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Detection of changes in semi-natural grasslands by cross correlation analysis with WorldView-2 images and new Landsat 8 data

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Abstract

Focusing on a Mediterranean Natura 2000 site in Italy, the effectiveness of the cross correlation analysis (CCA) technique for quantifying change in the area of semi-natural grasslands at different spatial resolutions (grain) was evaluated. In a fine scale analysis (2 m), inputs to the CCA were a) a semi-natural grasslands layer extracted from an existing validated land cover/land use (LC/LU) map (1:5000, time T1) and b) a more recent single date very high resolution (VHR) WorldView-2 image (time T2). The changes identified through the CCA were compared against those detected by applying a traditional post-classification comparison (PCC) technique to the same reference T1 map and an updated T2 map obtained by a knowledge driven classification of four multi-seasonal WorldView-2 input images. Specific changes observed were those associated with agricultural intensification and fires. The study concluded that prior knowledge (spectral class signatures, awareness of local agricultural practices and pressures) was needed for the selection of the most appropriate image (in terms of seasonality) to be acquired at T2. CCA was also applied to the comparison of the existing T1 map with recent high resolution (HR) Landsat 8 OLS images. The areas of change detected at VHR and HR were broadly similar with larger error values in HR change images.

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1. Introduction

Semi-natural and natural ecosystems are being increasingly converted to settlements and other forms of use particularly in highly developed and populated areas: forests are cleared, rivers are harnessed and wetlands and grasslands are converted into agricultural land with tremendous impacts on biodiversity and the conservation state of ecosystems and their services (Cardinale et al., 2012). In this framework, continuous and more refined mapping and monitoring actions are requested by conservation managers at multiple scales. As an example, Action 5 associated with Target 2 of the European Union (EU) Biodiversity Strategy to 2020 (European Commission, 2011) requires member states to map and assess the extension and state of ecosystems and their services regularly, as described in the reports of Maes et al. (2014). For practical purposes of mapping and assessment, such reports consider an ecosystem at the scale of habitats, which can be mapped through translation from LC/LU maps by integrating auxiliary additional information (e.g., water salinity, lithology) (Tomaselli et al., 2013; Kosmidou et al., 2014; Adamo et al., 2014).

When considering habitats, quantitative information on their areas and quality and changes in these over time is required (Hodgson, Thomas, Wintle, & Moilanen, 2009; Hodgson, Moilanen, Wintle, & Thomas, 2011; Olofsson, Foody, Stehman, & Woodcock, 2013), as this can contribute to the development, implementation and evaluation of conservation strategies and policies. Earth observation (EO) data and techniques are the most promising for monitoring such changes at multiple scales and high temporal frequencies and can provide new services for a wider user community (Nativi, Mazzetti, & Geller, 2013; Nagendra et al., 2013; Pettorelli et al., 2014), including ecologists and decision makers. However, the scale of observation depends upon the application. For regional decision making, data from moderate spatial resolution sensors such as the Landsat series or the European Space Agency’s (ESA) Sentinels (optical and radar) are most appropriate given the greater area and frequency of coverage. However, for more local decision making, finer scale data such as provided by airborne/spaceborne very high resolution (VHR) sensors (e.g., QuickBird, GeoEye, Worldview-2/3) are often preferred even though the repeat acquisition times are less frequent (Blonda, Lucas, & Ronrado, 2012; Blonda, Jongman, Stutte, & Dimopoulos, 2012; Kennedy, Andrefouet, & Cohen, 2014; Sorrano et al., 2014). In each case, estimates of uncertainty in the discrimination of habitats, mapping of areas and retrieving biophysical properties relevant to condition are needed (Foody, 2013; Olofsson et al., 2014; Nagendra et al., 2014; Turner et al., 2015).
When monitoring the state of habitats, end users are interested not only in time and place where changes occurred but also the type and magnitude of specific from-to class transitions and within class modifications over time, with these then used to identify pressures (Nagendra et al., 2014; Sorzano et al., 2014). Such transitions can be detected by the well-known post-classification comparison (PCC) of two thematic maps (e.g., LC/LU or habitats) independently produced at time $T_1$ and time $T_2$, with $T_2 > T_1$ (Bruzzone & Bovolo, 2013; Bovolo, Marchesi, & Bruzzone, 2012; Tarantino, Blonda, & Pasquiariello, 2007; Chen, Hay, Carvalho, & Wulder, 2012; Foody, 2013). The degree of success of this technique depends upon the reliability of the thematic maps made at $T_1$ and $T_2$ by image classification (Olofsson et al., 2013; Fuller, Smith, & Devereux, 2003) as the accuracy of the output change image is close to the product of the accuracies of the two maps being compared. If validated LC/LU maps are not available, a bi-temporal method based on direct comparison of a calibrated and co-registered image pair acquired at time $T_1$ and time $T_2$, is generally used (Bruzzone & Bovolo, 2013; Castellana, D’Addabbo, & Pasquiariello, 2007). As a result, the place where changes occurred can be identified but no specific transition can be described as class labels are not available.

