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A graph-based approach to detect spatiotemporal dynamics in satellite image time series

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Abstract

Enhancing the frequency of satellite acquisitions represents a key issue for Earth Observation community nowadays. Repeated observations are crucial for monitoring purposes, particularly when intra-annual process should be taken into account. Time series of images constitute a valuable source of information in these cases. The goal of this paper is to propose a new methodological framework to automatically detect and extract spatiotemporal information from satellite image time series (SITS). Existing methods dealing with such kind of data are usually classification-oriented and cannot provide information about evolutions and temporal behaviors. In this paper we propose a graph-based strategy that combines object-based image analysis (OBIA) with data mining techniques. Image objects computed at each individual timestamp are connected across the time series and generates a set of evolution graphs. Each evolution graph is associated to a particular area within the study site and stores information about its temporal evolution. Such information can be deeply explored at the evolution graph scale or used to compare the graphs and supply a general picture at the study site scale. We validated our framework on two study sites located in the South of France and involving different types of natural, semi-natural and agricultural areas. The results obtained from a Landsat SITS support the quality of the methodological approach and illustrate how the framework can be employed to extract and characterize spatiotemporal dynamics.

Keywords: Satellite Image Time Series, Monitoring, OBIA, Data Mining, Graph-based techniques, Land-cover.

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1. Introduction

Nowadays, satellite image time series (SITS) is a powerful source of information for monitoring purposes. Repeated satellite observations allow to follow the evolution (e.g. growing season, land-cover modifications) of a given area over the time in a systematic way. When repeatability and homogeneity of satellite observations are guaranteed it becomes possible to detect spatiotemporal evolutions and deduce their related dynamics (Bonn, 1996). However, the interpretation and the cross-comparison of several satellite images quickly become challenging.

Advanced methods used to process multitemporal optical imagery are related to trajectory analysis. In this context, high-temporal frequency SITS from coarse to moderate sensors, such as MODIS, are used to model temporal signatures and detect anomalies or trends (Lunetta et al., 2006; Verbesselt et al., 2010; Cai and Liu, 2015). Although powerful, these methods are hardly adaptable in finer spatial scales applications where the number of images available is lower and the temporal sampling is irregular. However, several local scale applications need high frequency of observations at intra-annual basis. Mapping and monitoring natural and agricultural areas with an enhanced revisit capacity allows monitoring phenology states, agricultural practices and seasonal processes. Recent reviews about conservation monitoring (Nagendra et al., 2013) and Natura 2000 habitat monitoring (Vanden Borre et al., 2011) pointed out remote sensing as a strong, but still underexploited, tool.

In the literature, methods used to process multitemporal optical imagery are commonly grouped under the change detection label. In a pioneer review article, Singh (1989) defined change detection as the process of identifying differences in the state of an object or phenomenon by observing it at different times. The author also categorised the main change detection techniques in ten different groups. A critical review about change detection methods in ecosystem monitoring was provided by Coppin et al. (2004). More recently, Hussain et al. (2013) expanded the change detection categories previously proposed by Singh (1989), including object-based change detection (OBCD) techniques. Regarding this last point, the works of Chen et al. (2012) and Blaschke (2005) provided a deep overview of the available OBCD methods.

Considering SITS of optical imagery, we can highlight twomain limitations in the current literature. Firstly, most of the existing methods focus their efforts on bi-temporal change detection situations, i.e. the study of temporal evolutions taking place between two dates. Usually, these methods include post-classification comparison (Yuan et al., 2005), image differencing (Lu et al., 2005), composite analysis (B. Descle, 2006), linear transformation (Qin et al., 2013) and change vector analysis (Malila, 1980). Secondly, the majority of works explored mainly pixel-based strategies (Petitjean et al., 2012; Inglada et al., 2015) whereas object-based image analysis (OBIA) are still among open challenges in remote sensing analysis (Blaschke et al., 2014; Chen et al., 2012).

Petitjean et al. (2012) constructed vector images from SITS and used classical unsupervised classification (k-means) at pixel level. The originality of the approach consisted in the integration of spatial relationships between pixels. Each pixel was enriched by some

54 contextual attributes coming from individual image segmentations performed at each times-
55 tamp. In this case, the temporal behavior (based on 15 FORMOSAT-2 images acquired in
56 the same year) was used to assign a unique land cover label (mainly crops) to each pixel.
57 These labels, derived from ground reference data, are static (e.g. corn) and do not describe
58 dynamics (e.g. bare soil -> growth of corn -> harvest); therefore it is not possible to per-
59 form further analysis, or monitoring, related to the intra-annual evolutions. Inglada et al.
60 (2015) evaluated the performance of state-of-the-art supervised classification methods for
61 generating accurate crop type maps on 12 sites spread all over the world. The classification
62 strategy giving the best results combined pixel-based temporal linear interpolation and fea-
63 ture extraction (radiometry derived features only). In this case, SITS were composed of a
64 variable number of SPOT-4 and Landsat-8 images (from 9 to 41 images depending on the
65 site) acquired in the same year. In general, important amounts of ground reference data
66 (from several dozens to a few thousands of hectares) were necessary for training the classifier
67 and achieving accurate results. Also here, the process chain generates a single outcome (i.e.
68 a map) representing static land cover classes. This flat representation, alone, is not able to
69 describe the evolutions and the temporal behaviors behind each class label.

70 Differently from previous approaches that mainly focus on the classification and/or de-
71 tection of abrupt changes between consecutive images, this paper aims to describe a new
72 methodology to explore SITS data detecting and describing spatiotemporal entities/phenomena
73 existing in the study area. More in detail, given a time series of remote sensing images and
74 an associated segmentation, our objectives are to: (i) detect the set of spatiotemporal enti-
75 ties/phenomena existing in the study area and (ii) supply a spatiotemporal description for
76 each of them. To this end, we propose an hybrid methodology combining OBIA and data
77 mining techniques. Our proposal firstly identifies a set of spatial entities covering as much
78 as possible the whole study site and, subsequently, for each of those spatial entities, it builds
79 an evolution graph to describe its temporal evolution.

80 We applied our approach on two study sites involving different types of natural, semi-
81 natural and agricultural areas. Since the task we address is completely exploratory and
82 different from most of the previous researches on SITS data (e.g. change detection, classifi-
83 cation), to verify and assess the quality of our proposal we performed in-depth qualitative
84 evaluations on the set of evolution graphs we extracted. More in detail, we showed how the
85 evolutions graphs well summarize the temporal profiles of the extracted spatiotemporal phe-
86 nomena and how they can be employed to synthesize the evolutions and temporal behaviors
87 extracted from a SITS.

88 The rest of the paper is organized as follows: Section 2 describes all the methodological
89 steps of the proposed approach. Section 3 presents the study case context, namely the time
90 series data, the preprocessing steps and the verification strategies. Experimental results are
91 presented and discussed in Section 4. Conclusions are drawn in Section 5.

92 **2. Methodology**

93 *2.1. Object-based temporal evolutions*

94 The type of phenomena we want to capture are spatiotemporal evolutions (and their
 95 related dynamics) describing how an entity (i.e. a lake, a saltmarsh area, a crop field,
 96 etc..) evolves along the time. To this purpose, within a given study site, the first goal
 97 of our approach is to automatically detect a set of spatiotemporal entities. Subsequently,
 98 a high-level description is constructed for each of those entities employing a graph-based
 99 representation. The general framework of our methodology is summarized in Figure 1.

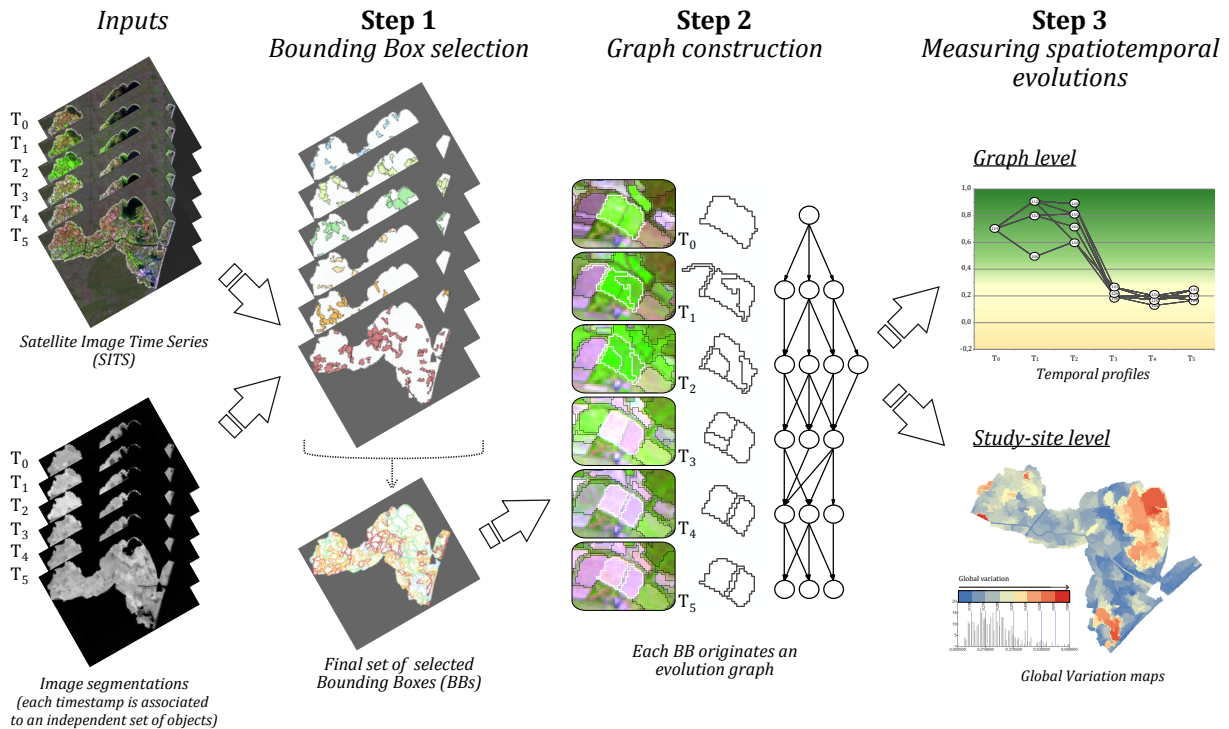


Figure 1: General framework showing the main steps of the methodology.

