



Change and Persistence in an Olive Landscape of Sicily. Geospatial Insights Into Biocultural Heritage

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Abstract

Intercropping landscapes characterised by the presence of certain plant features are usually considered traditional landscapes, important for their biocultural heritage. In recent decades, olive agroforestry systems previously widespread throughout Sicily have transitioned to monocultures alongside the disappearance of other tree species. To analyse the dynamics of land use, we combine mathematical representations and oral narratives of spatial change, focussing our case study on a rural area of inner Sicily, *Cozzo del Lampo*, characterised by a high presence of century-old olive trees. By using local geonarratives in combination with the results of change detection analysis using historical aerial images spanning 50 years (1955 – 2005), we gain insights into the relationality of people and places over time, highlighting how biocultural heritage is correlated to both local culture and ecology, and demonstrating the value of ecological perspectives to understand past and current human actions. The active engagement of the local population in the interpretation of their own (past-present) practices is key to access new ecological knowledge.

Keywords Change detection · Historical images · Ecological knowledge · Geonarratives · *Olea europaea* · Olive agroforestry · Cozzo del Lampo · Sicily

Introduction

In the Mediterranean region, intercropped landscapes characterised by the presence of certain long-lasting plant features (e.g., century-old olive trees in agroforestry systems) are usually considered traditional landscapes, extremely important for their biocultural heritage. Olive agroforestry systems were widespread in the past throughout Sicily (Ferrara & Lindberg, 2023; Ferrara et al., 2023). Recent intensification practices have moved to olive grove monocultures. These variations in spatial patterns reflect different landscape processes in action (Ferrara & Wästfelt, 2021), exhibiting non-random and clustered spatio-temporal distributions. Conceptualising human modifications to the environment in this way recognises that land use is spatially

arranged and dynamic across temporal scales (Munoz et al., 2014). In such a framework, the Biocultural Heritage of these systems (a fusion of the ‘natural’ and ‘cultural’ components of human-environment interactions) remains a fundamental component of routine practice, always subject to change and modification. Indeed, heritage, whether tangible or intangible, is best understood as a dynamic entity modified to meet contemporary needs and values as society changes (Ochungo et al., 2022).

For historical ecologists, present-day ecosystems’ structure and dynamics are the results of historical and spatial disturbance regimes, which may allow for various non-equilibrium states due to their complex history of disturbance. Building on disturbance ecology, the historical ecology framework recognizes that landscape elements and ecosystems may have evolved with human inputs to such an extent that abandonment of human interference may lead to the impoverishment of structural and biological diversity that is accentuated in fragmented agricultural landscapes (Lunt & Spooner, 2005). This approach emphasises that not all human activity leads to degradation and that humans are an integral component of landscape dynamics. Few studies have investigated the correlation between human disturbance and plant agency in botanical

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and ecophysiological terms, or combined historical ecology with the emerging sub-field of multispecies ethnography and multispecies studies in general (Kirksey & Helmreich, 2010; van Dooren et al., 2016; Hartigan, 2019; Shepard & Daly, 2022). Our research is theoretically positioned at this interface and methodologically developed adopting a geospatial approach to look at the spatio-temporal dimensions of land use transformation dynamics.

The concept of change explicitly connects space and time and understanding how things relate to each other in space and time matters because where and when things happen is critical to knowing how and why they happen (Yuan, 2020a). By thinking about space relationally, we can open up to the possibility of adopting a “dual approach,” merging analytical and quantitative geography with critical and qualitative spatial analysis, reimagining “hybrid” linkages between social-cultural and spatial-analytic approaches (sensu Norwood & Cumming, 2012). This can be done by combining geospatial analysis with qualitative fieldwork. Time-series remote sensing change analysis of land use transformations can capture change at multiple temporal scales, especially when integrated with other sources of information, e.g., oral histories and ethnographic observations (Ochungo et al., 2022). Change detection analysis is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). This process is usually applied to Earth's surface changes at two or more times. The primary source of data is geographic and usually in digital format (e.g., satellite imagery), analogue format (e.g., aerial photos), or vector format (e.g., feature maps), which can be used with ancillary data (e.g., historical, economic, etc.) (Théau, 2008). By comparing multitemporal remote sensing images, this type of analysis can highlight the contrast between changed and unchanged areas. Several change detection methods and algorithms have been developed over the past decades (cf. Ban & Yousif, 2016; Lu et al., 2004) and more in recent years due to the improvement in the quality of remote sensing images (Fatemi Nasrabadi, 2019; Kumar & Arya, 2021; Lv et al., 2022). The choice of the most appropriate change detection approach depends on a wide range of factors, including sensors' and imaging products' features, ground conditions and, above all, the specific characteristics of the phenomena under study. Due to such complexity, Lu et al. (2004) and Ban and Yousif (2016) highlight that there is no single optimal method for all types of change detection analysis, instead different approaches can be integrated and/or developed according to specific applications, types of data, and scientific goals. Change detection using multitemporal remote sensing imagery currently plays a crucial role in numerous fields of study, including urbanization, deforestation, desertification, flooding, disaster monitoring, and glacier change monitoring (review in

