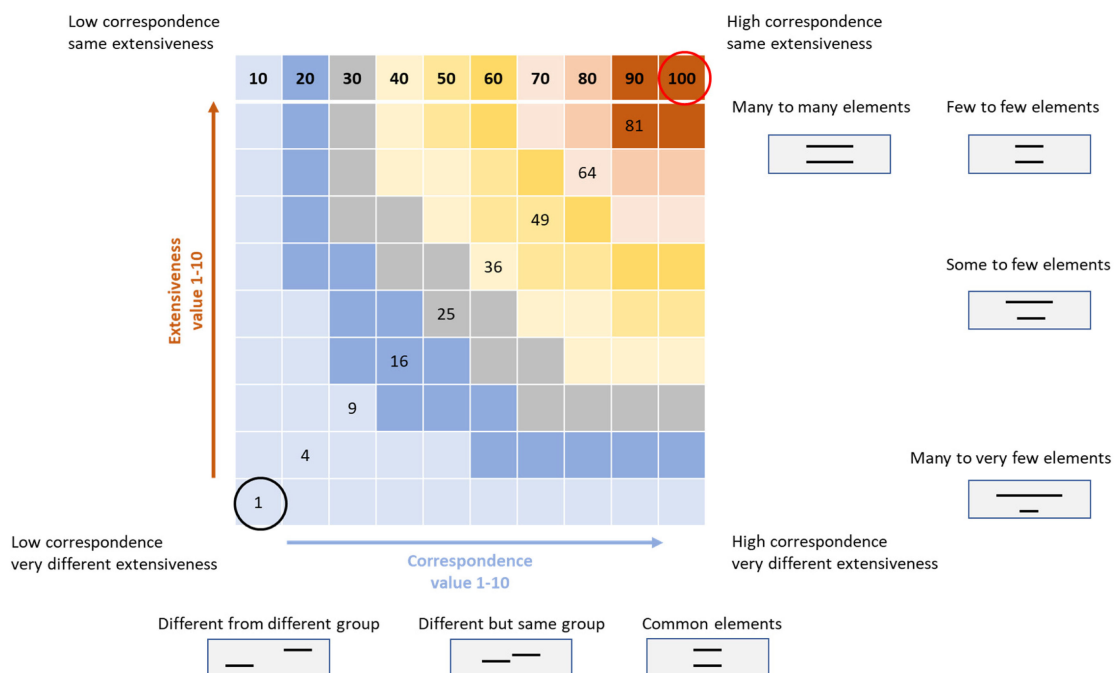


Fig. 4. The bivariate schema representing the possible combinations of “correspondence” and “extensiveness” metrics.

this work. The standard way of operating is to account for them in some measure on the extensiveness score by “counting” less elements in the classes definition that include nonmandatory elements.

For example, since “exclusive” group requires that just one of them must be present at a time, n mutually exclusive elements are counted as 1 for extensiveness sake. In this modality, a single score is still computed for each pair of reference/query classes: it is a tradeoff between accuracy and speed of execution, privileging speed.

In addition, this work introduces the concept of “variants” in an LC class. This means that when a query class uses one or more basic elements that are optional, the system basically creates many variants of the same query class where optional elements are selectively included or excluded from the description of the query class and, therefore, testing many versions (variants) of the same query class against a reference class. To each variant is assigned a similarity score, and the variant with the highest similarity score is considered for providing the matching score. Changes are limited to the “Phase 1” stage, i.e. consider just basic element types. Considerations on this choice are provided later while evaluating the results.

3) *Final Computation (Step 3)*: The final computation table is prepared by multiplying the values of “Correspondence” and “Extensiveness” with values ranging 1–100, as shown in Fig. 4.

The lower similarity value represents cases with both low “Correspondence” and “Extensiveness” values, whereas the upper right represents cases with both high “Correspondence” and “Extensiveness” values. Extensiveness score is high when the number of objects in the query class is comparable with the number of objects in the reference class. When the type of objects to be compared between the query class and the reference class is the same, the correspondence value is the highest.

D. Basic LCML Element Properties

The Basic LCML Element properties are considered a further enrichment of the LCML Elements and are very different from the LCML Element characteristics that can be considered “Qualitative” attributes of the LCML Elements. The particular nature of the Basic LCML Element properties make their calculation strictly correlated to the one previously described in the LCML Basic Element similarity calculation, and therefore the system in its first similarity output computes the averaged sum of these two values. This can be considered as the first and most important output of the overall similarity. The computation follows the same two metric approaches used for the computation of the “LCML Basic Elements.” Both “Correspondence” and “Extensiveness” are considered. Two different “Properties Correspondence” tables have been generated, for biotic and abiotic LCML Elements. Similarities for biotic properties are reported in Table III.

E. Similarity Assessment Implementation

Depending on the geographical area and taxonomy used, the description of site classes can change over time. It is worth noting that the class “forest” can represent different things to different people. Thus, the possibility to define and value some additional class properties using LCML, such as cover, enable users to better describe as well as understand the type of forest (e.g., dense forest and open forest) represented by the legend creator. The class similarity assessment is implemented by comparing reference classes already available in the site class database with the ones defined by any users, as reported in the example presented in the Appendix. The different similarity assessment steps are illustrated using general LC classes, i.e., forest, grasslands, open shrubland, and savanna.