100 Given a SITS data and its associated segmentation, firstly we select a set of objects
 101 that represent the spatial entities we want to monitor during the time. We call such subset
 102 of objects Bounding Boxes (*BBs*). The set of *BBs* can contain objects coming from any
 103 timestamp. The term spatial entities is used in this paper to designate a part (any portion)
 104 of a given study site. Then, for each Bounding Box (*BB*), we create an evolution graph con-
 105 sidering all the objects, in all the timestamps, that are covered by the *BB* area. Each vertex
 106 of a graph corresponds to an object. Two vertices are linked by an edge if they belong to
 107 two successive timestamps and the corresponding objects overlap each other. The procedure
 108 is applied to each *BB* and the result consists in a set of evolution graphs summarizing the
 109 different spatiotemporal phenomena existing in the study site. The set of evolution graphs
 110 is successively exploited, with the object related information (e.g. spectral, geometrical, tex-
 111 tural, etc.) in order to supply analysis at graph and study-site levels. The first level allows

112 namely the analysis of the temporal trajectories (or profiles) of a particular spatiotempo-
 113 ral phenomenon while the second level supplies a more general picture summarizing the
 114 temporal dynamics detected over the entire study site.

115 2.2. Bounding Box selection

116 The first step of our process consists in the selection of coherent *BBs* (i.e. spatial entities)
 117 to monitor along the different timestamps. This operation analyzes all the objects provided
 118 by the input segmentations (all the timestamps) and selects a subset of different spatial
 119 entities covering as much as possible the whole study site. To deal with this task we made
 120 some assumptions that are justified from the nature of the SITS data we manage.

121 The first assumption we made is related to the fact that each selected *BB* has, during
 122 the period considered by the SITS, a maximal extent (or footprint) from a spatial point
 123 of view. For instance, if we consider a temporary lake, in the time series we will have a
 124 timestamp in which it reaches its maximal spatial extent while for the other timestamps
 125 the same area may be segmented in different objects as water will cover a less important
 126 area. In our approach we attempt to select maximal footprints as *BBs*. To select the set
 127 of *BBs*, we adopted the following strategy: first we select a subset of the objects respecting
 128 the assumption on the maximal footprint, we named such set of objects *candidateBB*. Then,
 129 from *candidateBB* we filtered out a subset of objects that cover as much as possible the
 130 study site and that overlay as less as possible between each other from a spatial point of
 131 view.

132 Since all the images span over the same grid of pixels, we can retrieve for each pixel of
 133 each timestamp the object it belongs to and therefore select the largest one. The process
 134 is repeated over the whole study site and the selected objects are added to *candidateBB*.
 135 This pre-selection explicitly implements the maximal footprints assumption over the whole
 136 study site. However, this process may retain objects representing very similar geographical
 137 areas. To deal with this redundancy issue we designed an algorithm that, starting from
 138 *candidateBB*, selects a set of objects to minimize as much as possible the degree of overlay.
 139 More in detail, the algorithm iterates over the set of *candidateBB* until no more objects
 140 can be included in the final set of *BBs*. At the beginning, the set of *BBs* is initialized to
 141 the empty set. A data structure containing the grid pixels covered during the process is
 142 initialized with the empty set. We call this structure *PAC* (Pixel Already Covered). At
 143 each iteration, the more promising object is selected from the *candidateBB* and added to
 144 the final set of *BBs*. The more promising object is determined considering the following
 145 piecewise function (1):

$$weight(O) = \begin{cases} size(O) & \text{if } novelty(O) = 1 \\ novelty(O) & \text{if } \alpha \leq novelty(O) < 1 \\ 0 & \text{if } novelty(O) < \alpha \end{cases} \quad (1)$$

146 where:

- 147 • $size(O)$ is the size of the object, in this case the number of pixels

- 148 • $novelty(O)$ is the contribution of the object w.r.t. the current partial solution
- 149 • α is a threshold parameter defining the minimum value of novelty an object must show
- 150 to be added to the final set of BBs
- 151 1.

152 More in detail, the novelty numerically describes the contribution of each object (belonging
 153 to $candidateBB$) w.r.t. the partial solution achieved by the procedure. The novelty is defined
 154 as follows (2):

$$novelty(O) = \frac{|size(O) - PAC(O)|}{size(O)} \quad (2)$$

155 where:

- 156 • $size(O)$ = the number of pixels of the object
- 157 • $PAC(O)$ = the number of pixels already covered by the current partial solution for a
- 158 given object

159 In summary, the weight assigned to each $candidateBB$ object is dynamically recomputed
 160 during the procedure. This is done because we update the PAC variable whenever an object
 161 is added to the final set of BBs . According to the $weight(O)$ function, first we will select all
 162 the bigger and non-overlapping objects from $candidateBB$ as their novelty value is equal to
 163 1. Then, we will start to select the objects presenting the higher novelty values in order to fill
 164 the remaining uncovered areas of the study site. The process stops when all the remaining
 165 $candidateBB$ objects present novelty values lower than the parameter α or all the grid pixels
 166 of the study site are covered. The value of α is inversely proportional to the number of BBs
 167 in the final set. High values of α will lead the selection of a small set of BBs , while small
 168 values of α will allow the procedure to extract a bigger set of BBs . Another point we can
 169 stress on is that the BBs extracted with a big value of α (e.g. 0.5) will be a subset of the
 170 BBs extracted with a small value of α (e.g. 0.3). This is due to the fact that the proposed
 171 procedure is deterministic and has a monotonic behavior. Decreasing the value of α will
 172 relax the spatial overlay constraint going further in the selection process.

173 2.3. Graph construction

174 The final set of BBs defines the spatial entities (and their related phenomena) we will
 175 monitor throughout the SITS. Logically, each BB has a unique spatial extent (footprint)
 176 which is used to select and link the objects from one timestamp to the next one. Given
 177 a BB , we project its footprint over each timestamp of the time series and we select the
 178 objects overlapping with BB . In order to avoid the selection of non-representative objects
 179 (or parasite objects) w.r.t. the area we monitor, we established two parameters that can
 180 be translated to the following restrictive conditions: (a) at least τ_1 of the object should be
 181 inside of the BB footprint, (b) the object should represent at least τ_2 of the BB footprint
 182 where both τ_1 and τ_2 are two percentages. The first parameter (τ_1) is the most important

183 and control the selection of objects that should present most of their spatial extent outside
184 the *BB* footprint. The second parameter (τ_2) is used to keep all the objects filling more
185 than a certain percentage of the *BB* footprint, irrespective of any other statement.

186 After this selection, each *BB* will be associated to a set of objects which can be organized
187 and stored as an evolution graph. The graph is built linking the objects of timestamp i with
188 the objects of timestamp $i + 1$. Each object corresponds to a vertex of a graph and the
189 weight of the link (edge) represents the degree of overlap between two objects. In this way
190 we obtain graphs that have as many layers as the number of images in the time series.
191 Another intrinsic characteristic of an evolution graph is that, for a certain layer, it will
192 contain only one object (corresponding to the *BB*). Logically, objects belonging to the same
193 timestamp are not connected; this is also true for objects not belonging to two successive
194 timestamps. In other words, the graphs created by our procedure are oriented graphs, more
195 precisely temporal oriented graphs. An oriented graph is the same thing as a loopless simple
196 directed graphs (West, 2001), also called Directed Acyclic Graphs (DAGs) (Maurer, 2003).

197 2.4. Computing graph coverages

198 Each evolution graph is associated to an unique *BB* and can be represented by several
199 spatial coverages (see Figure 2). The simplest way is to use the spatial extent of the former
200 *BB* to represent the graph (e.g. in a map). We named this representation the *Bound-*
201 *ing Box Graph Coverage (BBCov)*. In order to get a *Whole Graph Coverage (WholeCov)*
202 we calculated the total spatial extent of all the objects contained in the graph at all the
203 timestamps. The *WholeCov* can be decomposed in two components, the *Ephemeral Graph*
204 *Coverage (EphemCov)* which groups the area(s) covered only once during the time series
205 and the *Core Graph Coverage (CoreCov)* which indicates the area(s) covered at least twice
206 during the time series. Such surfaces (*EphemCov* and *CoreCov*) can be expressed as per-
207 centages of the *WholeCov*. High percentages of *EphemCov* indicate unstable boundaries of
208 the graph objects and can be related to transitory evolutions in the study area. However,
209 sometimes this behavior can be produced by unsuitable segmentation results, e.g. under seg-
210 mentation. In such a case the input segmentation can influence the extraction of interesting
211 evolution graphs. This means that the *EphemCov* value can be employed as an indicator
212 to estimate the quality of the time series segmentation and suggest, if necessary, to provide
213 a better input segmentation that will impact positively the graph coverage results. How to
214 optimize and produce coherent individual segmentations from a SITS is out of the scope of
215 this work since, these two elements (SITS and segmentations) are the inputs of the proposed
216 methodology. *CoreCov* usually encompasses the whole surface of the *BBCov* as well as a
217 buffer area around it. A big discrepancy between *CoreCov* and *BBCov* usually indicates
218 that the *BB* does not provide a good spatial representation of the whole graph.

219 In the example showed in Figure 2, the *BB* used to create the evolution graph comes
220 from the first timestamp (T_0) and its coverage (*BBCov*) is highlighted in orange color.
221 It represents two agricultural parcels covered by the same type of crop. In the following
222 timestamps, the number of objects ranged from 3 to 4 and the evolution graph totaled
223 17 objects. The union of all these objects corresponds to the *WholeCov* which is showed
224 in black. We can notice an elongation in the upper left part of the *WholeCov* polygon if

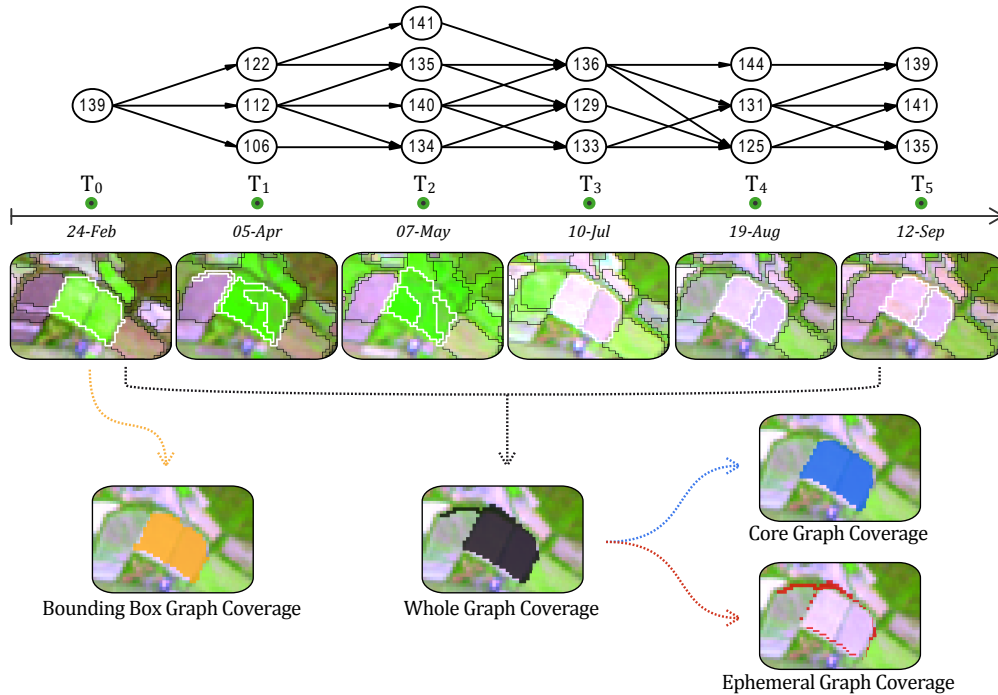


Figure 2: Example of an evolution graph extracted from a crop area. Graph nodes and edges are shown in the upper part, while the object boundaries (at each timestamp) are displayed below the timeline. The four types of spatial coverages computed for this evolution graph can be visualized in the bottom part of the figure.

