Automatic post-classification land cover change detection in Landsat images: Analysis of changes in agricultural areas during the Syrian crisis

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Within the EC-FP7 project G-SEXTANT (Geospatial services in support of EU external action), a novel two-stage information processing system for automatic post-classification land cover change (LCC) detection in Landsat images is designed and implemented. It comprises a first-stage automatic near real-time pixel-based pre-classification of radiometrically calibrated Landsat images and a second-stage bi-temporal object-based post-classification comparison (PCC). The proposed two-stage PCC system is implemented for automatic detection of changes in irrigated agricultural areas during the Syrian crisis, occurring in a pair of bi-temporal Landsat-5 and Landsat-8 images of Syria, acquired in the year 2010 and 2013 spanning the Syrian crisis. Collected LCC results are successfully validated by independent domain experts. The experimental conclusion of this work is that the proposed PCC approach scores high in operating mode: it is fully automated, fast, scalable, accurate and robust to co-registration errors.

1 Introduction and problem definition

Change detection approaches are well documented in the existing literature, e.g., COPPIN ET AL. (2004), LU ET AL. (2004), SINGH (1989) or CHEN ET AL. (2012). In a comparison study of quantitative change detection algorithms, MACLEOD ET AL. (1998) state that post-classification comparison (PCC) is one of the most straightforward change-detection techniques, although it is potentially the least accurate, since the PCC output map's accuracy is never superior to the product of the input map accuracies. COLDITZ ET AL. (2012) demonstrate various influences that affect PCC detection. In addition to the aforementioned upper bound of the PCC output map's accuracy, all PCC methods require conceptual matching (harmonization) of the input pair of map legends, whereas pixel-based PCC approaches require a nearly perfect alignment (< 1 pixel) between the two bi-temporal input maps. Within the EC-FP7 project G-SEXTANT (Geospatial services in support of EU external action), a novel two-stage information processing system for automatic post-classification land cover change (LCC) detection in Landsat images is designed and implemented. It comprises a first-stage automatic near real-time multi-source resolution-independent pixel-based pre-classification of two radiometrically calibrated Landsat images and a bi-temporal image-object-based PCC second stage, focused on vegetation changes in (irrigated) agricultural land.

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Typical challenges of the popular PCC approach for LCC analysis tackled by our approach are listed below:

- Improvement of the PCC system's accuracy, whose theoretical upper bound is the product of mapping accuracies of the input map pair.
- Improvement of the PCC system's degree of automation (ease of use), monotonically decreasing with the number of the system's free-parameters to be user-defined.
- Improvement of the PCC system's robustness to changes in the input data set, to guarantee the system transferability to large-scale Earth observation (EO) data domains.
- Improvement of the PCC system's scalability to changes in the target LCC map's legend, in compliance with changes in user's requirements (e.g. definition of specific change classes)
- Generation of LCC output products, which are easy-to-interpret by non-expert users.
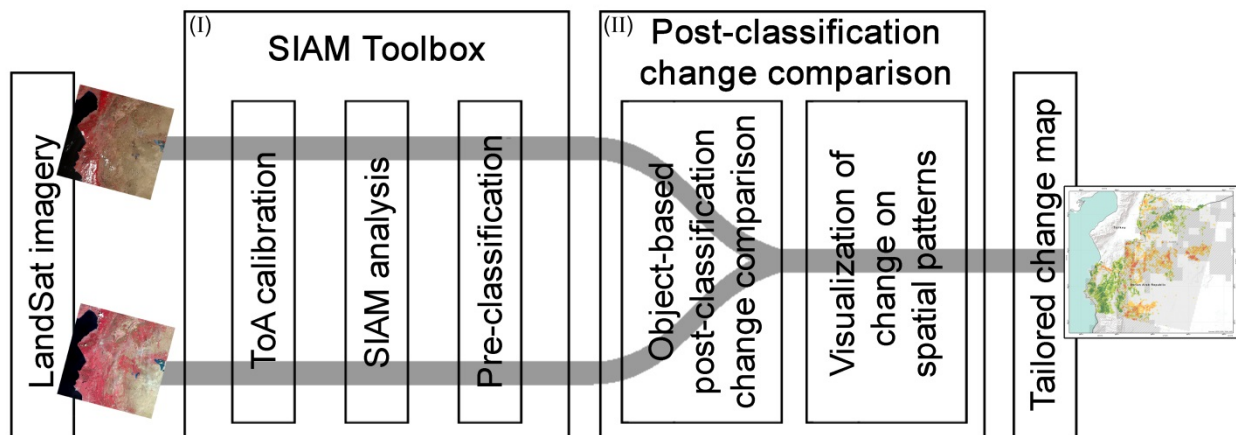- Reduction of the PCC system's sensitivity to co-registration errors in the input map pair.