Change detection with VHR images is generally more difficult to automate compared to when coarser spatial resolution data are used. This is due to a) the complexity of class description at fine scales and b) a less frequent availability of VHR time series data. Concerning the first issue, object-based techniques are often preferred to pixel-based approaches (Chen et al., 2012; Hall & Hay, 2003). The change detection phase is carried out by tracking objects in the two VHR maps and identifying differences in their spatial (existence, size and shape, location) and/or spectral attributes over time (Blaschke et al., 2014). This process can be computationally expensive when the entire set of thematic classes in the two $T_1$ and $T_2$ maps is considered. Chen et al. (2012) suggested applying a stratified change detection approach by considering only one target class in the landscape (e.g., grasslands) at a time. Concerning the second issue, this arises partly from the high costs of tasking VHR images, the selection of an appropriate change detection technique strongly depends on data availability. Often a pre-existent LC/LU map may be available at regional/local scales, with this frequently obtained by visual inspection of orthophotos and validated by in-field campaigns. Such a map can be used as a reference at time $T_1$ in change detection processes. To detect changes at $T_2$, both a PCC and a cross-correlation analysis (CCA), as proposed by (Koeln & Bissonnette, 2000), can be used. The advantage of CCA is that changes for the target class can be identified without the need for a complete classification process at time $T_2$ (see Section 3.1). CCA applications to high resolution (HR) (e.g., Landsat TM) and medium resolution (MR) imagery (e.g., MERIS) are reported in Koeln and Bissonnette (2000) and Civco, Hurst, Wilson, Song, and Zhang (2002) with very promising results. The CCA technique is also attractive for fine scale change detection, as it offers the possibility to reduce the costs of change detection when: a) the acquisition of several (multi-seasonal) VHR images at time $T_2$ (e.g., within year), which benefits habitat discrimination, is too expensive, and b) no archival VHR data are available at $T_1$ for direct image comparison with a new image tasked at $T_2$ with $T_1 < T_2$.

Focusing on semi-natural grasslands in a protected Natura 2000 site in southern Italy, the objectives of this research were: a) to apply the CCA technique for detecting change in semi-natural grasslands at both VHR (Worldview-2) and HR (Landsat 8 OLS) resolutions (i.e., different grains) and b) compare the changes with those detected using the more traditional PCC technique.

When dealing with LC/LU maps, this paper adopts the Food and Agricultural Organization (FAO) Land Cover Classification System (LCCS) taxonomy (Di Gregorio & Jansen, 2005), which was found to be the most useful for subsequent translation of LC/LU classes to habitats categories in Tomasselli et al. (2013) and Adamo et al. (2014). The results are based on the images tasked and the techniques developed within the FP7 BIO_SOS (www.biosos.eu) project, funded by the European Union to develop a pre-operational service for long-term monitoring of biodiversity in Natura 2000 sites.

2. Study site and input data

2.1. Study site

The study area, of almost 500 km$^2$, is located in southern Italy (Puglia Region) within the Natura 2000 “Murgia Alta” site (SCI/SPA IT912007, based on the European Union Habitat Directive 92/43/ECC and Bird Directive 147/2009/EC (Fig. 1(a))). It consists of a calcareous upland where semi-natural dry grasslands cover almost 24% of the total site, and represents one of the most important areas for the conservation of this type of ecosystem in Europe. Agricultural intensification, urbanization, fires and land abandonment together provide the main pressures on biodiversity (Mairota et al., 2013).