225 compared to *BBCov*. The elongation does not correspond to the agricultural parcels targeted
 226 by the *BB* but to a parasite object coming from T_1 . This undesirable inclusion is clearly
 227 visible in the *EphemCov* (red color) which highlights also other small border sections around
 228 the agricultural parcels. In this example, the *CoreCov* (blue color) is very similar to the
 229 *BBCov* as the borders of the targeted parcels remained substantially stable during the time
 230 series.

231 2.5. Measuring spatiotemporal evolutions at Graph and Study-site levels

232 In order to analyze and understand the information behind the evolution graphs, we
 233 defined two levels of analysis: (a) the graph level and (b) the study-site level. In the former,
 234 the focus is mainly on how the objects of the graph are linked (graph structure) and how
 235 their attributes (content) evolve in time. In the latter, the focus is related to the whole
 236 study site and especially on how the most stable and the most dynamic spatial entities are
 237 distributed.

238 Considering the graph level analysis, given a graph G , we indicate with G_i the set of
 239 objects covered by G at the timestamp i and with $w_{j,k}$ the weight of the link between object
 240 o_j and object o_k . We compute the Variation (*Var*) between two consecutive timestamps
 241 with the following formula (3):

$$Var(G_i, G_{i+1}) = \sum_{o_j \in G_i} \frac{size(o_j)}{size(G_i)} \cdot \frac{\sum_{o_k \in G_{i+1}} w_{j,k} \cdot dist(o_j, o_k)}{\sum_k w_{j,k}} \quad (3)$$

242 The first part of the *Var* formula is proportional to the importance of the object o_j over
 243 the set of objects at timestamp i . Therefore, $size(o_j)$ corresponds to the number of pixels of
 244 o_j while $size(G_i)$ represents the total number of pixels covered by the graph G at timestamp
 245 i . The second part of the formula evaluates the evolution between an object at timestamp i
 246 w.r.t. the objects at timestamp $i + 1$ linked to it. In particular, the variation between two
 247 timestamps is measured by a weighted sum of the euclidean distances between the attributes
 248 of the object o_j and o_k . The weight $w_{j,k}$ quantifies the strength of the interaction between
 249 o_j and o_k in terms of spatial overlay.

250 The Global Variation (*GlobalVar*) for a graph is obtained cumulating the contribution
 251 of each pair of consecutive timestamps as follows (4):

$$GlobalVar(G) = \sum_{i=1}^{n-1} Var(G_i, G_{i+1}) \quad (4)$$

252 The *GlobalVar* associated to an evolution graph estimates how much the area represented
 253 by this graph evolves during the period covered by the time series. Potentially, this score can
 254 vary between 0 and $+\infty$. A low value of *GlobalVar* implies stable temporal behavior while a
 255 high value indicates important temporal evolution throughout the time series.

256 Another option to perform graph-level analysis is by means of *Temporal Profiles* where
 257 the temporal variation of any object attribute can be plotted for all the nodes of a given
 258 graph. *Temporal Profiles* allow a more fine analysis of the graphs, facilitating the visualiza-
 259 tion and interpretation of temporal behaviors related to the graphs' underlying spatiotemporal
 260 phenomena. More in detail, given a graph G and an attribute we want to monitor (e.g. the
 261 NDVI), we can build a plot where the X-axis (resp. the Y-axis) represents the time (resp.
 262 the attribute to study, i.e. NDVI). Such plot will contain the objects of the graph temporally
 263 arranged from the first to the last timestamp. Such a representation combines the graph
 264 structure and the content (i.e. the attribute chosen to perform the analysis), allowing to
 265 follow the evolution of these elements conjointly all over the SITS. Examples of *Temporal*
 266 *Profiles* are reported in the experimental results (see Figure 8).

267 Considering the study-site level analysis, the *GlobalVar* scores (computed for each evo-
 268 lution graph) can be used to produce a *GlobalVar map*. In this kind of representation, any of
 269 the computed graph coverages (e.g. *CoreCov*) can be used to construct the map. According
 270 to the selected coverage, the polygons representing the graphs will be colored following a
 271 gradient proportional to their *GlobalVar* scores. The *GlobalVar map* summarizes the distri-
 272 bution of the different phenomena detected within the study site and provides information
 273 related to the intensity of the evolutions during the time. This kind of map, computed
 274 automatically and considering the whole SITS, is an useful tool for exploratory researches
 275 over areas where the spatiotemporal dynamics are unknown (or few studied). *GlobalVar*
 276 *maps* can also provide valuable information for planning field-campaigns and prioritizing
 277 the visits over such unknown or few studied areas. In the case of similar temporal sampling,

278 *GlobalVar maps* may be used to compared the spatiotemporal dynamics of two (or more)
279 different study sites.

280 While the *Temporal Profiles* are more suitable for analyzing one particular object at-
281 tribute at time, *GlobalVar* scores (and maps) can be also obtained considering all the
282 attributes or a subset of them (e.g. only a few spectral indices or a given combination of
283 spectral bands).

284 It is important to highlight that the *GlobalVar* score is more suitable for short-term
285 landscape analysis (e.g. intra-annual scale) and less appropriate for long-term landscape
286 evolution monitoring (e.g. multi-annual scale) since different temporal trajectories can col-
287 lapse to the same score value. Conversely, the information supplied by *Temporal Profiles* can
288 be adopted to study both short-term or long-term landscape evolutions since it preserves
289 the full temporal trajectories associated to an evolution graph.

290 2.6. Parameter Setting

291 As previously noticed, our methodology needs the setting of three different parameters:
292 α , τ_1 and τ_2 . The first parameter limits the overlay among the selected *BBs* while the re-
293 maining two parameters avoid the selection of non-representative objects in the construction
294 of the evolution graphs.

295 With the aim to facilitate the choice of these parameter values, we propose to consider
296 the coverage and the redundancy of the extracted evolution graphs. The coverage of the
297 evolution graphs is the union of the *WholeCov* of each of the graphs in the solution. This
298 measure quantifies how much of the study site is covered by the selected graphs. Concerning
299 the redundancy in the set of extracted graphs, we evaluate this quantity as the portion of
300 the study site that is covered, at least, by two different graphs. This quantity measures how
301 much redundancy exists in the obtained solution.

302 In order to determine the three initial parameters (and the corresponding set of evolution
303 graphs), we firstly generate different solutions varying the α , τ_1 and τ_2 parameters and then,
304 we fix a threshold (σ) that defines the minimum accepted coverage. The σ threshold is
305 expressed as a percentage of the whole study area. Once the threshold σ is fixed, we obtain
306 a set of solutions that meets this constraint. Among such set of solutions, we choose the one
307 with the minimum redundancy value. We remind that this analysis can be performed in a
308 completely unsupervised way, independently from a possible ground truth data associated
309 to the SITS.

310 3. Case study

311 3.1. Data and Study sites

312 3.1.1. Time series data

313 We used Landsat-5 TM and Landsat-7 ETM+ level-2A products available through the
314 THEIA Data Centre (France). Such images were already ortho-rectified and corrected from
315 atmospheric, environmental and slope effects as described by Hagolle et al. (2010). Each
316 Landsat product was composed by six spectral bands (approximate center in nm): blue (485),
317 green (565), red (665), NIR (820), SWIR-1 (1650) and SWIR-2 (2190). With a pixel size of

318 30 m, the raster data is expressed in surface reflectance. We selected six Landsat cloud-free
 319 images covering two study sites (described latter) between February and September 2009
 320 (see Table 1).

Timestamp	Acquisition date
T_0	24 Feb. 2009
T_1	05 April 2009
T_2	07 May 2009
T_3	10 July 2009
T_4	19 Aug. 2009
T_5	12 Sept. 2009

Table 1: Acquisition date of the selected Landsat images over the South of France.

321 The selected time series spreads from the end of the winter up to the end of the summer.
 322 Such temporal range encompasses the entire growing season for natural vegetation as well
 323 as the main agricultural cycles over the study sites.

324 3.1.2. Study sites description

325 Two sites were selected in the south of France, close to the Mediterranean Sea. Figure
 326 3 presents the spatial boundaries of the two sites: (A) Libron Valley and (B) Lower Aude
 327 Valley Natura 2000 site. Both sites are located inside the extent of the Landsat scenes
 328 composing our time series. Figure 4 shows the study areas at each timestamp.

329 Located less than 10 km northeast from the city of *Béziers* (France), the *Libron Valley*
 330 site is mainly composed by agricultural parcels and natural areas. The site has about
 331 1 655 ha and is crossed by the small coastal river named *Libron*. Agricultural parcels are
 332 concentrated principally along the *Libron* waterway. Cereal crops dominate its upstream
 333 section (northwest of the site) while the downstream section is mainly occupied by vineyards
 334 (southeast of the site). The natural areas are essentially composed by patches of forest
 335 (mainly coniferous) and scrubland. Most of these patches are in the north of the *Libron*
 336 River, some of them encircle a golf field situated in the northern part of the site. In a
 337 general way, the limits between agricultural and natural areas over this site can be easily
 338 recognized in the Landsat images. Such a task is possible because agricultural parcels and
 339 forest patches are usually bigger than 6-8 ha (i.e. 200 m x 400 m or wider for most of the
 340 crop fields).