Fig. 1: Overview of the proposed two-stage fully automated PCC system, consisting of a pixel-based SIAM™ preliminary classification first stage (I) in operating mode with an object-based PCC second stage (II)

2   Methodology

Figure 1 shows the novel two-stage PCC system implementation consisting of: (I) a first-stage Satellite Image Automatic Mapper™ (SIAM™) software product in operating mode (BARALDI ET AL. 2010), proposed in the existing literature as a physical model-based expert system for automatic near real-time multi-source resolution-independent preliminary classification (pre-classification) of multi-spectral (MS) images, and (II) a second-stage automatic object-based PCC system, driven (conditioned, stratified) by first-stage semi-symbolic knowledge. The sole requirement specification of the SIAM pre-classification first stage is to be input with a MS image radiometrically calibrated into top-of-atmosphere (TOA) reflectance, surface reflectance or surface albedo values. In this work, the input EO data set consists of a pair of 30 m resolution Landsat-5 and Landsat-8 images, radiometrically calibrated into TOA reflectance values. The

output LCC classes (e.g., vegetation loss/gain, deforestation, change in agricultural areas, etc.) and the LCC mapping units are selected (e.g., administrative units, regular-grid cells, etc.) in compliance with the user's requirements specification (TIEDE ET AL. 2012). Overall, the implemented two-stage PCC system is fully automatic, i.e., it requires no user's interactions, namely, neither training data selection nor input parameters to be user-defined, before mapping any new (unknown) pair of bi-temporal input images.
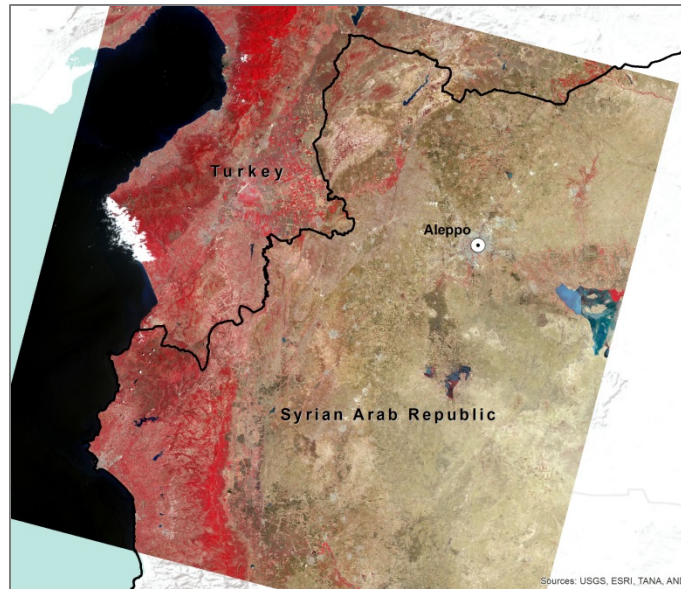

Fig. 2: Landsat-8 image (July 4, 2013), covering the north-western part of the Syrian Arab Republic, radiometrically calibrated into TOA reflectance values and depicted in false colors (R: band 5 – Near Infra-Red, G: band 3 – Visible green, B: band 2 – Visible blue). Data source: USGS, ESRI

Automatically generated from a single-date MS input image in near real-time, the SIAM™'s suite of output products comprises a set of multi-granule pre-classification maps. In the case of 7-band Landsat-like input images, up to 96 /48 /16 output spectral categories are detected by the SIAM™ at fine /intermediate /coarse semantic granularity. Noteworthy, the SIAM™ pre-classification map's legends consist of a discrete and finite set of semi-symbolic spectral categories, e.g., strong vegetation, whose degree of semantic information is always equal or inferior to that of traditional LC classes, e.g., deciduous forest. Operational qualities of the SIAM™ pre-classification expert system in operating mode, like degree of automation, mapping accuracy, computation time and robustness to changes in the input data set, are estimated as high in several application domains (cf. BARALDI ET AL. 2013, BARALDI AND BOSCHETTI, 2012).