These grassland ecosystems are mainly important for a) their ability to store carbon and the amount stored can be affected by changes in fire frequency, grazing intensity and land use and b) maintaining hydrological and nutrient cycling services both for terrestrial and aquatic ecosystems (Grassland Ecosystems, 2013; Nagendra et al., 2014). Consequently, the class transitions of major interest for the management authorities of the study site are from semi-natural grasslands to: i) croplands, ii) burned areas or iii) artificial structures.

2.2. Input data

For $T_1$, (2006), an existing LC/LU map (1:5000) based on visual orthophoto interpretation and validated (with 85% overall accuracy) by in-field campaigns, was available for the site and used as reference. The map was originally produced in CORINE and translated subsequently by the authors into the FAO-LCCS taxonomy (Tomasselli et al., 2013). For $T_2$, both VHR Worldview-2 (WW-2) and HR Landsat OLS data were obtained. The WW-2 data were acquired in April–May 2011 (as a mosaic), October 2011, January 2012 and July 2012 (Fig. 1(b)), with these considered necessary to differentiate habitats on the basis of differences in phenology and/or agricultural practices. An updated $T_2$ LC/LU map was obtained by a knowledge-driven classification of these four WW-2 images (Lucas et al., 2014; Adamo et al., 2015). The images were provided at no cost by the European Space Agency (ESA) under the Data Warehouse 2011–2014 policy during the FP7 BIO_SOS project. The two recent Landsat 8 OLS images (Irons, Dwyer, & Barsi, 2012) were acquired in August and October 2013, and were obtained from the US Geological Survey (http://earthexplorer.usgs.gov/). All images were orthorectified, coregistered and calibrated to top of atmosphere (TOA) reflectance values.

3. Methodology and experimental settings

3.1. The post-classification comparison analysis

PCC requires the comparison of classifications that have been constructed independently using, for example, supervised algorithms. This approach minimizes the problem of normalizing for atmospheric and sensor differences between two dates. The accuracy of the change map is close to the product of the accuracies of the two classified maps to be compared and, consequently, is smaller than each of them (Bruzzone & Bovolo, 2013).

3.2. The cross correlation analysis

CCA is a change detection method developed by the American company Earthsat, Inc. and evaluates the differences between an existing LC/LU map ($T_1$) and a recent single-date multispectral image ($T_2$) (Koeln & Bissonnette, 2000; Civco et al., 2002). All pixels of the $T_2$
image belonging to a specific thematic layer (target class) extracted from the T1 map are analysed to determine the expected reference class metrics in T2 (i.e., class average spectral response and standard deviation). Then, for each pixel in the layer, a statistical measure is computed to evaluate the distance between its spectral signature and the reference class metrics at T2. Large values of such measures evidence the occurrence of large likelihood class changes. This information is used to derive a Z-statistic for each pixel of the recent image falling within a target LC/LU class. The Z-statistic describes how close the pixel’s response is to the expected spectral response of the target class. Changed pixels will produce large Z-statistic values while pixels that have not changed will produce small Z-statistic values, as described by Eq. (1):

$$Z_{jk} = \sqrt{\sum_{i=1}^{n} \left( \frac{r_{jk} \cdot \mu_{icjk}}{\sigma_{icjk}} \right)^2}$$

where,
- $Z_{jk}$ is the Z-score for a pixel $jk$ belonging of a given class (stratum) $i$
- $i$ is the band number in the multispectral image
- $n$ is the number of bands
- $c_{jk}$ is the thematic class (stratum) being considered at T2, $jk$ is a pixel in the stratum
- $r_{jk}$ is the reflectance in band $i$ for pixel $jk$
- $\mu_{icjk}$ is the mean reflectance value in band $i$ of all pixels in a given class $c_{jk}$
- $\sigma_{icjk}$ is the standard deviation of the reflectance value in band $i$ of all pixels in class $c_{jk}$

Larger values in the output CCA Z-statistic image correspond to pixels characterized in T2 by a spectral signature very different from the target class’ average value. The selection of a threshold (TH) can thus help to identify most significant changes (Koeln & Bissonnette, 2000). Once changes are located, information about the specific class transitions can be obtained by local in-field campaigns or visual inspection of multi-temporal VHR imagery.