341 The *Lower Aude Valley* is a Natura 2000 site located in the terminal section of the *Aude*
 342 River. Before reaching the Mediterranean Sea, the *Aude* River crosses a flat wetland area of
 343 about 4 842 ha. From a biodiversity point of view, 56.3% of the site is composed of natural
 344 habitat types of Community interest (NHCI). In total, 19 NHCI are part of the site, including
 345 5 priority habitat types. The most widespread habitats are: Mediterranean saltmarshes and
 346 Saline coastal lagoons. The remaining area (43.7%) is principally occupied by vineyards,
 347 cereal crops and temporary or permanent meadows. In opposition to the *Libron* site, the
 348 agricultural parcels are often small within this site (usually around 1-2 ha) and therefore
 349 more difficult to identify using Landsat images. Another particularity, the site is exposed to

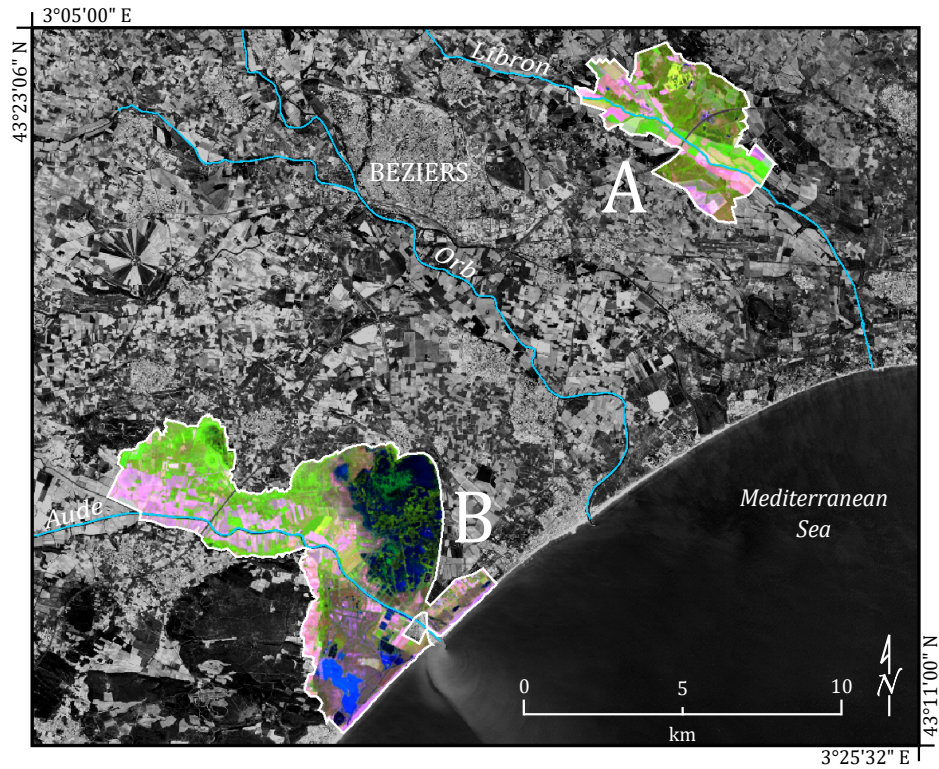


Figure 3: Location and boundaries of the selected study sites (A Libron Valley ; B Lower Aude Valley Natura 2000 site).

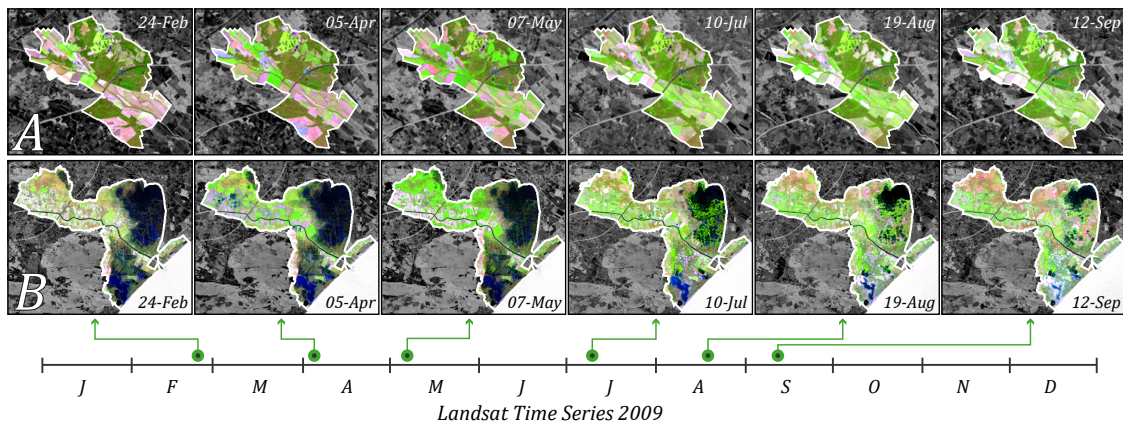


Figure 4: Time series for the selected study sites (A Libron Valley ; B Lower Aude Valley Natura 2000 site) during 2009.

350 flooding events (mostly during winter) as well as to drought episodes (maximum intensity
 351 occurring in the end of the summer). The flooding areas are situated predominantly around
 352 the two coastal lagoons: *Vendres* in the north part of the site and *Pisse-Vaches* in the south.
 353 The Mediterranean Sea has also an influence over the salinity across the site (soils and water
 354 bodies), with a general gradient increasing from northwest to southeast.

355 *3.2. Preprocessing and segmentation*

356 *3.2.1. Spatial subset and fine geometrical registration*

357 Although level 2-A products were already ortho-rectified, we observed some spatial im-
358 precision when overlapping all the time series images. For this reason, additional fine spatial
359 positioning corrections were necessary in order to keep the spatial shift between any times-
360 tamp less than a pixel. Afterwards, two spatial subsets (one for each study area) were
361 performed over each Landsat image.

362 *3.2.2. Spectral indices*

363 Spectral indices are commonly used in remote sensing as they can be helpful for detect-
364 ing and characterizing some specific features, like vegetation, soil, water, etc. In this work
365 we calculated three spectral indices compatible with Landsat data using the formula pro-
366 vided by the literature: a) Normalized Difference Vegetation Index NDVI (Rouse Jr et al.,
367 1974); b) Normalized Difference Water Index NDWI (Gao, 1996); c) Visible and Shortwave
368 Infrared Drought Index VSDI (Zhang et al., 2013). NDVI is sensitive to the amount of
369 photosynthetically active vegetation present in the plant canopy (Tucker, 1979) and has
370 been extensively used in remote sensing applications since the 1970s. NDWI is sensitive to
371 changes in liquid water content of vegetation canopies (Gao, 1996) and has been used to
372 estimate vegetation water content (Jackson et al., 2004). VSDI is sensitive to changes in
373 soil and vegetation moisture and was conceived to monitor drought over different types of
374 land cover during plant-growing season (Zhang et al., 2013).

375 *3.2.3. Time series image segmentation*

376 Image segmentation is a fundamental step in OBIA and it consists in merging pixels into
377 object clusters (Baatz et al., 2008). Objects (or segments) are regions generated by one or
378 more criteria of homogeneity in one or more dimensions of a feature space (Blaschke, 2010).
379 The principal aim of segmentation is to create a new representation of the image, more
380 meaningful and easier to analyze. This approach is similar to human visual interpretation
381 of digital images, which works at multiple scales and uses color, shape, size, texture, pattern
382 and context information (Lillesand et al., 2008). Image segmentation results in a set of
383 objects that collectively cover the entire image without any overlapping. With respect to
384 the homogeneity criteria, adjacent objects are expected to be significantly different between
385 them.

386 In this work, image segmentation was performed with the Multiresolution Segmenta-
387 tion Algorithm (MSA)¹. We choose the MSA algorithm instead of recent approaches based
388 on superpixel Achanta et al. (2012) since the objective of our strategy is to capture phe-
389 nomena that can lie at different scales. Adopting a superpixel segmentation method, like
390 SLIC (Achanta et al., 2012), will produce segments at equal scale and this will be in con-
391 trast with the main assumption of our work (maximal spatial extent detection). Conversely,
392 the MSA scale parameter is intrinsically related to the homogeneity criterion which takes

¹MSA algorithm: as implemented in *eCognition Developer* software, version 8.8.1

393 into account both shape and radiometry of objects in a combined manner. For this reason,
 394 over two areas of the same size, MSA may provide multiple small objects if the target is
 395 heterogeneous or, a single larger object if the target is more uniform.

396 Only the pixels within the boundaries of the study sites were used during the segmen-
 397 tations. Nine raster layers were simultaneously used for image segmentation. Six of them
 398 correspond to the Landsat spectral bands and the other three to the spectral indices. In
 399 order to obtain objects representing the natural and agricultural boundaries over the study
 400 sites, we conceived a segmentation rule-set composed of 3 main steps as showed in Figure
 401 5. For simplification purposes only the *Lower Aude Valley* site is presented in this figure
 402 as well as in the subsequent explanations. However, the same rule-set was applied over the
 403 *Libron Valley* site.

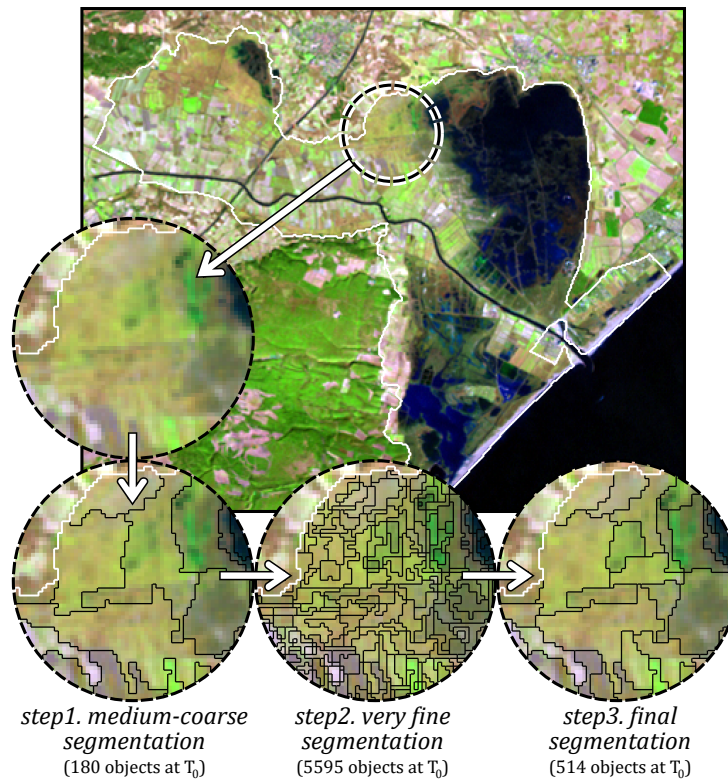


Figure 5: Segmentation rule-set outputs (at T_0) for the Lower Aude Valley Natura 2000 site.

404 The first step delimits the general zones through a medium-coarse segmentation. MSA
 405 was configured here to combine both color and shape components but using predominantly
 406 color (0.8). About 170-200 objects are obtained per timestamp over the *Lower Aude Valley*
 407 site. In the second step, a very fine segmentation is performed inside the object boundaries
 408 created at step 1. Focused exclusively on the color component, it creates about 6 000 objects
 409 per timestamp. In step 3, medium-fine segmentation is performed taking into account the
 410 results of the previous steps. With balanced weights for color and shape components, step 3
 411 segmentation creates about 500-600 objects per timestamp. The segmentation rule-set was

412 executed for each timestamp separately. In other words, the set of objects obtained at T_0
413 does not impact the segmentation process at T_1 and so on. The segmentations were also
414 separately performed over each study site. For both sites and timestamps, only the objects
415 obtained at the last level of segmentation (step 3) were exported and used as an input for
416 the subsequent processing steps.