In the present study, a SIAM™'s binary vegetation/non-vegetation output map is passed on as input to the PCC second stage for input data stratification purposes. The PCC second stage adopts a hierarchical knowledge design within an object-based image analysis (OBIA) approach, which is a well-established methodological framework for integrated image analysis (cf. BLASCHKE, 2010). This information processing framework is flexible in terms of: (I) number of LC/LCC classes to be integrated and analysed, (II) aggregation/combination of LC/LCC classes,

(III) number of time slots to be analysed in sequence and (IV) scale and form of the reporting units where the LC/LCC information primitives are spatially aggregated. In particular, bi-temporal pre-classification maps are embedded in a topologically enabled hierachy (consisting of topological relationships between objects in the vertical and horizontal directions), where they are compared and aggregated according to an LCC analysis layer (e.g., a user-defined regularly gridded layer). The PCC knowledge framework is programmed in the Cognition Network Language (CNL), available within the eCognition software environment (Trimble Geospatial).

3 Results

In the framework of the G-SEXTANT project, the proposed PCC system is implemented for automatic detection of vegetation changes in irrigated agricultural areas, depicted in a pair of bi-temporal Landsat-5 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) images, acquired in July 12, 2010 and July 4, 2013 (dry season), respectively, before and during the Syrian crisis. Figure 2 shows the test Landsat-8 OLI image covering the north-western part of the Syrian Arab Republic. In a mandatory radiometric calibration pre-processing phase, required to assure multi-source multi-temporal data harmonization and interoperability, the two Landsat images are radiometrically transformed into TOA reflectance values. Next, each Landsat image is input to the SIAM™ pre-classification first stage, whose calculation time in this case is below 5 minutes on a standard laptop computer. As an example, Figure 3 shows, on the left side, the SIAM™ pre-classification map at fine semantic granularity of the Landsat-8 image depicted in Figure 2 and, on the right side, the SIAM's binary vegetation map of the same Landsat-8 image.
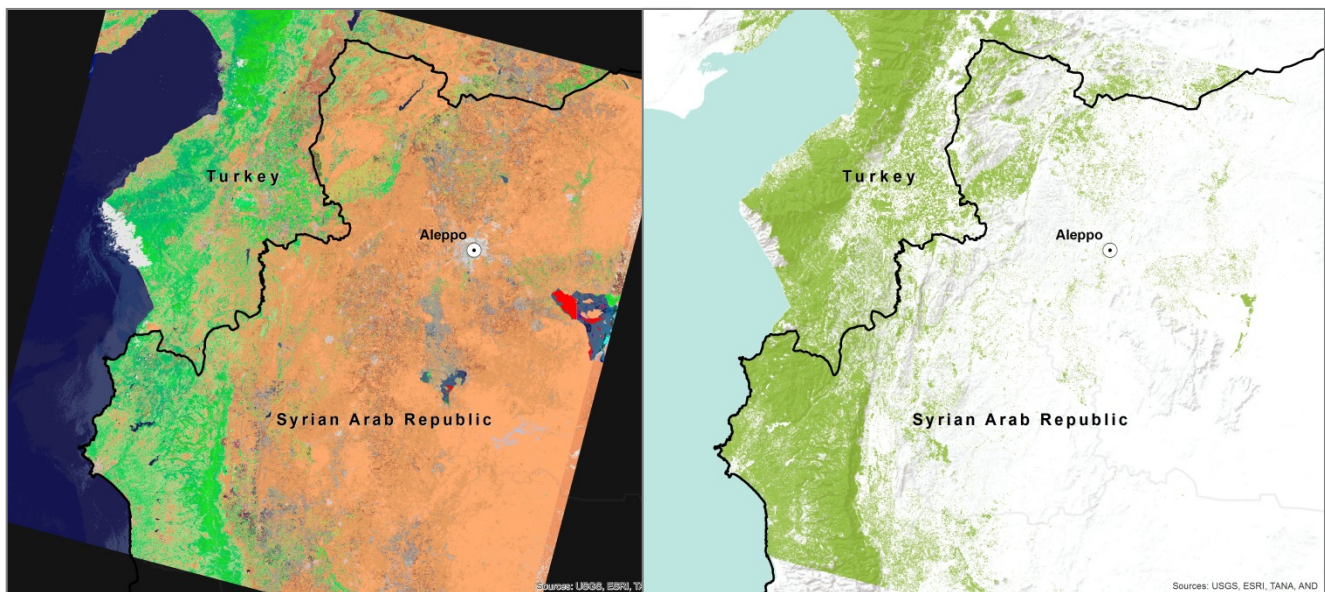