### 3.3. Experimental setting

Focusing on the FAO-LCCS class A12/A2.A6.E5 (natural terrestrial vegetated/herbaceous.graminoid.mixed (i.e., perennial and annual), different experiments (Table 1, Fig. 2) were carried out which compared the PCC and CCA techniques based on the comparison of the 2006 LCCS map, as the baseline (T1), and the updated LC/LU map or the VHR WV-2 and HR Landsat OLS data as the change layers at T2.

For all the experiments, the semi-natural grasslands layer patches in the LC/LU map at T1 was overlain on the LC/LU map or WV-2/Landsat8 image used at T2 (Table 1).

### Table 1

| Experiment | Description | Input data at T1 = 2006 | Input data at T2 |
|------------|-------------|--------------------------|------------------|
| 1          | Post-classification comparison at VHR (PCC_VHR) | Preexisting land cover/land use map used to extract the target class of interest | Land cover/land use map at VHR obtained from 4 multi-seasonal WV-2 images (LC/LU_VHR) |
| 2.1        | Cross-correlation analysis at VHR (CCA_VHR) | WV-2: October 5, 2011 | WV-2: October 5, 2011 |
| 2.2        | Cross-correlation analysis at VHR (CCA_VHR) | WV-2: July 6, 2012 | WV-2: July 6, 2012 |
| 3.1        | Cross-correlation analysis at HR (CCA_HR) | LandSat 8 OLS: October 10, 2013 | LandSat 8 OLS: October 10, 2013 |
| 3.2        | Cross-correlation analysis at HR (CCA_HR) | LandSat 8 OLS: August 7, 2013 | LandSat 8 OLS: August 7, 2013 |

Fig. 1. “Murgia Alta” Natura 2000 site. (a) Location of the study site and extension of “Murgia Alta” National Park in red line. Analyzed area in blue line. (b) Available Worldview-2 input image (17,000 × 7000 pixels wide), 2 m resolution, 6 July 2012. False colour composite: R = 5, G = 7, B = 2. The burned fields are visible in the middle lower part of the scene.
4. Results

Due to the complexity of VHR image analysis, the quantitative results obtained by the PCC_VHR, CCA_VHR and CCA_HR experiments are reported for only two image windows named AREA_1 (about 800 ha) and AREA_2 (about 400 ha) (Fig. 3).

4.1. Accuracy and uncertainty

For the two transitions in AREA_1 and AREA_2, a set of reference polygons was selected through visual inspection of the available multi-seasonal WV-2 images. Stratified random sampling was applied. When the sampling intensities differ for the map classes, correct calculation of overall accuracy (OA) requires that the within-class accuracies be weighted by the proportions of the study area represented by the map classes. Consequently, OA cannot be calculated as the sum of diagonal counts divided by the total count, as in the case of simple random sampling or systematic sampling design (Congalton & Kass, 2009). For this reason, for each experiment, the change error matrix was produced in terms of sample counts. For a more accurate quantification of change overall accuracy the protocol described in Olofsson et al. (2013, 2014) was adopted, with this based on a more informative presentation of the change error matrix with the advantage that change accuracy and area estimates can be computed directly from it.

When map categories are the rows ($i$) and the reference categories are the columns ($j$), $A_{\text{tot}}$ represents the total area of the map (window), $A_m$ is the mapped area (ha) of category $i$ in the map and $W_i = A_m / A_{\text{tot}}$ is the proportion of the mapped area as category $i$. $\hat{p}_{ij}$ is then:

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_j}$$

The unbiased stratified estimator of the area of category $j$ is obtained as:

$$A_j = A_{\text{tot}} \times \hat{p}_j = A_{\text{tot}} \sum_i W_i \frac{n_{ij}}{n_i}$$

where $\hat{A}_j$ can be viewed as an "error-adjusted" estimator of area because it includes the area of map omission error of category $j$ and leaves out the area of map commission error.