417 3.3. Verification strategies

418 To assess the quality and the accuracy of the results, we developed two verification
419 strategies. The first was based on the interpretation of the ancillary imagery plus two
420 thematic layers and was applied over the *Lower Aude Valley* site. The second strategy was
421 mainly based on the official farmer declarations (one of the available thematic layer) and
422 applied over the *Libron Valley* site.

423 Considering the ancillary imagery, two types of image were employed: (a) normal color
424 and color infrared aerial orthophotos (0.5 m spatial resolution) acquired during May 2009
425 and (b) one RapidEye satellite image (6.5 m spatial resolution) acquired in 24 June 2009
426 and only available for the Lower Aude Valley site.

427 Regarding the thematic layers, the first concerns both study areas and is related to
428 agricultural practices. It corresponds to the official farmer declarations indicating the main
429 cultures exploited during 2009. The second thematic layer is proper to the *Lower Aude*
430 *Valley* site. It corresponds to a detailed classification (scale 1:25 000) of the natural habitats
431 over the site. The classification was realized by botanists and ecologists of the Conservatory
432 for the Natural Spaces of the Languedoc-Roussillon Region (CEN-LR).

433 3.3.1. Ancillary imagery based verification

434 First, the aerial photographs were used to map the whole *Lower Aude Valley* Natura
435 2000 site. This task was carried out through a manual land cover digitalization process
436 at the 1:10,000 scale. Each individual map unit (polygons in our case) has been labeled
437 according to hierarchically structured land cover classes. This hierarchy contains three levels
438 of complexity and has, in the more detailed level (3), nineteen land cover classes. Eleven
439 of them are associated to artificial, cultivated and managed areas, while the other eight
440 classes are related to natural and semi-natural areas (see Table 2 for all the class names).
441 Considering the acquisition date of the aerial photographs, the obtained land cover map
442 represents the situation of the site in May 2009.

443 Then, the obtained land cover map was superimposed on the RapidEye satellite im-
444 age. All the initial polygons received a new land cover label (using the same hierarchical
445 scheme) according to the situation observed on the RapidEye image (24th June 2009).
446 When necessary, new boundaries were digitalized and some polygons of the former map
447 were consequently divided into two or more smaller polygons. Thus, a second land cover
448 map was produced representing the situation of site in late June 2009. In order to estimate
449 the evolutions between the two land cover maps we computed an exhaustive set of from-to
450 evolution classes. Then, we analyzed each from-to evolution class (about 50) and assigned
451 a particular level (or intensity) of change: low, medium, high or very high. Finally, these

Level 1	Level 2	Level 3
Artificial, cultivated and managed Areas	Artificial surfaces and associated areas	Highway and major road sections
		Other built-up and associated areas
	Artificial waterbodies	Artificial lakes and ponds
	Cultivated and managed areas	Crops - dense cover and high greenness values
		Crops - moderate/sparse cover and high greenness values
		Crops - low greenness values
		Crops - harvested parcels
		Crops - floating row covers and bare soils (very high reflectance)
		Vineyards - sparse cover
		Vineyards - dense/moderate cover
Orchards		
Natural and semi-natural areas	Natural and semi-natural vegetation areas	Dense/moderate cover and high greenness values
		Dense/moderate cover and moderate greenness values
		Dense/moderate cover and low greenness values
		Sparse cover
		Bare areas
	Natural areas covered by water	Unvegetated dunes and beaches
		Shallow waters
		Deep waters

Table 2: Hierarchically structured land cover classes used for mapping the *Lower Aude Valley* site. This scheme was used to create two maps, one derived from the aerial photographs and the other from a RapidEye image.

intensities of change (derived from the ancillary imagery) were compared to the *GlobalVar* scores, obtained from the evolution graphs (described in Section 2.5).

3.3.2. Thematic layer based verification (official farmer declarations)

The second verification procedure consisted in drawing up a parallel between the Global Variation results and the principal groups of culture declared annually by the farmers. In France, the reference parcel representation is the Farmers block/ilot in regard to the European regulation (*Comm. Reg. N 796/2004*). This kind of parcel representation corresponds to an association of one or more agricultural parcels into blocks. Each block is the property of a single farmer and may contain one or several crop groups (Sagris and Devos, 2008). In practice, the official farmer declarations (the public version of the data) consists in a set of georeferenced polygons (one for each block) where a code indicates the principal groups of culture exploited during the year. Within the *Libron Valley* site, 11 groups of culture have been declared in 2009 which corresponds to 59 polygons. Nevertheless, this thematic layer contains some erroneous declarations, imprecise polygon boundaries and some gaps (i.e. when an agricultural parcel has not been declared). In order to attain a more precise comparison, we verified each polygon and selected only those without visible errors. Also, we eliminated all the polygons smaller than 4 ha to preserve an order of magnitude comparable with the graph objects. The obtained subset contains 32 polygons belonging to the following groups of culture: *cereals (excepted wheat), flower-fruit vegetables, orchard, seeds, sunflower and vineyard*. As these cultures are associated to dissimilar agricultural practices

	<i>Lower Aude Valley</i>			<i>Libron Valley</i>		
	Min	Mean	Max	Min	Mean	Max
Number of nodes	7	15.2	38	6	13.0	26
Number of edges	7	24.5	77	5	18.9	53
Number of paths	2	79.7	1050	1	46.7	480
BBCov (ha)	1.6	16.2	125.0	3.2	13.8	67.1
WholeCov (ha)	5.3	46.2	175.7	6.1	34.5	107.9
CoreCov (ha)	2.1	29.9	142.5	3.4	22.6	94.6
CoreCov (%)	13.9	65.1	90.9	14.4	66.3	93.3
EphemCov (ha)	0.8	16.4	134.0	1.2	11.8	65.1
EphemCov (%)	9.1	34.9	86.1	6.7	33.7	85.6

Table 3: Global graph statistics obtained for each study site

and temporal dynamics all along the year, it is expected some noticeable differences among the graphs representing these areas (especially w.r.t. the *GlobalVar* results).

4. Experimental Results and Discussion

4.1. Overall results and statistics

To generate the evolution graphs on the two study sites we used the procedure introduced in Section 2.6. We fixed the σ threshold (the minimum accepted coverage) equals to 95% and generated the set of different solutions varying the three parameters (α , τ_1 and τ_2) in the range $[0.1, 1]$ with a step-size of 0.05. The procedure selected the following values for α , τ_1 and τ_2 : 0.3, 0.25 and 0.20 respectively. The values are the same for both sites.

We obtained a total of 340 graphs for the *Lower Aude Valley* site and a total of 142 graphs for the *Libron Valley* site. The total number of objects per graph ranges from 6 (a single object per timestamp) to 38 (about 6.3 objects per timestamp). The mean value, considering both study sites, was 14.6 (about 2.4 objects per timestamp). Also considering the two study sites, the mean number of edges per graph was 22.9 while the mean number of paths per graph was 69.9. Taking into account all the 482 graphs, the whole spatial coverages (*WholeCov*) ranges from 5.3 ha to 175.7 ha with a mean value of 42.7 ha. Although some graphs present very high coverages (>100 ha), most of the values (about 97%) range between 10 and 90 ha. In other words, the areas monitored by our graphs correspond mostly to patches ranging from 100 to 1000 Landsat pixels. As another global result, the core graph coverages (*CoreCov*) correspond, in average, to 65.5% of the *WholeCov* areas. As expected, *EphemCov* is usually smaller than *CoreCov* and this is true for 87.5% of the graphs. Even if all the processing steps were identical for the two study sites, we noticed some differences in the graph derived statistics. Table 3 shows the main statistical results obtained separately for each study site.

We can observe that the *Lower Aude Valley* graphs have a bigger number of nodes if compared to those of the *Libron* site. In general, they tend to present a more complex structure with a higher number of paths per graph. Another noticeable difference is related to the size of the objects and the derived graph coverages. All the greatest objects (>70 ha)

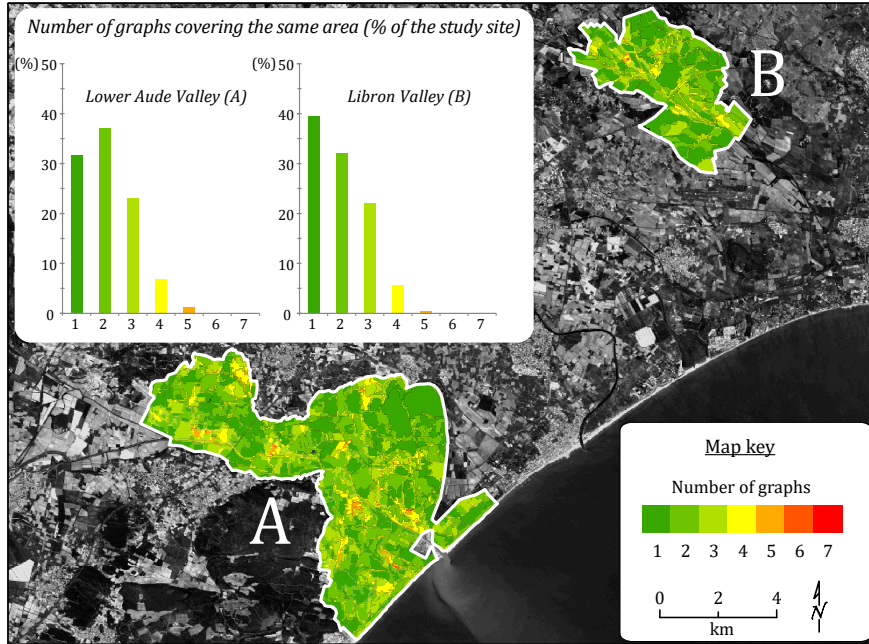


Figure 6: Degree of spatial overlapping among graphs for both study sites. The histogram indicates the relative areas (% of each study site) considering number of graphs covering the same area.

500 comes from the *Lower Aude Valley* as well as most of the widest graphs (>100 ha w.r.t. the
 501 *WholeCov*). This can be explained by the exclusive presence of water bodies and temporally
 502 flooded areas in the *Lower Aude Valley* site. The spectral homogeneity of these particular
 503 areas contributes to generate large objects during the image segmentation step.

504 As the graph coverages may partially overlap, it becomes interesting to detect the spatial
 505 distribution of the less and most overlapping areas. Figure 6 shows such spatial distribution,
 506 in terms of number of graphs representing the same area, over the two study sites. The spatial
 507 overlapping is related to the value of the parameter α (novelty threshold) used during the *BB*
 508 selection strategy presented in Section 2.2. This threshold allows a certain level of overlay
 509 among the *BBs*, it is expected that all the other derived graph coverages will present some
 510 degree of overlap as well. As a consequence, the higher is the α parameter, the lower will
 511 be the number of selected *BBs*, the lower will be the degree of spatial overlapping among
 512 the generated graphs. On both study sites we have observed that, when α is lower than 0.2
 513 the degree of overlay becomes particularly high (more than 75% of the study site is covered
 514 by two or more graphs) while α values larger than 0.4 lead to important gaps (areas not
 515 covered by any graph).