Fig. 3: Left – SIAM™'s pre-classification map at fine semantic granularity of the Landsat-8 image depicted in Figure 2. The output spectral categories are depicted in pseudo-colors: vegetation types are shown in shades of green, bare soils types in shades of brown and grey, *etc.* Right: SIAM™'s binary vegetation map of the Landsat-8 image depicted in Figure 2.

For testing and comparison purposes, image-object-based PCC detection experiments are conducted with different reporting units, e.g., hexagon tessellation or administrative units. Once the second-stage knowledge framework is designed, the user intervention is reduced to a minimum, e.g., to select reporting units, and the two-stage PCC system is fully transferable to similar surface areas, like the whole northern part of Syria, also for different time slices. Final LCC mapping results are overlaid with a FAO geospatial information layer, roughly showing the irrigated areas in the region (FAO Global Map of Irrigation Areas, DÖLL AND SIEBERT, 2000). Figure 4 shows the detected changes in vegetation, spatially aggregated according to two different reporting units, overlapped with irrigated agricultural areas.
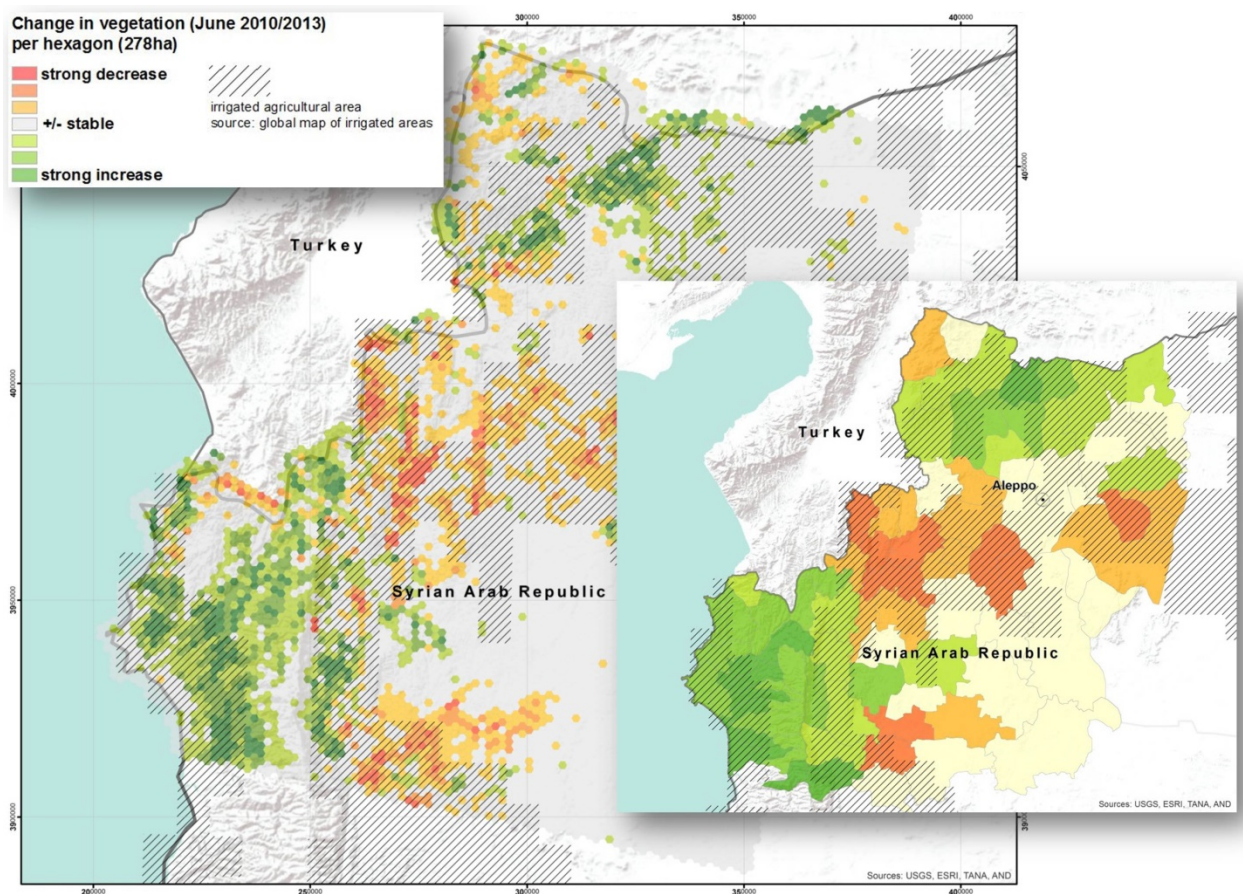