TABLE IV
SIMILARITY ASSESSMENT BETWEEN BANGLADESH AND SEEA LEGENDS FOR COX'S BAZAR DISTRICT

	lcc1: Artificial surfaces	lcc2: Herbaceous crops	lcc3: Woody crops	lcc4: Multiple or layered crops	lcc5: Grassland	lcc6: Trees covered areas	lcc7: Mangroves	lcc8: Shrub covered areas	lcc9: Herbaceous vegetation aquatic or regularly flooded	lcc10: Sparsely natural vegetated areas	lcc11: Terrestrial barren land	lcc12: Permanent snow and glaciers	lcc13: Inland water bodies	lcc14: Coastal waterbodies and intertidal areas	N/A
FP: Forest Plantations	10%	49%	60%	37%	60%	54%	18%	48%	20%	50%	37%	10%	10%	10%	
ShT: Shrubs with scattered trees	10%	35%	90%	43%	63%	43%	25%	55%	22%	50%	37%	10%	10%	10%	
RS: Rural settlement	5%	14%	16%	21%	14%	15%	24%	15%	22%	20%	17%	9%	9%	9%	N/A
PCs: Single Crop	10%	100%	30%	60%	100%	75%	15%	75%	60%	90%	68%	10%	10%	10%	
SP: Salt Pan	10%	10%	10%	6%	10%	10%	5%	10%	6%	10%	90%	10%	10%	10%	
Fmp: Mangrove Plantation	6%	12%	29%	16%	14%	29%	56%	29%	48%	44%	25%	24%	17%	17%	
Bwa: Brackish Water	8%	41%	15%	11%	24%	42%	24%	42%	30%	56%	39%	28%	33%	33%	
Acquaculture															
R: Rivers and Khals	10%	10%	10%	6%	10%	75%	50%	75%	45%	75%	75%	80%	100%	100%	
PCm: Multiple Crop	10%	100%	30%	32%	65%	45%	10%	45%	23%	50%	37%	10%	10%	10%	
FH: Hill Forest	10%	30%	90%	41%	68%	100%	45%	75%	41%	90%	68%	10%	10%	10%	

similarity scores of the most important matches (or missed ones) were analyzed. Moreover, some general considerations valid for the whole set of classes will be provided later.

A. Similarity Assessment of Basic Elements Through the Original Logic

The results of basic element analysis are reported in Table IV. It shows possible mappings between Cox's Bazar and SEEA classes obtained using the original logic proposed for similarity assessment in the FAO internal report. Before embarking in the discussion, it is worth remembering that only basic element data are exploited by the similarity assessment at this stage, meaning that additional info that might be attached to the class, like the fact that is natural or cultivated, is not exploited for differentiation here.

Forest plantations generally consist of two strata, with trees as a mandatory element and herbaceous growth forms as a second, optional, element. Observing query classes shown in the SEEA legend, it can be noted that all query classes with vegetated elements score well when matched against forest plantations. However, no score comes close to even 80%. A different class structure, different types of vegetated elements, or kind of presence type required are common "cause" for this just average similarity. "Woody crops" and "Grassland" are the best matches (although with an average score). "Tree covered

areas" is somewhat close, but a different class structure puts it at a disadvantage w.r.t. the other mentioned query classes.

The "shrub with scattered trees" (ShT) is usually an area dominated by "Shrubs" as a mandatory element. Occasionally, there are "Trees," but they are very scattered and declared as optional. The highest match is given by "Woody crops." It seems important to highlight that when considering the basic elements only, the high score is valid. It is worth noting that "Woody crops" include cultivated and managed vegetation, whereas ShT consists of by natural or seminatural vegetation. Therefore, when looking to the complete "picture," with properties and characteristics, the match could be considered wrong. However, since the judgment here is based just on the basic elements, the reported similarity value seems justifiable.

"Rural settlement" is a peculiar class with several mandatory and optional elements, both biotic and abiotic (water, buildings). It is therefore difficult to match it with SEEA classes, mostly modeled after natural resources, with direct references of buildings completely missing. In this case, however, one might suggest that "artificial surfaces" should map better, but considering the different extensiveness of the reference and query classes and the limited "likeness" between "Artificial surface" basic element and "Buildings," getting a low score appears much more reasonable.

"Single Crop" (PCs) is synonym with classes containing "herbaceous growth forms," and many query classes containing

“herbaceous growth forms” as a mandatory element seem like good candidates as “end classes,” especially if they contain a few other optional basic elements. Two SEEA classes match PCs with the highest score, namely Herbaceous Crops and Grassland. Both contain “herbaceous growth forms,” with the Grassland query class also containing an optional element (and being optional, PCs is still a valid match for the query class).

Limiting the judgment to the basic elements only, without considering the “contextual” information contained in the characteristics (not considered in this study), these matches are therefore pertinent.

“Salt Pan” (SP) is mapped with a high score on “Terrestrial Barren Land.” The latter has a more complex structure, but since most of the strata are optional, a high score is achieved by mapping the mandatory basic element “Inorganic Deposits” on “Natural Surface”.

“Mangrove plantation” (FMp) is mapped on SEEA “Mangroves” with an average score (but still the best), whereas the other query classes are consistently under 50%. In this case, the fact that FMp does not match better with SEEA Mangroves is related to its different description of basic element tuple (“Trees” and “Water Body”) instead of (“Woody Growth Forms” and “Water Body”).

“Brackish Water Aquaculture” gets the best match with “sparsely natural vegetated areas,” but with an average score. It does not get a good match with neither “inland water bodies” nor “coastal waterbodies and intertidal areas,” due to the way exclusive elements are treated in the extensiveness test.

“Rivers and Khals” is another “generic” class when considering just the basic elements. The mandatory water body is able to narrow down the classes reaching the maximum score to “inland water bodies” and “coastal waterbodies and intertidal areas” that have a different structure but still rely on different versions of the same “water body” basic element building block.