516 However, the spatial overlapping depends also on the inner characteristics of each study
 517 site, in particular on how the spatial boundaries of their objects evolve during the time
 518 series. In the case of our study sites, the *Libron Valley* presented a lower degree of spatial
 519 overlapping w.r.t. the *Lower Aude Valley*. This can be explained by two main factors: (a)
 520 the spatial arrangement of the sites, e.g. in the *Libron* site the limits between agricultural
 521 and natural areas are easier to recognize (bigger and more homogeneous patches) and (b)

522 nature of the temporal evolutions, e.g. modifications in the shape of the objects are more
523 frequent in the *Lower Aude Valley* since the site is exposed to flooding events. In addition,
524 the fact of having many small parcels (near to the limit of detection) may contribute to
525 shape instability from a timestamp to the next one.

526 4.2. Spatiotemporal Dynamics

527 When repeatability and compatibility of satellite observations are guaranteed it becomes
528 possible to detect spatiotemporal evolutions, from which the related dynamics can be de-
529 duced (Bonn, 1996). In that light, we consider spatiotemporal dynamics as derived from
530 a set of consecutive evolutions we detected throughout the time series. In particular, we
531 performed analysis at both graph and study-site levels (as described in Section 2.5).

532 4.2.1. Graph Level Analysis

533 In order to better illustrate graph structure and content, we selected 4 graphs represent-
534 ing different evolutions in time (see Figure 7). *Graph A* represents a natural area composed
535 mainly by scrubland and forest. Its *BB* came from the fourth timestamp which corresponds
536 to the beginning of the summer. At this time, the area is the most homogeneous while the
537 most heterogeneous situations are observed in the first (winter) and third (spring) times-
538 tamps. In those two timestamps it is possible to better distinguish the deciduous vegetal
539 community (brown at T_1 and light green at T_3) from the surrounding coniferous community
540 (dark green during the whole time series). Conversely, *Graph B* has a particular structure
541 with two very distinct portions: first there is a single object per timestamp from T_0 to T_3
542 whereas from T_4 to T_5 there are several objects per timestamp (8 and 6 respectively). The
543 huge spatial fractioning observed between T_3 and T_4 corresponds to the drying-up process
544 of the *Pisse-vaches* coastal lagoon. High evaporation rates combined to weak precipitations
545 during the summer leads to the replacement of the lagoon by a wide dry salt flat in the end
546 of this season. *Graph C* presents a quite similar, but inverted, structure w.r.t. *Graph B*. In
547 fact, this saltmarsh and salt meadow area is more heterogeneous in the beginning of the time
548 series (T_0 up to T_2). At this time, the area is partially covered by water and hygrophilous
549 vegetation, which explains the dissimilarities on the objects boundaries during these three
550 timestamps. Afterwards, water is no more present and the dry summer conditions lead to
551 a fast decrease of the photosynthetic vegetation, as a consequence, the area becomes much
552 more homogeneous in the three last timestamps. Finally, *Graph D* represents the evolutions
553 over two adjacent cereal crop fields. The plant-growing season is visible from T_0 to T_2 (late
554 winter to spring) although we can notice that plant-growing is not homogeneous all over the
555 field area. Then, the crops are harvested in early summer (between T_2 and T_3) and both
556 fields remain unvegetated until the end of the time series.

557 In addition to graph structure and visual analysis of image objects, it is important to
558 consider the changes in the content of the objects. For that purpose, each graph can be
559 also finely analyzed thanks to *Temporal Profiles* representing the variation of any object
560 attribute. As examples, we can use the previously discussed graphs B and D (see Figure 8).
561 In the case of *Graph B*, the temporal behavior of VSDI furnishes reliable information about
562 the drying-up process of the coastal lagoon as this spectral index is sensitive to changes in soil

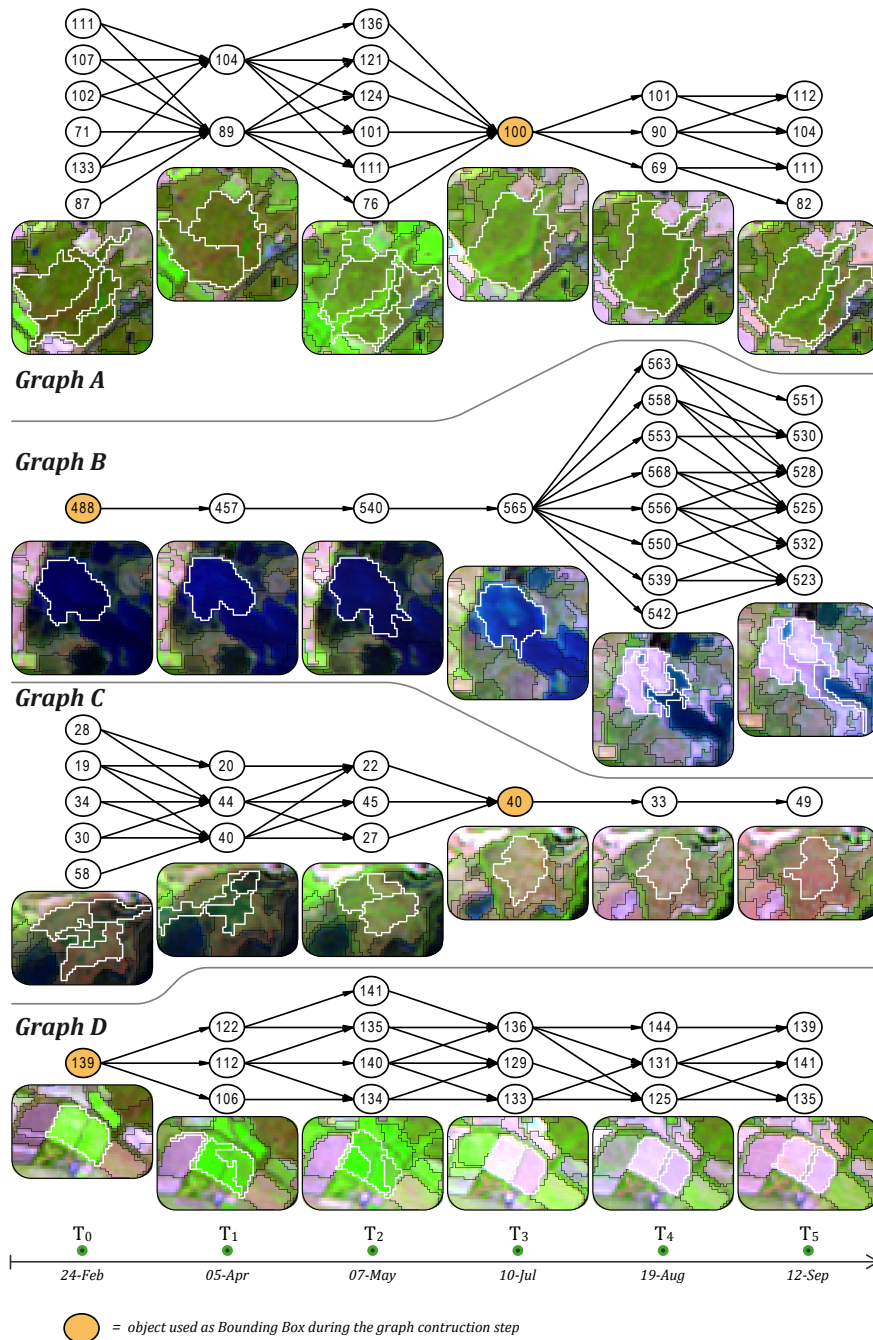


Figure 7: Examples of graphs showing different structures and representing distinct evolutions in time. A- a scrubland and forest area (central part of the *Libron* site), B- a coastal lagoon (southern part of the *Lower Aude Valley*), C- a saltmarsh area (northern part of the *Lower Aude Valley*), D- two crop fields (near to the central part of the *Libron* site).

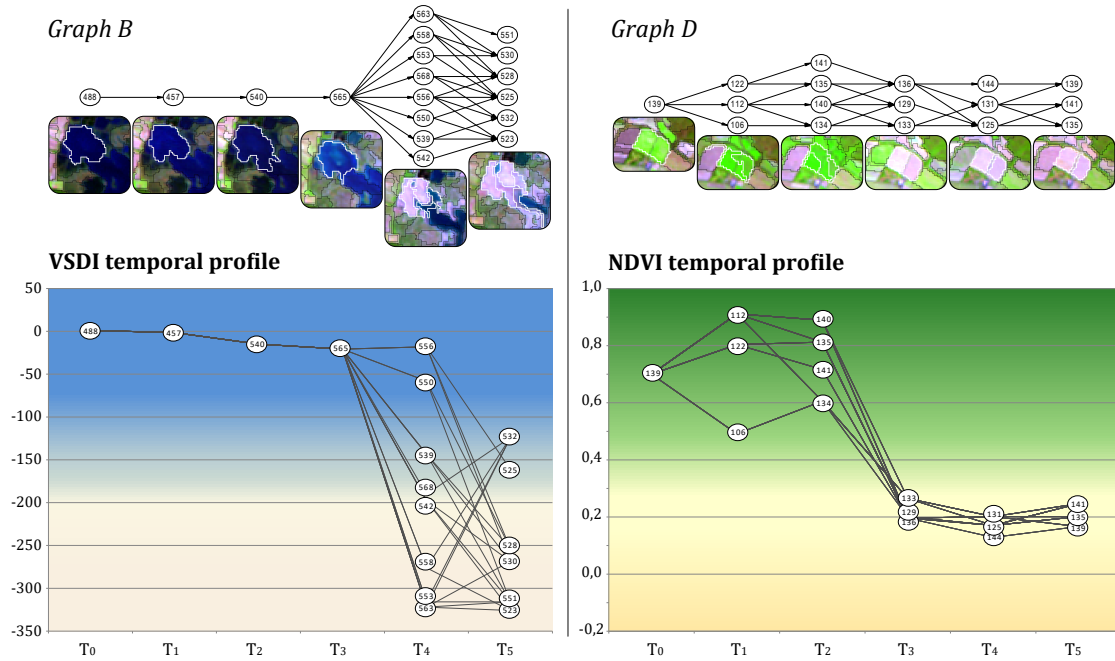


Figure 8: Temporal profiles for two selected graphs (see 7). For *Graph B* (left) the temporal profile corresponds to the variation of the VSDI (each object is represented by its mean VSDI value) while for *Graph D* (right) it corresponds to the variation of the NDVI (each object is represented by its mean NDVI value).

563 moisture and to the presence of surface water. Likewise, for *Graph D*, the NDVI temporal
 564 profile is useful to follow the changes observed over the cereal crop fields, i.e. plant-growing,
 565 harvest and long-lasting bare soil.