Ban & Yousif, 2016). The scientific community is moving towards computer-based automation and the unsupervised detection of changes (Gioia & Danese, 2021).

Change analysis has been used in historical ecology (Bazan et al., 2019; Byrd et al., 2004; Jaworek-Jakubska et al., 2020; Kefalas et al., 2018; Ochungo et al., 2022) and biocultural heritage studies (Banerjee & Srivastava, 2013), stressing the importance of the spatial context within which humans use and manage space, land, and the surrounding ecosystem (Coughlan, 2014). Historical ecologists have also been the first to emphasize the importance of working with historical aerial images for studying land use processes over time and space. Historic photographs are especially useful for providing insights into how past land use activities can explain current land use and land cover patterns (Byrd et al., 2004; van Dyke & Wasson, 2005). Historical aerial photographs can provide crucial baseline data for quantitative mapping and monitoring of landscape composition and heterogeneity over time (Pinto et al., 2019). The use of historical aerial photographs within change detection approaches has increased due to technical developments (Liu et al., 2018; Malandra et al., 2019; Nebiker et al., 2014; Pinto et al., 2019; Ratajczak et al., 2019; Ripa et al., 2013; Rodman et al., 2019; Sluiter & de Jong, 2007).

Geonarratives are geographically placed narratives (Ajayakumar et al., 2019; Curtis et al., 2019; Yuan, 2014, 2020b) or GIS-based narratives (Kwan & Ding, 2008) developed to facilitate the creation and interpretation of contextualized cartographic or visual narratives (Kwan & Ding, 2008). Understanding GIS largely as a quantitative method forecloses many opportunities to productively engage geospatial analysis in qualitative research. Here, we used geonarratives in the form of “spatialised” local observation of environmental change in land use practices to better understand and complement results from the geospatial change detection. As georeferenced oral histories, geonarratives allow us to interpret contemporary observations of spatial patterns in light of past practices (Kwan & Ding, 2008; Yuan, 2020b). The importance of integrating geonarratives in image interpretation is that they can provide qualitative information on changes that, with standard change detection analysis, are only quantitative. Such a combination of geospatial analysis and qualitative data can also enable identification of new issues or raise questions that would not be apparent when using one method alone. For this research, we adopted the “walking with” method to elicit geonarratives, based on the idea of geographic embeddedness or emplacement. Data are more easily collected and new insights gained, particularly on environmental perceptions and spatial practices (Kusenbach, 2003), from participants as they move through a particular place or space (Bell et al., 2015, 2017; Curtis et al., 2019; Yuan, 2020b), emphasising the importance of physical environment,



Fig. 1 Location of the case study area, Cozzo del Lampo hill, from a satellite image (source: Google Earth) and field view (photo by Vincenza Ferrara)

environmental features, and place in shaping discussions. A major advantage of walking interviews is to access people's attitudes and knowledge about the surrounding environment (Evans & Jones, 2011), as well as their relational space with the landscape (Macpherson, 2016). In our research, the place and its changes become the central theme of the "walking with" conversations (sensu Riley, 2010).