“Multiple Crop” (PCm) matches well with “Single Crop” but, rather unexpectedly, does not match well with “Multiple or layered Crops.” In this case, when looking closely to the latter, it is possible to note that both strata are set as mandatory, whereas the basic elements in PCm are four with three of them optional. It does not help either that PCm basic elements are all defined as herbaceous growth forms (with differentiations taking place in attached characteristics) while “Multiple or layered crops” use a mixture of woody growth forms and herbaceous growth forms. Therefore, although getting a stronger match on “Multiple or layered crops” is what the name might suggest (and probably recommended), the class description, the real information handled by the similarity algorithm, supports the computed similarity score.

“Hill Forest” gets a perfect score when matching with “Tree covered areas,” and the second-best match is with “Woody crops,” as expected.

Overall, the similarity assessment at the basic element level and in its original formulation performs well. A common issue is that query classes with many optional elements when matched with classes using similar basic elements but with a simpler structure are at a disadvantage. While further investigations (and probably discussions) are required on this behavior, this is a topic

that will be addressed in the next section, with the logic based on “variants.”

B. Similarity Assessment of Basic Elements Using the “Variants” Logic

As mentioned before, a second logic has been implemented for better handling complex cases with many optional or exclusive basic elements. This logic basically generates multiple permutations, where optional and exclusive elements are introduced in some of these variants. Each variant score is recorded, and the maximum one is chosen and used as the similarity assessment score. Results are shown in Table V.

The mapping provided by the variants algorithm handles better several cases. The “Forest Plantations” (FP) is reported as 100% similar to “Tree covered areas” with “Woody Crops” and “Grassland” both receiving a better score, as advisable. The variants algorithm gets this result through permutations and number crunching: one of the variants, by excluding “shrubs” and “water body” in the query class, just leaves trees (as mandatory) and herbaceous growth forms as (optional), exactly matching the basic element structure of FP.

“Shrub with scattered trees” (ShT) is matched at 100% with both Tree-covered areas and Shrub-covered areas, thanks to the “permutation game.” Note that in Phase 1, properties are not considered, and these SEEA classes look indeed very similar at the basic element level. In this case again, the variants logic seems to bring benefit to the similarity assessment.

The “Rural Settlement” (RS) case seems to show something unexpected, which is a similarity with the “Mangroves” SEEA class. However, RS contains trees, herbaceous growth forms (optional), building, and water body. These match well with growth forms and water body, as in mangroves, in the variant where the optional herbaceous growth forms are excluded. In this case, it is just the missing building that impacts the score, bringing it down.

“Single crop” (SP) shows the best score with two SEEA classes, with the real one included in this set. It also grants a 90% score to “sparsely natural vegetated areas” by “dropping” its water body basic element, since it is optional.

The algorithm performs well with “Salt Pan” (similar to the original algorithm) since “Inorganic deposits” is used in just this class and most of the others are concerned with vegetated elements.

“Mangrove Plantation” (FMp) is easily mapped on “Mangroves.” This happened with the original logic as well, but the similarity score gets a big boost by the new logic, better mimicking human judgment.

“Brackish Water aquaculture” (BWA) gets a perfect match with two query classes, both very reasonable.

“Rivers and Khals” gets a perfect match with the same classes of BWA, which are “Inland Water Bodies” and “Coastal waterbodies and intertidal areas.”

The number of potential matches for “Multiple Crop” (PCm) is reduced to two (herbaceous crops, grassland). It does not surprise that by dropping optional elements, PCm is matched with herbaceous crops, as well as the perfect score achieved

TABLE V
SIMILARITY ASSESSMENT BETWEEN COX'S BAZAAR AND SEEA LEGEND, CONSIDERING BASIC ELEMENTS ONLY USING "VARIANTS" LOGIC

	lcc1: Artificial surfaces	lcc2: Herbaceous crops	lcc3: Woody crops	lcc4: Multiple or layered crops	lcc5: Grassland	lcc6: Trees covered areas	lcc7: Mangroves	lcc8: Shrub covered areas	lcc9: Herbaceous vegetation aquatic or regularly flooded	lcc10: Sparsely natural vegetated areas	lcc11: Terrestrial barren land	lcc12: Permanent snow and glaciers	lcc13: Inland water bodies	lcc14: Coastal waterbodies and intertidal areas	N/A
FP: Forest Plantations	10%	75%	90%	57%	95%	100%	30%	80%	33%	90%	50%	10%	10%	10%	
ShT: Shrubs with scattered trees	10%	40%	90%	39%	65%	100%	30%	100%	15%	90%	50%	10%	10%	10%	
RS: Rural settlement	4%	38%	41%	75%	43%	53%	77%	46%	76%	50%	37%	32%	40%	40%	
PCs: Single Crop	10%	100%	30%	60%	100%	30%	15%	40%	60%	90%	10%	10%	10%	10%	
SP: Salt Pan	10%	10%	10%	6%	10%	10%	5%	10%	6%	10%	90%	10%	10%	10%	
FMp: Mangrove Plantation	6%	18%	53%	50%	18%	70%	95%	56%	65%	67%	39%	42%	53%	53%	
Bwa: Brackish Water Acquaculture	8%	75%	23%	25%	75%	49%	39%	53%	60%	71%	41%	80%	100%	100%	
R: Rivers and Khals	10%	10%	10%	6%	10%	10%	50%	10%	45%	10%	10%	80%	100%	100%	
PCm: Multiple Crop	10%	100%	30%	39%	100%	65%	12%	70%	33%	90%	50%	10%	10%	10%	
FH: Hill Forest	10%	30%	90%	41%	30%	100%	45%	60%	18%	90%	10%	10%	10%	10%	

with Grassland (in the variant with just an herbaceous growth forms stratum and the second optional stratum dropped). The algorithm is, therefore, operating as expected.

Last but not least, "Hill Forest" reports a good match with three SEEA classes with the best one being "Trees covered area" as a human expert would do by judging just the basic elements.