The estimated standard error of the estimated proportion of area is:

$$S(\hat{p}_j) = \sqrt{\frac{\sum_i W_i^2}{n_j} \left( \frac{1 - n_j}{n_j} \right)}$$

Finally, the standard error of the stratified area estimate can be expressed as:

$$S(\hat{A}_j) = A_{\text{tot}} \times S(\hat{p}_j)$$

and an approximate 95% confidence interval for $A_j$ is:

$$\hat{A}_j \pm 2 \times S(\hat{A}_j)$$

4.2. AREA_1: from semi-natural grasslands to croplands transition

For AREA_1, the input and output images for all the experiments are shown in Fig. 4.

4.3. Accuracy and uncertainty

For AREA_2, the sampling intensities differ for the map classes, and the change error matrix was produced in terms of sample counts. For a more accurate quantification of change overall accuracy the protocol described in Olofsson et al. (2013, 2014) was adopted, with this based on a more informative presentation of the change error matrix with the advantage that change accuracy and area estimates can be computed directly from it.

When map categories are the rows ($i$) and the reference categories are the columns ($j$), $A_{\text{tot}}$ represents the total area of the map (window), $A_m$ is the mapped area (ha) of category $i$ in the map and $W_i = A_m / A_{\text{tot}}$ is the proportion of the mapped area as category $i$. $\hat{p}_{ij}$ is then:

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_j}$$

The unbiased stratified estimator of the area of category $j$ is obtained as:

$$A_j = A_{\text{tot}} \times \hat{p}_j = A_{\text{tot}} \sum_i W_i \frac{n_{ij}}{n_i}$$

where $\hat{A}_j$ can be viewed as an "error-adjusted" estimator of area because it includes the area of map omission error of category $j$ and leaves out the area of map commission error.

The estimated standard error of the estimated proportion of area is:

$$S(\hat{p}_j) = \sqrt{\frac{\sum_i W_i^2}{n_j} \left( \frac{1 - n_j}{n_j} \right)}$$

Finally, the standard error of the stratified area estimate can be expressed as:

$$S(\hat{A}_j) = A_{\text{tot}} \times S(\hat{p}_j)$$

and an approximate 95% confidence interval for $A_j$ is:

$$\hat{A}_j \pm 2 \times S(\hat{A}_j)$$

Fig. 3. Change map obtained by CCA_VHR applied to WV-2 image of 6 July 2012. No threshold is applied to Z-statistic image. The two green rectangles correspond to areas affected by class-transition: from semi-natural grasslands to croplands (in Area_1) and burned fields (in Area_2).
4.2.1. Experiment 1. Post-classification comparison at VHR

The results of the PCC_VHR quantitative analysis are reported in Tables 2 and 3. More specifically, Table 2 contains the information useful for quantitative change evaluation in support to stratified estimation. When the stratified estimator is adopted (Table 3), as it takes into account the sampling design used for accuracy assessment, the stratified change area estimate (Table 3) is larger (186.05 ha rather than 159.83 ha) than the change area value obtained solely from the map (Table 2), and should be considered when accounting for the omission error of changes. The PCC results in Table 3 are used as reference in the comparison with all CCA experiments, reported in Table 4.

4.2.2. Experiment 2. Cross correlation analysis at VHR

The CCA_VHR analysis used the October and July WV-2 images separately as the T2, with these compared to T1, the existing 2006 LCCS map (according to Experiments 2.1 and 2.2, Table 1). The October image was selected as croplands (wheat) fields were ploughed in this month and exhibited a spectral signature that differed from the more productive (green) semi-natural grasslands. Based on the output Z-statistic image histogram, three different threshold values were empirically selected (i.e., 5.0, 10.0 and 20.0, respectively) by considering that changes are mainly located far in the tails of the Z-statistic. According to the protocol of Olofsson et al. (2013); Pettorelli et al. (2014), the largest overall accuracy (percentage) was obtained when a TH of 5.0 was used (Table 4).

Using the July image, a TH of 25 provided both quantitatively and qualitatively more accurate results compared to when the October image was used and these were more comparable with the results obtained using PCC.