566 4.2.2. Study-site Level Analysis

567 Beside such fine temporal information, the *GlobalVar* (*GlobalVar*) synthesizes
 568 how much the area represented by a given graph evolves during the whole time series and a
 569 *GlobalVar* map can be built from this information. Several *GlobalVar* maps can be produced
 570 by combining different object attributes. Indeed, *GlobalVar* maps are useful to compare
 571 graphs and promptly detect the most and the less stable areas within the considered study
 572 sites. In our case, as both study sites have the same timestamps, *GlobalVar* maps can also
 573 be used to compare the two zones (see Figure 9).

574 Regarding Figure 9, we can observe that choosing different attribute combinations results
 575 in somewhat different *GlobalVar* maps. We can also underline that the two study sites
 576 exhibit different behaviors considering different attribute combinations. In other words, the
 577 attributes showed in Figure 9 are differently correlated according to each site and, in general,
 578 they are not highly correlated among them. Regardless of the attribute selection, the *Libron*
 579 site presents invariably higher values of *GlobalVar* if compared to the *Lower Aude Valley*.
 580 This is more evident when only the NDVI is employed (map 1) or only the raw bands (map
 581 2) to produce maps by means of *GlobalVar*, instead of map (3) where all the spectral indices
 582 were used.

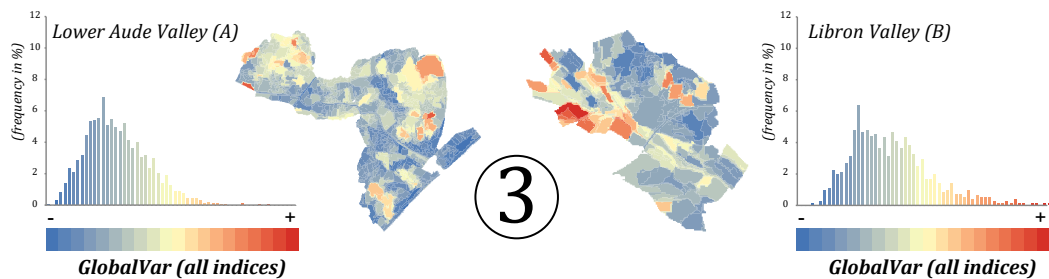
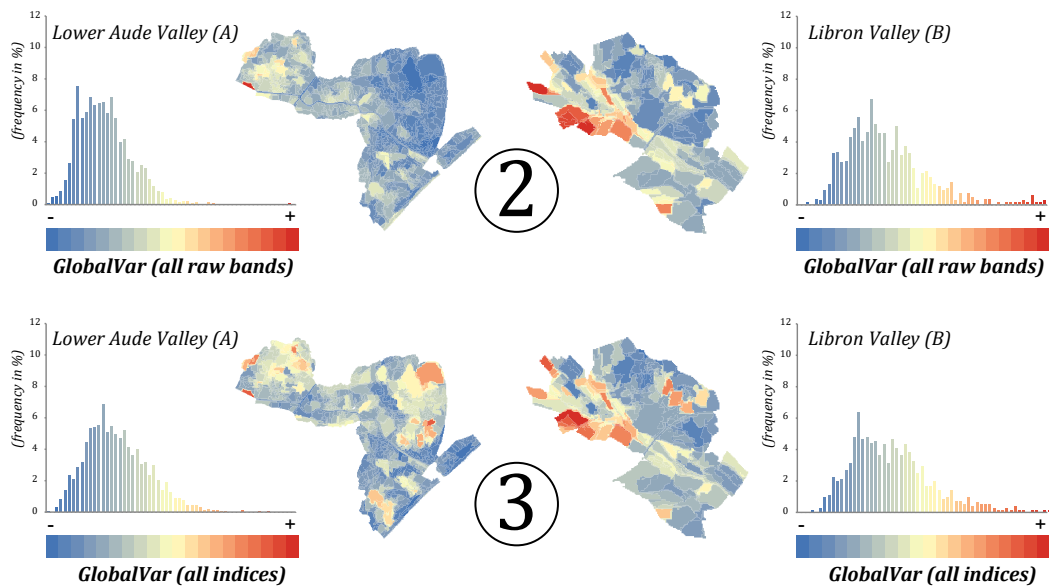
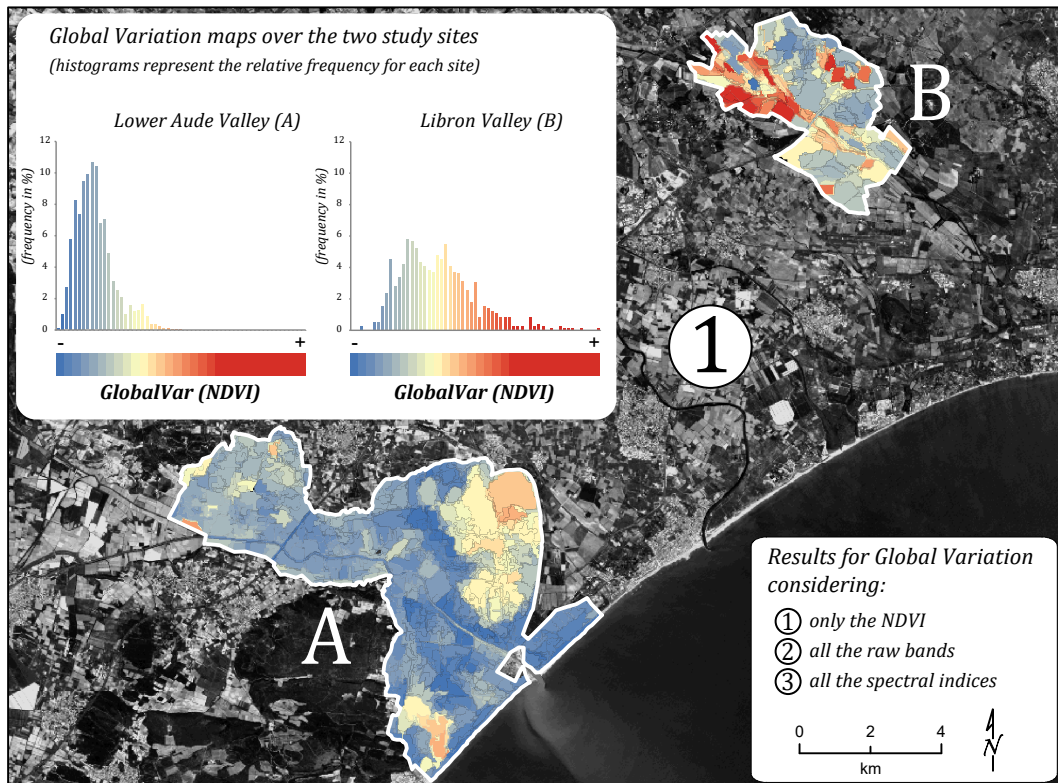


Figure 9: Global Variation (*GlobalVar*) maps and the corresponding frequency histograms for the two study sites (A-Lower Aude Valley, B-Libron Valley). The following attributes were used for the *GlobalVar* maps: (1) only the NDVI, (2) all the raw bands and (3) all the spectral indices. As graph coverages may partially overlap, the *GlobalVar* values has been recalculated, for all the overlapping areas, considering the proportional contribution of the involved graphs.

583 Considering only the *Lower Aude Valley*, one can suppose a very stable situation based
584 on the analysis of the second map (all raw bands). Excepting few cereal crops in the western
585 part of the site, all the remaining areas present low values of *GlobalVar*, including all the
586 temporary flooded areas. Alone, the six spectral bands provide a very partial representation
587 of the temporal dynamics since only some radical evolutions (i.e. bare soil/dense vegeta-
588 tion/bare soil) are highlighted, while the other evolutions are not took into account. Over
589 the *Libron Valley* site such kind of radical evolution is more frequent and widespread, espe-
590 cially in the crop areas located along the upstream *Libron* waterway (red and orange hues
591 in map 2). However, even in this case the results are not satisfactory as some crops areas
592 presenting radical evolutions displays medium values of *GlobalVar* instead of high values.

593 Conversely, the *GlobalVar* map derived from the NDVI furnishes much more reliable
594 information related to landscape dynamics in both study sites. In the *Libron Valley*, the
595 highest values correspond to the agricultural areas where important changes are observed
596 throughout the year (e.g. cereals, sunflower, flower-fruit vegetables and seeds). Vineyards
597 and orchards generally experience less noticeable inter-annual variations and are therefore
598 assigned with medium or medium-low *GlobalVar* values. The lowest values correspond
599 mostly to natural scrub and forest areas, in particular those dominated by coniferous. In
600 the *Lower Aude Valley*, the lowest values are also principally related to natural areas, more
601 specifically to herbaceous/scrub vegetation covering sand dunes (southeast of the site) or
602 some not submerged areas surrounding the *Vendres* lagoon (center of the site). In addition,
603 some build-up areas like camping and recreational facilities (all located along to the coast)
604 present low *GlobalVar* values. Vineyards and orchards, as well as saltmarsh and salt meadow
605 areas, are generally assigned with medium or medium-low *GlobalVar* values. Finally, the
606 most dynamic areas are clearly associated to the two coastal lagoons (*Vendres* and *Pisse-*
607 *vaches*) and, in a minor extent, to the few cereal crops located in the western part of the
608 site. The graphs representing the coastal lagoons and surrounding areas are characterized by
609 important changes in the objects shape and content. The *Pisse-vaches* sector is temporarily
610 covered by shallow and brackish waters. It is scarcely colonized by the vegetation either
611 during the submerged periods (very few aquatic macrophyte during winter and spring) either
612 during the waterless period (very limited growth of pioneer communities during the summer
613 and autumn). The *Vendres* sector also presents important seasonal water level fluctuations
614 but possess a permanently flooded area (northeastern portion). Salinity is less important
615 in this sector where dense aquatic and terrestrial vegetation can be observed during spring
616 and summer.

617 Finally, the third map of Figure 9 combines the three spectral indices to compute the
618 *GlobalVar* (all indices). The spatial distribution of the less and the most dynamic areas
619 is somehow similar to those described for the NDVI *GlobalVar* map, which is logical as
620 the NDVI is one of the three spectral indices considered here. Nevertheless, the inclusion
621 of VSDI and NDWI draw attention to some temporal evolutions unnoticed by the NDVI,
622 in particular over the areas where the contribution of the soil is greater than those of the
623 vegetation.

	Pearson's r	Spearman's rho
All raw bands	0.574	0.476
NDVI	0.767	0.659
NDWI	0.787	0.672
VSDI	0.719	0.580
All indices	0.789	0.676

Table 4: Correlation coefficients results for ancillary based verification. The value of change from ancillary imagery (VCA) was compared with five sets of GlobalVar (all raw bands, NDVI, NDWI, VSDI, all indices)

624 4.3. Ancillary imagery based verification

625 As explained in section 3.3.1, the ancillary imagery was processed in order to estimate
626 the intensities of change all over the Lower Aude Valley Natura 2000 site. Such intensities of
627 change were obtained by comparing two land cover maps and their related from-to evolution
628 classes. The first map (derived from aerial photographs) represented the study site in May
629 2009, while the second one (based on a RapidEye image) represented the site in late June
630 2009. This time interval corresponds roughly to the timestamps T_2 (7 May 2009) and T_3
631 (10 July 2009) of our Landsat time series. To perform a coherent verification, we calculated
632 an extra set the *GlobalVar* values considering only these two timestamps of the former time
633 series.