In summary, the variants logic seems to bring benefits to the similarity assessment in several cases, like Forest Plantation, Shrubs with scattered trees, and Mangrove Plantation, to name just a few. In this case, the "singularity" (the element of doubt) is provided by "Rural settlement," where a superficial human comparison with mangroves might consider the similarity as wrong, but as soon as the basic element structure is considered closely, system judgment seems much more reasonable and effective.

C. Similarity Assessment With Basic Elements and Properties (Using Variants for Basic Elements)

In this test, all basic element properties are added to the mix (by contrast, in the "basic elements only" phase, just the presence type and basic element type are considered).

Three general considerations are necessary before proceeding. First, the properties' evaluation phase examines only the "winner" of the previous phase, which considered just the basic elements. Although there is the possibility that the ranking of

scores attributed to different variants in the previous phase is changed consistently by adding properties into the mix, this chance is very slim and a choice was made to keep things "simple" in the second phase in order to avoid computational costs ballooning.

Second, including properties in the similarity assessment makes a difference only when both the reference and query classes being matched have the same kind of properties defined on both classes. For example, the cover property has a value in the reference class and at the same time is defined on the query class too. When this is not the case, the property is ignored and does not contribute in computing the degree of similarity at all.

For this reason, most of the values presented in Table V are exactly the same as in Table VI, where just the basic elements were considered. Examples of these cases are the matches for "Single Crop" and "Multiple Crop."

Last but not least, by considering properties in the computation, the similarity value can increase or decrease, since the basic element component of the similarity assessment is weighted differently, that is, the score gives 60% of importance to the basic elements part and 40% to properties evaluation.

By comparing Table V with Table VI, is evident that most of the proposed mappings are confirmed by additionally using properties. There are, however, some important situations where using properties bring benefits. This can be seen when finding the right mapping for reference classes "Forest Plantations" and

TABLE VI
SIMILARITY ASSESSMENT CONSIDERING BOTH BASIC ELEMENTS AND RELATED PROPERTIES, USING THE VARIANTS LOGIC for BASIC ELEMENTS

	lcc1: Artificial surfaces	lcc2: Herbaceous crops	lcc3: Woody crops	lcc4: Multiple or layered crops	lcc5: Grassland	lcc6: Trees covered areas	lcc7: Mangroves	lcc8: Shrub covered areas	lcc9: Herbaceous vegetation aquatic or regularly flooded	lcc10: Sparsely natural vegetated areas	lcc11: Terrestrial barren land	lcc12: Permanent snow and glaciers	lcc13: Inland water bodies	lcc14: Coastal waterbodies and intertidal areas	N/A
FP: Forest Plantations	10%	75%	90%	57%	60%	100%	55%	82%	33%	58%	30%	10%	10%	10%	
ShT: Shrubs with scattered trees	10%	40%	90%	39%	41%	81%	55%	100%	9%	58%	30%	10%	10%	10%	
RS: Rural settlement	5%	38%	41%	75%	28%	38%	52%	34%	48%	32%	22%	32%	40%	40%	N/A
PCs: Single Crop	10%	100%	30%	60%	100%	30%	15%	40%	60%	90%	10%	10%	10%	10%	
SP: Salt Pan	10%	10%	10%	6%	10%	10%	5%	10%	6%	10%	90%	10%	10%	10%	
FMp: Mangrove Plantation	6%	18%	53%	50%	11%	74%	92%	52%	39%	44%	39%	65%	72%	72%	
Bwa: Brackish Water	6%	75%	23%	25%	75%	49%	39%	53%	60%	71%	41%	80%	100%	100%	
Acquaculture R: Rivers and Khals	10%	10%	10%	6%	10%	10%	50%	10%	45%	10%	10%	80%	100%	100%	
PCm: Multiple Crop	10%	100%	30%	39%	100%	65%	12%	70%	33%	90%	50%	10%	10%	10%	
FH: Hill Forest	10%	30%	90%	41%	18%	100%	64%	68%	11%	58%	10%	10%	10%	10%	

“Shrubs with scattered trees” on query classes “Tree covered areas” and “Shrub covered areas.” These have very similar structure at the basic element level, and their differences start to emerge only when properties such as cover (and hence coverage and predominance on an area) are considered. For this reason, the score for the pair “Shrubs with scattered trees” - “Trees covered area” decreases significantly (from 100% to 81%).

Another case where properties make a difference is with “Rural settlement.” The variants logic suggested that by dropping the “building” element, the class was “reminiscent” of “Mangroves.” However, since there are additional properties information that can be matched, such as cover, by exploiting it, the “dissimilarity” between these two classes gains strength, the score decreases from 77% to 52%, and the system does not suggest a possible mapping between these classes anymore (a match with “Multiple or layered crops” is suggested instead).

The final result is that by using both basic element and property information, the suggested associations are refined and gain robustness.

V. DISCUSSION AND CONCLUSION

Assessing LC similarity using traditional map legends has always been challenging, due to the symbolic, succinct, and ambiguous nature of the symbols used by the legends. Such

legend inconsistency is a well-known issue that survived the GIS revolution of the last 30 years. Even though geospatial technological progress provides access to new images, tools, and approaches, the inconsistency of classification systems still hampers the way the world is represented and managed. Progressively, nomenclatures have been created to normalize geographic representation of our environment, such as for Africa [37], Europe [38], or at global level [39], but without addressing the issue of adequate representation of LC semantic meaning.

In [40], an expert-based assessment of the similarity between the Corine Land Cover (CLC) and National Land Cover Dataset (NLCD) nomenclatures was attempted. Expert background knowledge of the two taxonomies was considered, and expert capabilities to comprehend and take into account contextual relationships between pattern objects of LC classes influenced the results quality. The expert difficulties were mainly related to the lack of semantic class description in the taxonomies under study. Actually, CLC taxonomy provides only text class description and includes both LC and land use concepts [23].