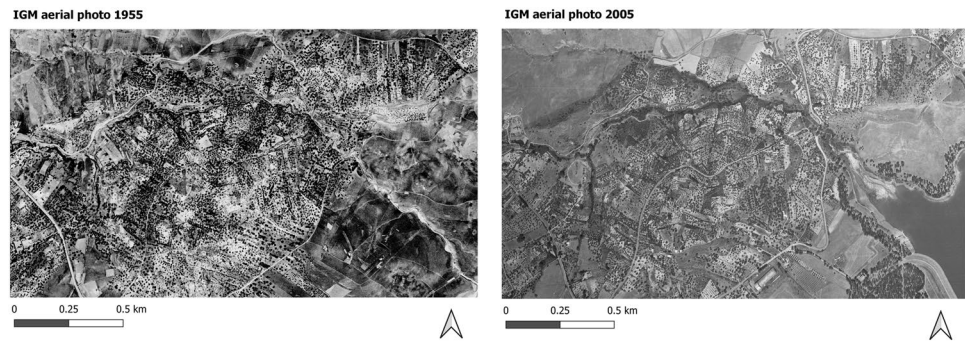
We addressed the questions of the possibility of mapping the transformation dynamics of land use practices in our study area in inner Sicily and we interpret these changes to improve our understanding of local biocultural heritage. Combining historical ecology and critical geography, we first developed a change detection method to extract and map the spatial dimension of land use transformations. Secondly, we interpreted these mapped spatialities with geonarratives—spatialised local observations of environmental change. The combination of mathematical and narrative representations of spatial change allow us to reach new insights on how biocultural heritage is correlated to both cultural aspects and ecological components of a place.

Study Area

The Cozzo del Lampo and the surrounding *contrade*¹ (Vigne Grandi, Quattro Aratate, Barone) is located in the municipality of Villarosa (province of Enna), an inner and rural area of the Morello Valley, a fluvial system of a larger extent, inhabited since prehistory. Cozzo del Lampo is a hill with an elevation of approximately 550 m.a.s.l. and the area covering the surrounding *contrade* is nearly 2km² (Fig. 1). The area was part of a large estate (*feudo*) in the middle of the seventeenth century AD (Verga, 1993). The first cartographic map showing the area is in Catasto Borbonico, the first cadastral register of the whole Sicily (1837–1853). Unfortunately, the map does not show any vegetation cover. The Atlante Fisico Economico d'Italia (1940) indicates that in the 1930s the area was characterised by 1% of specialised olive tree (*Olea europaea* L.) cultivation (Dainelli, 1940). This is confirmed by the Italian Military Geographic Institute

¹ A medieval Italian term used to indicate small rural districts.

Fig. 2 The two historical aerial photos (year 1955 and 2005) used for the analysis (source: IGM)



(IGM) topographic map of 1931 showing the area covered by olive trees and woody vegetation, as well as roads, paths, and small houses, some still present. Cozzo del Lampo is now a homogeneous mosaic of olive orchards surrounded by cereal and fallow fields. While the cereal and fallow fields are part of the small local farms, the olive orchards are family smallholdings maintained for self-consumption and/or leisure (e.g., country house).

A closer examination reveals a great variety and heterogeneity of olive tree patterns for such a relatively small area: a mosaic of olive trees in pocket terraces, scattered, ancient olive trees, geometric olive groves, mixed crops, etc., forming a living cultural landscape. The differentiated olive trees and the different spatial patterns characterise the hill with a high level of patchiness that has contributed to its interest for historical ecology (Ferrara et al., 2022) and for developing geo spatial methods to investigate the space-time complexity of the area (Ferrara & Wästfelt, 2021).

Methods and Data Collection

We first extracted and mapped spatial transformations of land use from change detection analysis of historical aerial images from 1955 and 2005. We then analysed and interpreted the mapped changes by eliciting geonarratives through “walking with” semi-structured interviews with local informants.

Mapping Spatial Transformations of Land Use – Change Detection Analysis of Historical Aerial Images

Geospatial change detection analyses are mathematical calculations of change processes that document changes in quantitative terms. Different change detection algorithms have different merits and no single approach is optimal and applicable to all cases. Thus, to extract and map the spatial transformations of land use in the study area, we developed a change detection hybrid approach (sensu Théau, 2008; Lu et al., 2004; Kumar & Arya, 2021) based on the application

of algebra-based post-classification comparison. We tested our approach on two historical aerial images of the area (1955 and 2005).

Acquisition and Georeferencing

We purchased the two historical aerial photos from IGM (Fig. 2). The two images have the same IGM standards (scale 1: 33.000, format 23×23 cm) to not incur in normalisation issues when processing the data. The images are panchromatic B/W. Georeferencing was done in QGIS, using as reference layer the latest orthophoto ATA available (2012–2013) from the Sistema Informativo Territoriale – Regione Sicilia. Georeferencing work takes into account distortion issues when working with old historical cartographic material (Wästfelt, 2019) and rectification problems with monochromatic and panchromatic aerial images (Ma et al., 2020; Ratajczak et al., 2019), due mainly to the lack of historical ground control information and the change in land cover between the two images. As ground control features to georeference the old image with the more recent orthophoto, we used the century-old olive trees on the hill that are visible in both the images (1955 and 2005).