Table 2
AREA_1: Error matrix as sample counts ($n_{ij}$) of the change map, $A_{mi}$ is the mapped area (ha) of category $i$ and $W_i$ is the proportion of the mapped area as category $i$.

| PCC_VHR | Reference categories |
|---------|----------------------|
|         | Change | No change | Total | $A_{mi}$ (ha) | $W_i$ |
| Map categories |       |       |       |              |      |
| Change   | 51,915 | 307    | 52,222| 159.83       | 0.211|
| No change| 4,510  | 94,554 | 99,064| 596.46       | 0.789|
| Total    | 56,425 | 94,861 | 151,286| 756.39       | 1.000|

Table 3
AREA_1: Estimated error matrix obtained from previous Table 2 with cell entries expressed as the estimated proportion ($p_{ij}$) of area in cell $ij$. Accuracy measures are presented with a 95% confidence interval.

| PCC_VHR | Reference categories |
|---------|----------------------|
|         | Change | No change | Total | User's acc. % | Producer's acc. % | Overall acc. % | Stratified changed area estimate with 95% conf. interv. (ha) |
| Map categories |       |       |       |              |                    |                |                                          |
| Change   | 0.210  | 0.001  | 0.211 | 99.41 ± 0.03  | 85.40 ± 0.10       | 96.29 ± 0.05   | 186.05 ± 0.78   |
| No change| 0.044  | 0.753  | 0.797 | 95.45 ± 0.07  | 99.84 ± 0.02       |                |                                          |
| Total    | 0.254  | 0.754  | 1.000 |                |                    |                |                                          |

Fig. 4. (a) LC/LU used as T1 input map in all the experiments. (b) LC/LU_VHR used as T2 input map and (c) output change map of the PCC_VHR experiment. (d) WV-2 July image, in R = 5, G = 7, B = 2 composite, used as T2 input image and (e) output change map at TH = 25.0 of CCA_VHR. (f) Landsat 8 OLI August image, in R = 4, G = 5, B = 2 composite, used as T2 input image and (g) output change map at TH = 2.0 of CCA_HR. Focus area is highlighted in red polygon.
Table 4
Change detection matrix for AREA_1: semi-natural grasslands to croplands transition. Results obtained from CCA_VHR and CCA_HR techniques. Producer’s and overall accuracies are based on stratified estimation. TH refers to the threshold value applied to the Z-statistic image. Am is the mapped changed area.

| Method   | TH  | Change user’s acc. % | Change producer’s acc. % | No change user’s acc. % | No change producer’s acc. % | Overall acc. % | Am (ha) | Stratified changed area estimate with 95% conf. interv. (ha) |
|----------|-----|-----------------------|--------------------------|-------------------------|----------------------------|----------------|---------|---------------------------------------------------------------|
| CCA_VHR  | 5.0 | 79.22 ± 0.18          | 61.01 ± 0.14             | 84.01 ± 0.12            | 92.75 ± 0.09              | 82.86 ± 0.10   | 181.45  | 235.62 ± 1.48                                                  |
|          | 10.0| 95.14 ± 0.12          | 40.48 ± 0.01             | 77.16 ± 0.12            | 98.98 ± 0.03              | 79.69 ± 0.11   | 106.10  | 249.36 ± 1.59                                                  |
|          | 20.0| 96.65 ± 0.20          | 12.18 ± 0.05             | 65.93 ± 0.13            | 99.75 ± 0.01              | 67.36 ± 0.12   | 35.24   | 279.64 ± 1.81                                                  |
|          |     |                       |                          |                         |                            |                |         |                                                               |
|          | 10.0| 82.32 ± 0.15          | 86.87 ± 0.10             | 95.19 ± 0.07            | 93.31 ± 0.10              | 91.61 ± 0.07   | 210.59  | 199.57 ± 1.01                                                  |
|          | 25.0| 91.40 ± 0.12          | 83.16 ± 0.10             | 94.86 ± 0.07            | 97.56 ± 0.07              | 94.13 ± 0.06   | 163.60  | 179.81 ± 0.93                                                  |
|          | 50.0| 98.46 ± 0.06          | 61.78 ± 0.12             | 88.31 ± 0.10            | 99.67 ± 0.02              | 89.95 ± 0.08   | 121.70  | 193.96 ± 1.25                                                  |
|          |     |                       |                          |                         |                            |                |         |                                                               |
|          | 10.0| 58.01 ± 2.72          | 56.30 ± 2.12             | 81.72 ± 2.01            | 82.74 ± 1.92              | 74.87 ± 1.63   | 217.89  | 224.49 ± 24.57                                                 |
|          | 2.0 | 75.98 ± 3.00          | 45.20 ± 2.12             | 78.96 ± 1.83            | 93.50 ± 1.15              | 78.40 ± 1.59   | 140.31  | 235.86 ± 24.00                                                 |
|          | 5.0 | 73.08 ± 4.37          | 16.17 ± 1.68             | 69.28 ± 1.89            | 96.94 ± 0.63              | 69.57 ± 1.78   | 56.61   | 255.76 ± 26.79                                                 |
|          |     |                       |                          |                         |                            |                |         |                                                               |
|          | 1.0 | 52.67 ± 2.36          | 78.31 ± 1.37             | 90.91 ± 1.81            | 75.50 ± 2.39              | 76.23 ± 1.44   | 289.71  | 194.84 ± 21.68                                                 |
|          | 2.0 | 76.90 ± 2.48          | 77.95 ± 1.79             | 91.04 ± 1.41            | 90.54 ± 1.56              | 86.91 ± 1.23   | 220.14  | 217.16 ± 18.58                                                 |
|          | 5.0 | 75.78 ± 3.80          | 24.49 ± 1.83             | 71.65 ± 1.88            | 96.06 ± 0.75              | 72.10 ± 1.73   | 81.63   | 252.62 ± 26.07                                                 |