Thus, some ambiguities emerged in class similarity assessment. As a result, the comparison became difficult and time-consuming for the different experts involved (scientists, geographers and environmentalists) and also evidenced misinterpretation of the LC class definitions. As a consequence, four days were needed to find only three one-to-one class matching and

partial similarity of one CLC class to-many NLCD classes in 17 cases. To justify omission and commission errors, the authors highlighted the intrinsic subjectivity of expert assessment.

The approach followed in this work is different because it works by exploiting the semantic richness of LCML. Actually, the publication of the LCML and the LCCS v.3 software has been a critical step to engage geographers and other users in describing the information behind class names by fostering the interoperability between different class sets. However, parts of this extensive dedication in going beyond ambiguous text would be lost without appropriate automatic (or semiautomatic) tools: the comparison burden would fall back to the user. Therefore, the availability of semantic class description has stimulated research efforts aimed to develop similarity assessment procedures, such as the one proposed in our study.

It is worth noting that LCML allows to define extremely detailed LC classes, able to capture a series of “nuances” of the represented class. Actually, LCML modular structure, as well as the use of elements and attributes characterizing the LC features, offers the opportunity to describe the LC classes of any area once and reuse them in different applications and studies.

This is impossible with other taxonomies (e.g. Corine, IGBP) mainly based on a limited number of simple class names, even though still very widespread. Their ability to respond to the need to represent low-resolution spatial information, both from the ground and from the satellite, has served well in the past. However, for today standard and requirements, they seem to sacrifice part of the class characterization that could be useful for different purposes.

In this article, the following has been proposed:

- 1) a viable way for assessing the similarity between LC classes by exploiting the intrinsic modularity of the LCML standard;
- 2) an application of the similarity assessment criteria to a study area located in Bangladesh for translating its specific LCML legend into a different taxonomy, i.e., the SEEA;
- 3) a Python implementation of the proposed methodology.

The similarity measure proposed in this article can exploit the granularity of the information embedded in an LCML class description and recombine it according to the objectives of the specific application domain of interest. LCML already offers the necessary “building blocks” that can handle information richness from multiple sources, such as satellites, drones, or ground observations.

According to an interesting review [32], semantic similarity measurements can be classified in geometric, feature, network, alignment, and transformational models.

In this context, our similarity measurement can be considered as a hybrid measurement type. When only basic elements are considered, the measurement acts mostly as a semantic network model in the similarity assessment process. The reason is that the data representation can be natively expressed in a UML language, where nodes and relationships in the form of edges among nodes are used. These relationships enable to describe generalization (and specialization), inclusion, associations, and many other links connecting basic elements with properties and

characteristics. Similarity is then based on the notion of various types of distances that work on these entities at various stages and levels, choosing the fittest one in each case.

For example, the main difference between the similarity measurement used in this work (when dealing with basic elements) and the network model described in [32] consists in the fact that our measure is based on the similarity between basic class elements, whereas their features (e.g., rock and tree features) are different, and thus no ambiguity may affect the similarity evaluation process. The traditional network models evaluate semantic similarity between classes as a whole (concept). This may introduce some ambiguities since there is no evidence on which class components are considered in the comparison process.

When properties are used, the used distance acts more like in the geometric- or feature-based model, since properties are simpler entities, most of the times numerical values. Thus, the hybrid nature of the semiautomatic similarity assessment procedure implemented can exploit the semantic content of class description and reduce ambiguities.

Future work will focus on the enhancement of the similarity assessment criteria, to deal with the characteristics that are part of the LCML standard but not yet exploited here. Both class characteristics and basic element characteristics have an important part to play in assessing the degree of similarity of classes. Class characteristics are a key part of what makes an area labeled “Hill Forest” really a hill forest object—its differentiation is given by topographical aspects, such as its altitude. In the same way, the characteristics that are attached to the basic elements of “Multiple Crop” in Cox’s Bazar legend can provide additional information that can be exploited by the similarity assessment in an even more robust manner. Additional research is required for better handling advanced LCML concepts, such as temporal sequence relationships between basic elements. These relationships may be used to evidence phenology class feature, which could be used to map LC to land use classes.

It is commendable that even in the absence of logic for handling these cases, LCML semantics richness is still able to provide so much information and meaningfulness to similarity assessment already. Moreover, the current implementation is not optimized for computational costs and might benefit of supplemental work, especially when comparing hundreds or thousands of LC classes. Nonetheless, it provides an important milestone for the development of even higher level functionalities, such as simplification or rethemization of the maps.

LC is an essential variable for global environmental monitoring in many application domains (e.g., biodiversity and ecosystems, climate change, natural hazards). The detection of both short-term and long-term changes in the LC can support the understanding of complex local and global environmental dynamics, such as those related to the conservation status of ecosystems, land degradation, planetary boundary interactions. However, when comparing LC from different dates either in the same country or different countries, existing LC classifications and legends used show a high degree of inconsistencies that significantly reduce their use in support of global environmental monitoring and natural resources management.