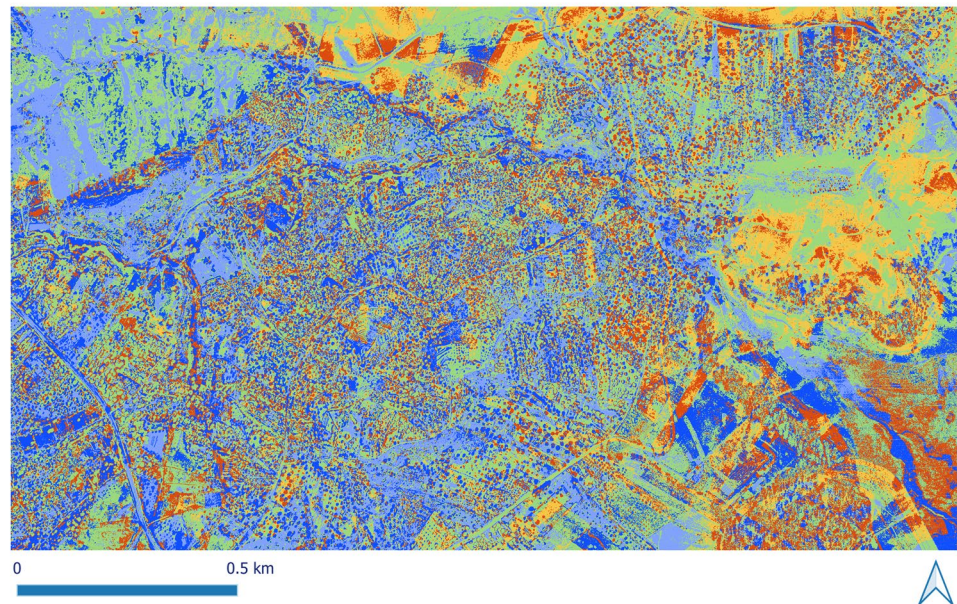
Unsupervised Classification Into Three (3) Classes with KMeans OTB

The two georeferenced images were classified using the K-means algorithm in Orfeo ToolBox (OTB). K-means is one of the simplest and most popular unsupervised learning algorithms. The main idea of the algorithm is to define a partition of N observations into K clusters in which each observation belongs to the nearest cluster (Barbu et al., 2012). K-means has also been used successfully to extract features from a raster that is not RGB or a satellite image (Herrault et al., 2013; Richards, 2013). KMeans OTB is an unsupervised image classification application available as open source. The unsupervised classification we performed in this step with the K-means algorithm is identifying natural groups, or structures, within the spectral data (our images).

Fig. 3 Change detection results shown as a raster product (change detection map)

Change Detection 1955 - 2005

- -2 vegetation cover (grass, crops) present in 1955, absent in 2005
- -1 vegetation cover (trees, shrubs) present in 1955, absent in 2005
- 0 no change in soil and vegetation cover
- 1 vegetation cover (trees, shrubs) present in 2005, absent in 1955
- 2 vegetation cover (grass, crops) present in 2005, absent in 1955



An unsupervised classification algorithm minimises human error during the clustering process since no prior knowledge about the study area is required to run the classifier (Ban & Yousif, 2016; Sapucci et al., 2021). In unsupervised classification, after the identification of pixels is made, each pixel is assigned to one of the class clusters desired, which, for this work, we have quantified in three (3) classes. Working with black and white images, since they were taken in May 1995 and May 2005, according to assumptions on the land cover during that month, we could at least cluster and distinguish between trees/shrub vegetation (black/dark in the aerial image), grasses/fallow and cereal crops (different shades of grey) and bare soil and concrete (bright grey, white).

The output of this step was two maps (one for the year 1995 and one for 2005) classified into three (3) classes, which have been visually interpreted to assess that the classes obtained represented in the real world the intended categories to be clustered (1. trees/shrubs; 2. grass/crops; 3. bare soil). The main species are:

- Class 1- trees/shrubs (*Rhus coriaria* L. and shrublands with predominance of thorny and deciduous species);
- Class 2- grasses/crops (grasses, fallow, and cereal crops).