Fig. 4: Results of the automatic two-stage PCC system focused on detection of changes in irrigated agricultural areas (hatched map regions show the FAO Global Map of Irrigation Areas), aggregated into reporting units as hexagons (left) or administrative units (right).

LCC detection results are validated by independent project partners, using visual inspections of additional multi-temporal Landsat images covering a randomly selected subset of 51 hexagons, each of nearly 2.78 km² in size. This validation phase shows a high agreement of the reference information with the spatial distribution and intensity of the automatically detected vegetation changes. A detailed analysis of the discrete (quantized) layers of the vegetation change/no-change map shows that the single-date vegetation map of the 2010 Landsat-5 image is lower

quality than the vegetation map of the 2013 Landsat-8 image. This evidence can be justified with the superior radiometric quality of the latter imaging sensor.

Noteworthy, detected spatial patterns of vegetation decrease/increase across irrigated agricultural areas match with reports on the Syrian crisis. According to SNAP (2013), reasons for vegetation decrease in irrigated areas are many: besides the security issue, a lack of fuel, widespread damages to the irrigation infrastructure and a lack of essential spare parts and maintenance are severely affecting the irrigation practice.

Compared to traditional per-pixel LCC detection approaches, typically affected by a salt-and-pepper classification noise effect due to co-registration errors between the two bi-temporal input images, additional experiments with the proposed PCC system reveal its high robustness to co-registration spatial errors as large as several pixels.

4   Discussion

We present a novel automatic two-stage post-classification comparison (PCC) system in operating mode suitable for bi-temporal land cover change (LCC) detection in spaceborne multi-spectral (MS) images. A radiometric calibration pre-processing stage is considered mandatory, to guarantee multi-source multi-temporal data interoperability. The proposed PCC first stage consists of an automatic near real-time Satellite Image Automatic Mapper™ (SIAM™) software product for MS image pre-classification. The PCC second stage consists of an object-based PCC system driven by first-stage knowledge. Once the PCC knowledge framework is designed and implemented, e.g., once the target LCC classes are defined and the reporting units are selected, the proposed PCC implementation is transferable to similar EO surface areas and different satellite sensors (cf. BARALDI ET AL. 2010). Focused on vegetation changes in irrigated lands of Syria during the crisis, the implemented PCC system in operating mode proves to be fast, fully automated, scalable and accurate. It can therefore be considered as suitable for monitoring aspects e.g. within a post-conflict needs assessments. In the proposed application domain, output LCC maps are not required at the spatial resolution of the sensor; hence the aggregation of LCC information occurs in reporting units, e.g., hexagons. This spatial aggregation of LCC information shows high robustness to co-registration errors between the two bi-temporal input images.

5   Acknowledgements

6   References

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