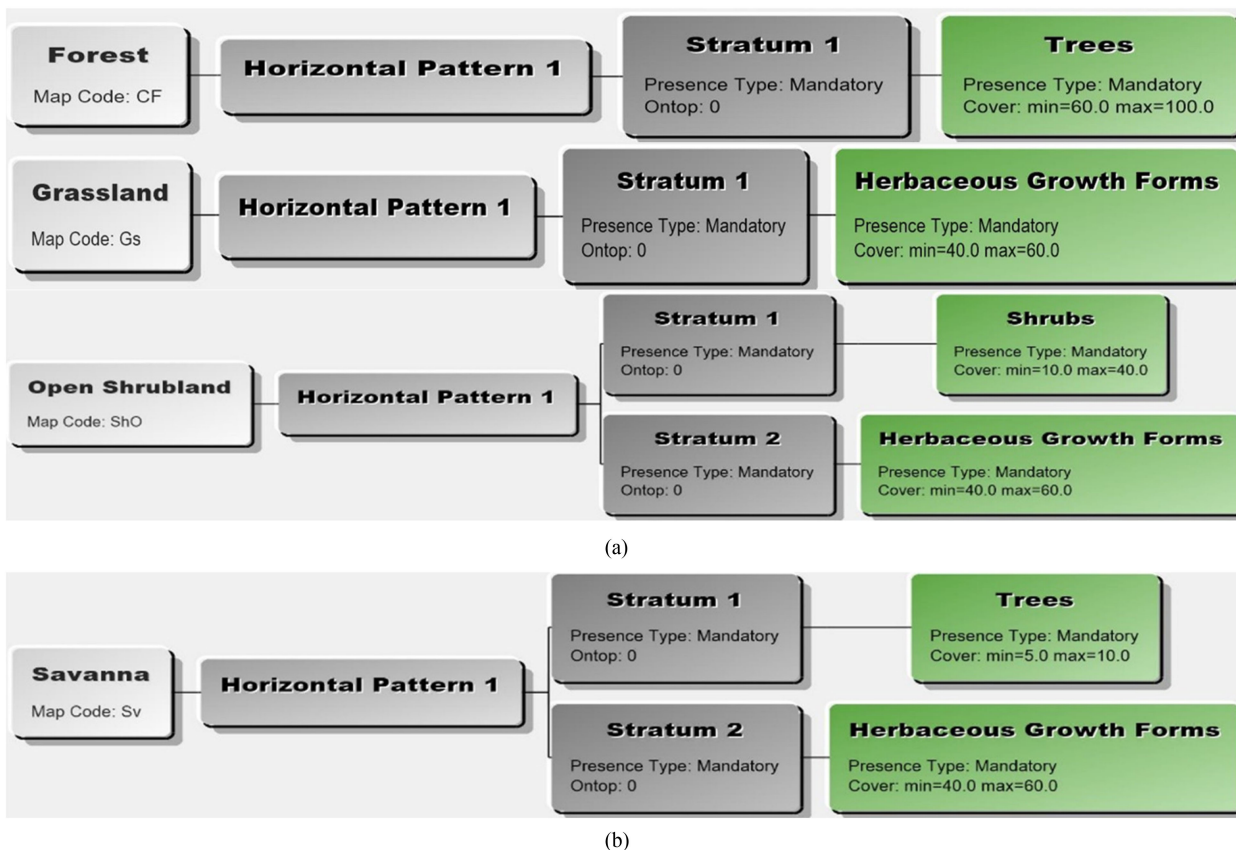


Fig. 6. Basic LCML for LC classes used for computing the similarity analysis. (a) Example of class already present in the database. (b) One or more new query classes that are defined by the operator to assess the similarity w.r.t. previously used classes.

The research work proposed in this study can support change detection and variable trend extraction since LC taxonomy harmonization is a critical step toward LC maps comparison.

APPENDIX

A. Sample Class Similarity Assessment

The example of forest class provided in Fig. 6 uses Basic LCML Element “Trees” with a property “cover” ranging 60%–100%. The grassland class has a structure similar to the forest class, but uses a different basic LCML element, “herbaceous growth forms”, with a cover ranging 40%–60%.” The open shrubland has a more complex structure, since it describes a mixed area with two elements with different properties, shrubs cover ranging 10%–40% and herbaceous growth forms cover ranging 40%–60%. The class Savanna has two strata with elements “Trees” with cover ranging 5%–10% and “Herbaceous growth forms” with cover ranging 40%–60%. The LC classes present in the database (forest, grassland and open shrubland) are then compared with the class savanna, and the results are presented in Figs. 7 and 8.

1) *Step 1 (Basic LCML Element Correspondence and Extensiveness)*: The savanna contains two basic LCML elements, “Trees” and “Herbaceous growth forms,” whereas the forest contains just “Trees.” Both classes contain “Trees,” and those two nodes of the respective class graphs match. The correspondence score between the basic LCML elements “Trees” as reported in

TABLE VII
RESULTS FROM THE SIMILARITY ASSESSMENT BETWEEN THE CLASSES

Query class	Reference classes		
	Forest	Open shrubland	Grassland
Savanna (query)	42,54%	52,33%	47,44%
The similarity assessment shows that the savanna has higher similarity with Open shrubland (similar structure and cover).			

Table I is higher (10), whereas the one between “Herbaceous growth forms” and “Trees” results in is lower (3). Looking to the extensiveness value table in Table II, the cell with reference count 1 and input count 2 reports a score of 7. Using the bivariate schema while combining correspondence and extensiveness for the basic elements provides a score of 70.

2) *Step 2 (Basic LCML Element Properties)*: The second step concerns the comparison of the Basic LCML Element properties of the common nodes identified during step 1. In the example mentioned above, input and reference classes have the common basic LCML Element “Trees” with different cover values. Because the Basic LCML Element properties match, the correspondence score is 10. However, the extensiveness score is still 7. Basic LCML element property correspondence and extensiveness scores are averaged together giving a similarity between LCML properties score of 8.5.