Change Detection 1955–2005

We then performed a post-classification change detection on the two classified images, using map algebra image

differencing (Lu et al., 2004; Yang et al., 2018; Kumar & Arya, 2021). Very simply, image differencing subtracts the first-date image (1955) from a second-date image (2005), pixel by pixel or, in a post-classification framework (as is our case), class by class. Post-classification is a term describing the comparative analysis of spectral classifications for different dates produced independently (Singh, 1989). The output of our change detection has been a map (Fig. 3) that highlights the regions of the study area where changes (in terms of gain and loss) and no changes have occurred, per each of the classes extracted from the original aerial images in the previous step.

Accuracy Assessment

Accuracy assessment is very important and has become a standard component of any map derived from remotely sensed data. To evaluate the accuracy of the change detection done, the assessment followed the error matrix approach (Lu et al., 2004), which compares the relationship between the reference field data (ground truth) and the corresponding results of a classification. Among the methods used to collect ground reference data for assessing the accuracy of classification results (Jensen, 2005), we combined systematic sampling (observations are placed at equal intervals for each class) and a modified version of stratified random sampling (since in each of our class the minimum number of observations have not been randomly placed, being instead placed

thanks the visual interpretation and comparison between the two historical images and the most recent base map). For each class, we assigned one hundred (100) sampling points, and fieldwork was carried out to validate the photo-interpretation of the points. We combined methods because accuracy assessment for change detection is particularly difficult when related to past conditions not anymore present due to evident problems in collecting reliable temporal field-based datasets for changing classes (De Mûelenaere et al., 2014; Fatemi Nasrabadi, 2019; Lu et al., 2004). Such limitations require integration with ancillary data and other sources of information about the past conditions, as we integrate our analysis with visual interpretation in the accuracy assessment stage and with geonarratives later on.

Geonarratives as an Interpretative Approach

Despite the technical advances in extracting information from remote sensing products, what all the change detection approaches miss is the capacity to establish linkages between changes in land use or land cover and the contextual social-relational dimension. In other words, these methods can tell us and quantify what has changed, but they cannot tell us why (Pricope et al., 2019). For these reasons, to answer our research questions we adopted a dual approach (*sensu* van Dyke & Wasson, 2005; Lauer & Aswani, 2010; Wales et al., 2021), combining geospatial analysis in the form of change analysis done on/with historical aerial images and the use of alternative narratives of change/transformation in the form of geonarratives. These two geospatial techniques not only complemented each other, providing independent evidence for the observed trends, but we used the spatialised “narration” of change (geonarrative) as the primary “key” to access the past and understand more in-depth the mathematical representation of change/temporal dynamics done with the quantitative change detection.

We used historical aerial photography to detect land use change over a 50-year period, from 1955 to 2005. Then, we cross-referenced and integrated this information with local people’s geospatial perceptions and narratives of environmental and agricultural change to investigate how local people perceive and interpret the mapped land use changes and which narratives of change they give.

To further cross-validate and interpret the results obtained from the change analysis, we started from the overall assumption that geospatial knowledge is produced by practical engagement with the local context. For this reason, by “walking with” locals in the field and interviewing them, we elicited geonarratives that could better explain the transformation changes of land use, extracted and mapped thanks to the change detection analysis. Accordingly, we “walked with” (Bell et al., 2015; Evans & Jones, 2011; Kusenbach, 2003; Sundberg, 2014) local experts (small-holders, farmers,

TEK holders, etc.), conducting five (5) open and semi-structured interviews and one (1) group interview (with a group of four people), a typical accepted number in ethno-geographical studies of reduced populations (*cf.* Holloway, 2002; Paniagua, 2017). Interviews were collected within the framework of the LICCI “Local Indicator of Climate Change Impacts” project (Ferrara & Lindberg, 2023; Reyes-García et al., 2023). The place and its transformations over time was the central theme of the discussion (*sensu* Riley, 2010). We interviewed informants while they were working in the field (e.g., pruning, cutting grass, foraging). We collected the ecological memory these experts have on the local spatial configurations in the study area, asking also how they would interpret the results from the change detection. We also collected their tacit knowledge on native terms and their links to landscape, and their management practices in these agroecosystems.