**Fig. 5.** (a) LC/LU used as T1 in all the experiments. (b) LC/LU_VHR map used as T2 input to PCC_VHR. (c) Output change map from PCC_VHR. (d) WV-2 October 2011 image, as R = 5, G = 7, B = 2 composite, used as T2 input image to CCA_VHR. (e) Output change map for TH = 10.0 from CCA_VHR. (f) Landsat 8 OLI August 2013 image, as R = 4, G = 5, B = 2 composite, used as T2 input image to CCA_HR. (g) Output change map from CCA_HR at TH = 2.0. Focus area is highlighted in red polygon.
4.3.2. Experiment 2. Cross correlation analysis at VHR

The overall accuracy values obtained one year after the fire from the Landsat 8 OLS August 2013 image are smaller (76%) than the ones from both CCA_VHR (96.5%) and PCC_VHR (89.8%) with quite large errors in the stratified changed area estimate (Table 7).

4.3.3. Experiment 3. Cross correlation analysis at HR

The overall accuracy values of PCC_HR (96.45%) larger than the one from PCC_VHR (89.76%). The changed area estimate was smaller than the mapped area. This is probably because the change producer’s accuracy from the stratified estimator remains quite large and change user’s accuracy was not so large indicating the change area is inaccurate (Table 7).

5. Conclusions

By comparing a reference LC/LU map produced at time T1 and single date VHR recent T2 image, change detection can be carried out with the CCA technique, with this reducing overall costs (e.g., associated with image tasking). The change map overall accuracy is comparable with the one from PCC technique in large changed areas and even better in small changed areas. For accuracy and uncertainty evaluation, stratified estimation (Olofsson et al., 2013, 2014) was applied to obtain an estimate of the changed area.

When the reference map at T1 is compared by CCA to coarser images, i.e. new Landsat 8 OLS images acquired in August and October 2013 for the same area and so same seasons of VHR images (July and October),
the stratified changed area estimate is similar to the one produced by PCC_VHR but with larger errors and reduced overall accuracy. The selection of the VHR or HR image seasonality at T2 requires prior knowledge of the class transitions occurred in the area and class phenology. In “Murgia Alta” site, the summer image appears more effective than autumn image for the detection of the transitions considered (i.e., from grasslands to croplands and burned fields). One pitfall of the methodology is that the label of class at T2 should be validated by in-field campaigns or visual interpretation of the VHR image, due to the lack of semantic labels in the T2 image. However the in-field visit is reduced to only limited areas.

Based on such findings, fine scale monitoring of protected area and ecosystems can be carried out at reduced costs with the proposed methodology. However, the cost component related to the regular acquisition of VHR imagery is still unsustainable for use by public bodies and decision makers. As clearly evidenced in [Blonda et al. (2013)] and in [Turner et al. (2015)], agreements between space agency and national authorities should be encouraged to reduce such costs for a widespread EO data application to ecosystems monitoring.

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