TABLE VIII
COX'S BAZAR LC CLASSES WITH SHORT DESCRIPTION

Code	Class	Description	Area %
BWa	Brackish Water Aquaculture	This class includes the geographic areas, which are used for year round brackish water aquaculture. This class may include the areas where it is practiced after harvesting the rice crop.	1.91
FH	Hill Forest	It consists of moist tropical evergreen, semi-evergreen and deciduous trees and generally uneven-aged. Shrubs and herbs occur fewer in number as undergrowth in this forest. The tree cover ranges from 10% - 100% and tree height ranges from 5-35 m.	2.65
FP	Forest Plantation	The geographic area where trees are planted under long-term or short-term management for production of high volume of timber and fuel wood is known as forest plantation. Trees are generally even-aged, planted and managed in rows, consist of a single species and cover a large area. Tree height is ranging from 5-45 m and its coverage is ranging from 10% - 100%. Sometimes annual agricultural crops are also incorporated with the forest plantation (Agroforestry).	3.3
FMp	Mangrove Plantation	This class includes mangrove plantations on newly accreted land in the estuaries of the Bay of Bengal to provide protection against natural calamities and land erosion.	2.22
PCm	Multiple Crop	This class includes agriculture lands which are cultivated with more than one herbaceous crop (two or three) in different growing season sequentially (crop diversified in time) within a year and the same crop rotation is practiced in the same land for several years. Some of these agricultural lands are flood free and others are flooded due to river flood or rainfall flood in monsoon period after harvesting the crops.	10.23
R	Rivers and Khals	The rivers and khals are natural water courses which are serving as water drainage channels.	16.21
RS	Rural Settlement	The rural settlement are geographic areas of clustered or linear rural dwellings which are covered by fruit trees and other plantation and functionally linked with small scale vegetables gardens, open spaces and ponds around the dwellings. Rural markets or growth centres within the rural environment are also included in this class.	15.34
SP	Salt Pans	The artificial land surfaces which are used for salt production from seawater by solar evaporation.	13.27
ShT	Shrubs with scattered trees	The shrub dominated area is natural woody vegetation of less than 5m in height and its cover exceed 10%. The uppermost canopy layer may be dominated by trees. The shrub foliage can be either evergreen or deciduous.	18.64
PCs	Single Crop	This class includes agriculture lands cultivated with a single herbaceous crop in a year and the same herbaceous crop is cultivated in the same land for several years. It includes both herbaceous rice fields and non-rice fields where only one crop is practiced in a year.	13.12
Total %			96.89

TABLE IX
SEEA 2011 SIMPLIFIED LC TYPES (ADAPTED FROM ANNEX VII OF THE UNITED NATIONS TECHNICAL NOTE)

Code	Title	Description
01	Artificial surfaces	The class is composed of any type of areas with a predominant artificial surface. Any urban or related feature is included here.
02	Herbaceous crops	The class is composed of a main layer of cultivated herbaceous plants. All the non-perennial crops that do not last for more than two growing seasons are included here.
03	Woody crops	Composed of a main layer of permanent crops (trees or shrub crops)
04	Multiple or layered crops	This may refer to two cases. On one hand, it describes two layers of different cultivated crops. On the other hand, it is used for areas where there is a dominant layer of natural vegetation that covers one layer of cultivated crops.
05	Grassland	This class includes any geographical area dominated by natural herbaceous plants with a cover of 10% or more, irrespective of different human and/or animal activities.
06	Tree covered areas	This class includes any geographical area dominated by natural tree plants with a cover of 10 per cent or more. Other types of plants (shrubs and/or herbs) can be present.
07	Mangroves	This class includes any geographical area dominated by woody vegetation that is permanently or regularly flooded by salt and/or brackish water located in the coastal areas or in the deltas of rivers.
08	Shrub covered area	This class includes any geographical area dominated by natural shrubs having a cover of 10 per cent or more. Trees can be present in scattered form if their cover is less than 10 per cent.
09	Shrubs and/or herbaceous vegetation aquatic or regularly flooded	This class includes any geographical area dominated by natural herbaceous vegetation (cover of 10 per cent or more) that is permanently or regularly (at least two months a year) flooded by fresh or brackish water.
10	Sparsely natural vegetated areas	This class includes any geographical areas where the cover of natural vegetation is between 2 per cent and 10 per cent. This includes permanently or regularly flooded areas.
11	Terrestrial barren land	This class includes any geographical area dominated by natural abiotic surfaces (bare soil, sand, rocks, etc.) where the natural vegetation is absent or almost absent.
12	Permanent snow and glaciers	This class includes any geographical area covered by snow or glaciers persistently for 10 months or more.
13	Inland water bodies	This class includes any geographical area covered for most of the year by inland water bodies. In some cases, the water can be frozen for part of the year (less than 10 months)
14	Coastal water bodies and inter-tidal areas	The class is defined on the basis of geographical features of the land in relation to the sea and abiotic surfaces subject to water persistence.



1 A Correspondence Trees vs Shrubs value (1 to 10) = 6
 1 B Correspondence Herbaceous vs Herbaceous = 10
 Averaged values 1A and 1B = 8
 2 Extensiveness query classes Basic Elements vs reference class Basic Elements 2 vs 2 = 10 Bivariate score Correspondence * Extensiveness = 8
 1A Correspondence Cover Trees vs Shrubs = 5
 1B Correspondence Cover Herbaceous vs Herbaceous = 10
 Averaged values at 1A and 1B = 7,5
 2 Extensiveness 2 vs 2 = 10
 Values at 1 and 2 are averaged - Step 2 Stage 1 score = 8,75
 Step 2 (Stage 2A) Overlap cover values Trees vs Shrubs 5-10 vs 10-40 (partial overlap) = 1,9
 Step 2 (Stage 2B) Overlap cover values Trees vs Shrubs 40-60 vs 40-60 (full overlap) = 10
 Averaged values at 2A (25%) and 2B (75%) = 7,97
 Averaged values at Step Stage 1 and 2, (1=20% and 2=80%) and multiplied each other = 10,8
 Weighted average value of step 1 stage 1 (60%) and step 2 (40%), (60% of 80)=48 and (40% of 10,8)=4,33 TOTAL SCORE = 52,33

Fig. 7. Results from the similarity analysis between savanna versus open shrubland.