Results

Results from Change Detection

Change detection can shed light on four important aspects: 1) detect if change has occurred, 2) identify and 3) quantify the nature of the occurred change, and 4) map the spatial patterns of change. The result of our change detection is a map (Fig. 3) showing both the spatial extent of positive (gain) and negative (loss) changes per each class (1. trees/shrubs; 2. grass/crops; 3. bare soil) between 1955 and 2005.

Class -2 (orange) represents the spatial extent of vegetation cover (grass and crops) present in 1955, but absent in 2005. It thus represents a loss of “old” grass and crop vegetation.

Class -1 (red) represents the spatial extent of cover in trees and shrubs, present in 1955, but absent in 2005. It thus represents a loss of “old” trees and shrub vegetation. Class 0 (light green) represent no change in both the categories of bare soil and vegetation cover, between 1955 and 2005. Class 1 (blue) represents the spatial extent of trees and shrubs cover present in 2005, but absent in 1995. It thus indicates new plantations, overgrowing and successional processes after abandonment. Class 2 (light blue) indicates the spatial extent of vegetation cover (grass and crops) present in 2005, but absent in 1955. It thus indicates regrowth processes or a new land use type for some areas.

Our change detection map is built upon spatial algebra operations (Fig. 4). The map product derived from a change detection analysis first gives information about the spatial extent of the presence, absence, and persistence of certain classes, all in the same image (Fig. 5). By visually comparing it with both the aerial images from 1995 and 2005, it is clear how Class 1 and Class 2 represent gains in 2005 (absent in 1995), while Class -1 and Class -2 represent features lost in

Classes from unsupervised KMeans	1955 ✓ presence X absence	2005 ✓ presence X absence	Map Algebra Image Differencing 2005 – 1955 =	Change Detection Classes
Grass/crops	✓	✓	No Change	Class 0
	✓	X	Change (from grass/crops to trees/shrubs or bare soil)	Class -2 Grass/crops present in 1955, absent in 2005
	X	✓	Change (from trees/shrubs or bare soil to grass/crops)	Class 2 Grass/crops present in 2005, absent in 1955
	X	X	No Change	Class 0
Trees/shrubs	✓	✓	No Change	Class 0
	✓	X	Change (from trees/shrubs to bare soil or grass/crops)	Class -1 Trees/shrubs present in 1955, absent in 2005
	X	✓	Change (from bare soil or grass/crops to trees/shrubs)	Class 1 Trees/shrubs present in 2005, absent in 1955
	X	X	No Change	Class 0
Bare soil	✓	✓	No Change	Class 0
	✓	X	Change (from bare soil to trees/shrubs or grass/crops)	Class 1 or Class 2
	X	✓	Change (from trees/shrubs or grass/crops to bare soil)	Class -1 or Class -2
	X	X	No Change	Class 0

Fig. 4 Spatial algebra operations behind the map product shown in Fig. 3

2005 (present in 1995). This is quite visible if we focus on the trees standing in the empty field in the 1995 image, then disappeared in the 2005 image, but equally shown as “absence” classes (thus in red and yellow) in the map product.

Change detection as a geospatial technique also allows calculation of change over a large scale by quantifying each class value in percentage of the total area covered by the change analysis (Table 1). In terms of negative changes (loss