634 As the spatial boundaries between the evolution graphs and the land cover maps are not
635 similar, we employed the following strategy to compare their intensities of change. Starting
636 from the *CoreCov* of each graph, we clipped the corresponding polygon(s) of the land cover
637 maps. If a given graph is represented by more than one map polygon, we computed a
638 weighted average of the intensities of change of those polygons. This is done by taking
639 into account the relative area of each map polygon (inside the *CoreCov*) and multiplying
640 it by a coefficient of change. The coefficient varies according to the intensities of change
641 (low=1, medium=2, high=3 and very high=4) assigned to the from-to evolution classes. As
642 consequence, each graph received a new numerical value of change (VCA) that is derived
643 from the ancillary imagery and can be therefore compared to the *GlobalVar* values.

644 Table 4 summarizes the correlation coefficients obtained from the comparison of VCA
645 against five sets of *GlobalVar* (all raw bands, NDVI, NDWI, VSDI, all indices). We used two
646 coefficients of correlation: (a) the Pearsons coefficient which measures the strength of the
647 association between two variables and (b) the Spearmans ranked coefficient which assumes
648 that the two variables under consideration were measured on an ordinal scale.

649 The strength of association is particularly high between VCA and three sets of *GlobalVar*
650 (all indices, NDWI and NDVI). This assertion is valid for the two correlation methods:
651 (a) Pearson's r ranging from 0.767 to 0.789 and (b) Spearman's rho ranging from 0.659 to
652 0.676. For both Pearson and Spearman, the correlation coefficient is very highly significantly
653 different from zero (p-value <0.0001).

654 It is worth noting that we eliminated the areas with potential water level fluctuations
655 from this comparison. This was necessary because the acquisition dates of the images
656 (Landsat and ancillary imagery) are not the same (i.e. 15 days separates the RapidEye

657 image from its corresponding Landsat image). As the water level is highly variable around
658 the two coastal lagoons, we cannot assume that the observations made with several days of
659 interval are comparable. During this time interval, other short-time evolutions (such as crop
660 harvesting or plant growing) can occur and dramatically change the observed landscape.
661 However, the detection of all these not comparable areas over the entire study site would
662 require a very careful and meticulous visual confrontation of the 4 images employed in the
663 verification process. Even without performing such deep data-cleaning task, we obtained
664 high correlations between VCA and most sets of *GlobalVar* values. As expected, the strength
665 of association was stronger when using spectral indices instead of raw bands. The best
666 correlation coefficient was obtained with the *GlobalVar(all indices)*, which considers the
667 behavior of the three spectral indices together. Individually, both the *GlobalVar(NDVI)*
668 and the *GlobalVar(NDWI)* are highly correlated to VCA. Although the difference is small,
669 the combination of the three indices furnished an automated evaluation of the evolutions
670 that is the nearest of those obtained from manual digitalization and visual interpretation of
671 the ancillary images.

672 4.4. Thematic layer based verification (official farmer declarations)

673 As the boundaries of the thematic layer are not similar to those of the evolution graphs,
674 we employed the following strategy. Starting from the 32 polygons representing the declared
675 groups of culture by the farmers in 2009, we clipped the corresponding evolution graphs
676 representing such areas (the *CoreCov* of each graph). If a given polygon of culture is
677 represented by more than one evolution graph, we computed a weighted average of the
678 *GlobalVar* values of those graphs. This is done by taking into account the relative area of
679 each graph (inside the polygon of culture) and multiplying it by the corresponding *GlobalVar*
680 values. At the end, each polygon of culture was assigned with five values of *GlobalVar* (all
681 raw bands, NDVI, NDWI, VSDI, all indices) derived from the evolution graphs representing
682 such agricultural areas.

683 Figure 10 summarizes, for each group of culture, the mean *GlobalVar* value obtained
684 for the five sets of attributes (all bands, NDVI, NDWI, VSDI, all indices). The number of
685 polygons available for each group of culture is indicated in Figure 10 as well as the error
686 bars related to the mean values (excepted for the sunflower crop that possesses only a single
687 polygon).

688 The general analysis of Figure 10 allows grouping the cultures into two subsets: (a) vine-
689 yard and orchard which presented low *GlobalVar* values and (b) cereals (excepted wheat),
690 sunflower, seeds and flower-fruit vegetables which presented high *GlobalVar* values. This
691 separation in two main subsets can be observed in any of the five plots but is most evident
692 in *GlobalVar* (NDVI).

693 Although the number of polygons is quite small (32), the results are consistent with the
694 dynamics we can observe for those types of culture. Orchards and vineyards parcels present
695 almost the same temporal evolutions with a gradual augmentation of the greenness during
696 spring and early summer. Then, the greenness level remains nearly stable for most of the
697 parcels while for some others it can decrease thinly up to late summer. One interesting
698 difference between these cultures is that the maximum of greenness is attained firstly for

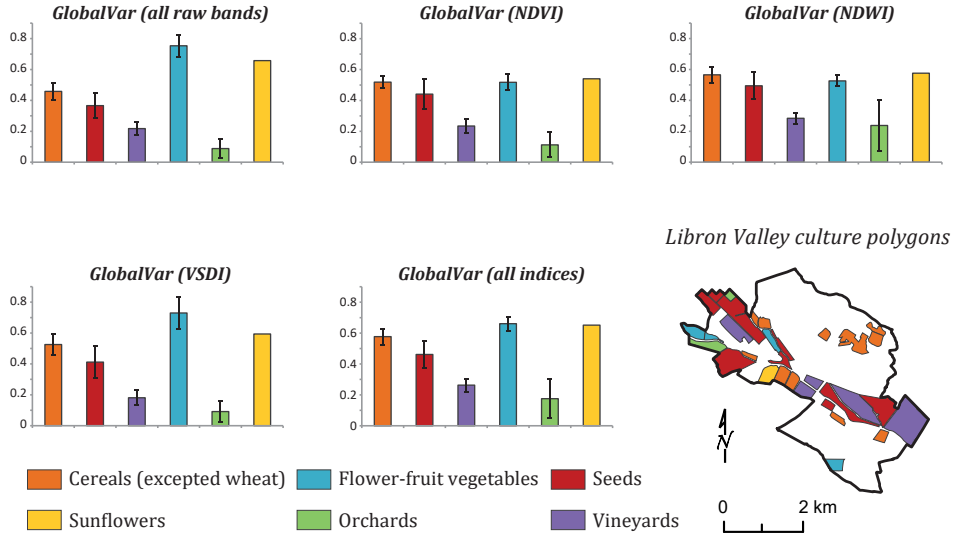


Figure 10: Thematic layer verification using official farmer declarations.

699 the orchards (usually at T_2 in our time series) and lately for the vineyards (usually at T_3 in
700 our time series). These may explain why the mean values of *GlobalVar* are smaller for the
701 orchards if compared with those of the vineyards. The second subset assembles four types of
702 crops: cereals, sunflower, seeds and flower-fruit vegetables. Those crops present dissimilar
703 temporal dynamics but all of them are composed by the same general evolutions, or phases:
704 plant-growing, harvest and bare soil. According to the calendar of each crop, such phases
705 are observed in different periods of the time series. In a simplified way, they are temporally
706 distributed as follows: (i) between T_0 and T_2 plant-growing for cereals and bare soil for the
707 other cultures, (ii) between T_2 and T_3 harvesting for cereals and plant-growing for the other
708 cultures, (iii) between T_3 and T_4 bare soil for cereals, harvesting for flower-fruit vegetables
709 and plant-growing for sunflower and seeds, (iv) between T_4 and T_5 bare soil for cereals and
710 flower-fruit vegetables, harvesting for sunflower and seeds. As we can observe, the evolutions
711 are shifted in time, but their corresponding length over the entire time series is very close.
712 As a consequence, the *GlobalVar* calculated for these crops generally fit in the same range
713 of values (taking into account the error bars).

714 According to the results of the two independent verifications presented in this section,
715 our framework produced reliable results that are consistent with the ground truth we em-
716 ployed. More in detail, we have seen that our methodology is able to automatically detect
717 spatiotemporal dynamics in natural, semi-natural and agricultural areas.

718 The object-tracking mechanism we conceived is able to describe those dynamics by means
719 of objects coming from different images of the time series. Once the graph structure is built,
720 it can be analyzed considering different combinations of the object attributes (e.g. raw
721 bands, spectral indices). Modifying the combination of object attributes introduces some
722 kind of flexibility and it allows to customize the proposed framework according to the task
723 the user wants to deal with.

724 The proposed framework can be also exploited in order to plan field campaigns on un-
725 known areas since it supplies an exploratory tool to draw a global overview of a study area.
726 The practical interest is twofold: firstly, it provides a synoptic view based on spatially co-
727 herent areas over the time; secondly, for each of these areas is automatically characterized
728 by an estimation how much it evolved during the whole period covered by the SITS.

729 **5. Conclusion**

730 In this paper we proposed a new methodological framework to automatically extract
731 spatiotemporal information from SITS. We combined OBIA and data mining techniques
732 to extract graph structures describing spatio-temporal dynamics from SITS. Our approach
733 starts with classical OBIA image processing which results in separate sets of objects for each
734 timestamp. Then, a graph-based approach is employed to detect spatially coherent areas and
735 connect the objects belonging to different timestamps generating a set of evolution graphs.
736 From these graphs, spatio-temporal dynamics are computed and summarize the temporal
737 behavior of each particular area over the time.

738 The proposed framework was evaluated in two study sites located in the South of France,
739 near to the Mediterranean Sea. The experiments underlined how the extracted information
740 can be deeply explored at the evolution graph scale, as well as to supply a general picture
741 at the study site scale, but also to be used for comparing different study sites. The robust-
742 ness of the framework is verified via ancillary imagery, field campaigns and official farmer
743 declarations.

744 The framework described in this paper can be potentially used with any kind of SITS.
745 In particular, Sentinel-2 images will shortly improve the observational capabilities for moni-
746 toring purposes (the first satellite started operational acquisition in the beginning of 2016).
747 Enhanced revisit capacity, i.e. 5 days when the two satellites will become operational, as-
748 sociated to 10m resolution for visible and NIR bands, will open new possibilities for several
749 applications including the monitoring of natural and agricultural areas.

750 As a future work we plan to exploit deeply the knowledge supplied by the graph-based
751 representation. One of our ongoing works is related to automatically grouping similar spa-
752 tiotemporal entities in order to define categories (or families) of evolutions that characterize
753 a given study site.

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