1 Correspondence Trees Herbs vs Herbs value (1 to 10) = 10
 2 Extensiveness query classes Basic Elements vs reference class Basic Elements 2 vs 1 = 7
 Bivariate score Correspondence * Extensiveness = 70
 1 Correspondence Cover Herbs vs Herbs = 10
 2 Extensiveness 2 vs 1 = 7
 Values at 1 and 2 are averaged = 8,5
 Step 2 (Stage 2) Overlap cover values Herbs vs Herbs 40-60 vs 40-60 (full overlap) = 10
 Averaged values at Step Stage 1 and 2, (1=20% and 2=80%) and multiplied each other = 13,6
 Weighted average value of step 1 stage 1 (60%) and step 2 (40%), (60% of 70)=42 and (40% of 13,6)=5,44 TOTAL SCORE = 47,44

Fig. 8. Results from the similarity analysis between savanna versus grassland.

However, while both matched nodes contain a basic LCML element property “cover,” the match between the two classes is low because the range of cover do not match and the resulting score is 1.

When considering properties, the overlap score weighs more with respect to step 2 stage 1. By averaging them with a 20%/80% fashion, the overall score for the properties is 1.36.

3) Step 3: Computation of the Total Score: Final scores of steps 1 and 2 are finally combined together, in the proportion of 60% for step 1 (60% of 70) to 40% (40% of 1.36), providing a total score of 42.54 for forest, whereas the maximum similarity score is obtained for shrubland. Indeed, the similarity assessment was able to identify the structure similarity between savanna and shrubland, by harnessing the inherent similarity between tree and shrub basic elements. Results are reported in Table VII.

B. Similarity Assessment Tool: LCMLUtils

The LCML similarity assessment method described above was used for the development of a Django package “LCMLUtils,” which includes a Python library and considers Basic LCML Elements (step 1 as described later) or Basic LCML Elements and related properties (characteristics are not considered yet). In addition, the library provides basic implementation for models designed for managing LCML legends, classes, validators with

standard Django ORM architecture as well as a set of utilities for handling basic elements, properties, and characteristics.

The similarity assessment works by comparing one or more query classes (input classes) with the reference classes already stored in the system. This enables to check the similarity of new classes with respect to the ones already present in the system. The similarity module relies on an internal conversion of the XML payload in which LCML classes are usually stored in a more manageable and task-oriented representation, that is, in python-friendly JSON representation, where all data that are important for the similarity measure are transcoded.

Remaining properties are then split into two groups: scalar or range values. Similarity between scalar values is computed as reported in [31, section 3.1.3]. An extension is instead provided for ranged values. For example, while comparing a cover ranging from 20 to 30 with another ranging from 25 to 30, the standard score is equal to: $1 + (30 - 25 + 1) * 0.09 = 1.54$. On the contrary, the normalized computed score is 5, since there is a 50% overlap on the cover range. The normalized score is used by default.

Moreover, the system loads the various correspondence and extensiveness look-up tables that enables to establish the exact similarity values for the atomic basic elements and properties that compose LC class description.

Look-up tables are stored in the system as Excel sheets. These tables are stored separately, since biotic and abiotic elements

Name	Type	Attributes	Additional Info
height		max: xs:decimal, min: xs:decimal	
depth		max: xs:decimal, min: xs:decimal	
LC_WoodyGrowthLeafPhenology	LC_WoodyGrowthLeafPhenology		
LC_WoodyGrowthLeafType	LC_WoodyGrowthLeafType		
elements	list of characteristics LC_ElementCharacteristic		
sequential_temporal_relationship	dict of type and length		
presence_type	xs:string		allowed: Mandatory(Optional)Exclusive(Temporal Sequence Depending)
cover		max: xs:decimal, min: xs:decimal	

Fig. 9. Screenshot of website presenting some of the services available in LCMLUtils, such as the possibility to inspect the schema of the basic elements.

each has its own tables. However, the system, at startup, collects all individual correspondence tables and put them in a single one. A similar operation is performed for the tables supporting the computation of the extensiveness score.

1) *LC Classes, Legends, and Validators*: The LC similarity assessment analysis can be performed on classes that are coded using the LCML syntax. The LMCLUtils package provides a basic support for storing and managing LC classes and legends using LCML standard by harnessing standard Django ORM functionalities. XML payload of classes/legends is stored in text fields and subsequently handled with standard Python lxml package. Additionally, a model is provided for storing information related to validators. While LCML is an ISO standard and therefore most of the changes (like adding new basic elements) need to strictly follow ISO rules, the LCMLUtils implementation allows some degrees of flexibility to create and manage different validators, therefore enabling to experiment with the standard and eventually proposing possible evolutions (please note that while several functionalities can harness this flexibility, currently the similarity assessment relies on the current LCML standard by interpreting a subset of properties and characteristics in a fixed way).

2) *Additional LCMLUtils Functionalities*: A set of utility functions for handling basic elements, properties, and characteristics is provided in the LCMLUtils. These functions provide “introspection” in the basic elements of the LCML standard through the use of one of the validators that can be loaded into the system.

There are functions for several tasks, including list all valid basic elements, list all basic elements derived from another basic element, provide a schematic description of the properties and characteristics definable for a basic element, list the legends and classes loaded into the system and provides a graphical view of LC classes contained in a legend. An example of the provided services is reported in Fig. 9.

The library provides support for the evolution of the LCML standard, at least for incremental upgrades (like with the definition of new basic elements, new properties, and characteristics) and the development of web tools by providing a common

interface for accessing both properties and characteristics of the basic LCML elements.

A demo is available at <http://www2.lcmlutils.eu>. For further information about source code, refer to <http://www2.lcmlutils.eu/code/>.

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