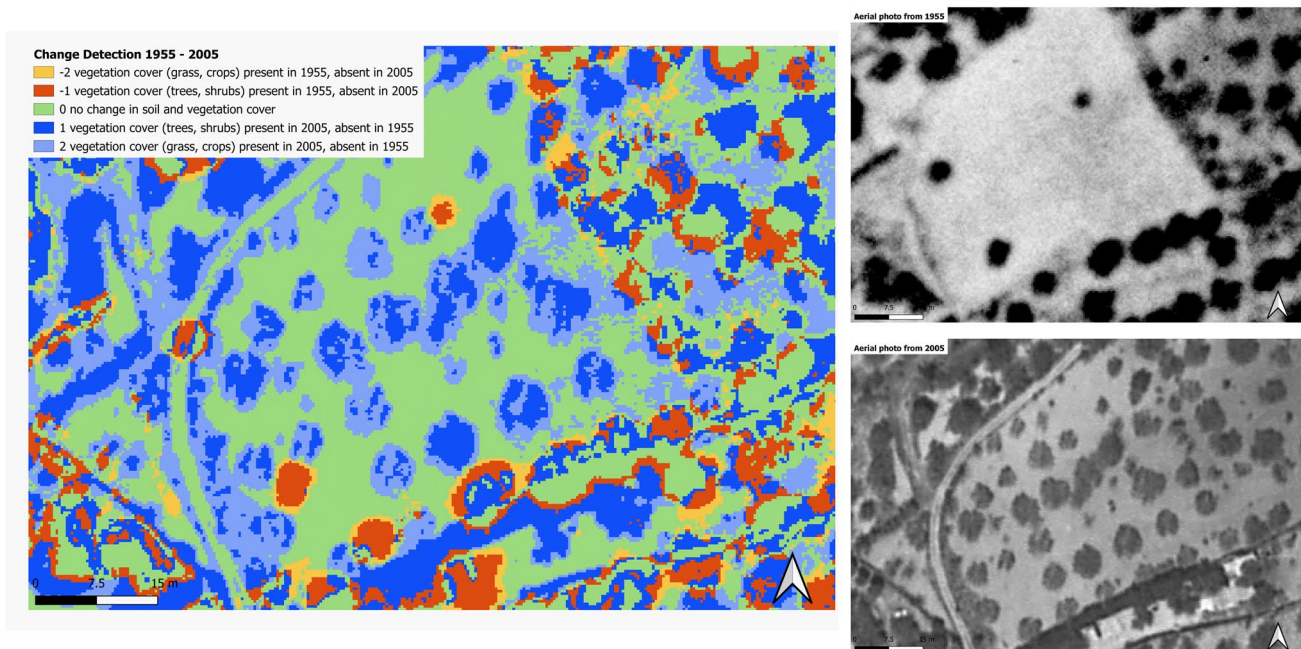


Fig. 5 Local detail of the larger raster product (cartographic map) result of the change detection analysis. Spatial objects in orange (Class -2) and red (Class -1) represent features present in 1995 but

absent in 2005, while spatial objects in blue (Class 1) and light blue (Class 2) represent features present in 2005 but absent in 1995. In green, the spatial extent is unchanged from 1995–2005

Table 1 Classes value in percentage of the total area covered by the change detection analysis 1955 – 2005

Class	% Value
C -2 Grass and crops present in 1955, absent in 2005	12.68%
C -1 Trees and shrubs present in 1955, absent in 2005	20.09%
C 0 No change in soil and vegetation cover	29.30%
C 1 Trees and shrubs present in 2005, absent in 1955	22.88%
C 2 Grass and crops present in 2005, absent in 1955	15.04%

of vegetation from 1955 to 2005), Class -2 (grass and crops) constituted 12.68% of the total area, while Class -1 (trees and shrubs cover) was 20.09%. If we sum both the values, we have a total negative change (loss of vegetation) equal to 32.77%. The positive changes are respectively equal to 22.88% for Class 1 (trees and shrubs cover) and 15.04% for Class 2 (grass and crops), for a total of 37.92%. The area that has not changed corresponds to 29.30% of the entire surface. On a scale from larger to smaller, results from change analysis show that positive changes (new vegetation cover) have the largest spatial extent (37.92%), followed respectively by negative changes (loss of vegetation, 32.77%) and finally by the surface not affected by change (29.30%).

The accuracy assessment gives an overall accuracy of 81.4% derived from the sum of correctly classified pixels (assessed with validation points, Fig. 6) divided by the total

number of validation points (Fig. 7). The minimum overall accuracy for performing a change detection analysis based on mapping products should be above 85% (Anderson et al., 1976; Kefalas et al., 2018; Thomlinson et al., 1999). However, considering that we are working with panchromatic (B/W) images more difficulties may arise in the validation process of change analysis performed with historical aerial images. For this reason, we believe that an overall accuracy of 81.4% could be considered acceptable in this case.

Results from Geonarratives: From Interpretation to Discovery

Our results from change detection analysis are essentially quantitative. Our “walking with” interviews, however, provided data on the relation that people and place have had over time, thus allowing interpretation of the patterns of spatial change in light of past practices. Our informants were able to interpret changes in the study area and give qualitative descriptions of the dynamics in the period of 1955–2005. Some of the interviewees were able to readily identify the trees no longer visible in the 2005 image as fruit trees in 1955. They were also able to specify the varieties (*Pyrus pyraeaster* L. (Burgsd.), *Punica granatum* L., *Crataegus azarolus* L., *Prunus spinosa* L. subsp. *spinosa*, etc.), while pointing out some sprouting in a plot where no tilling

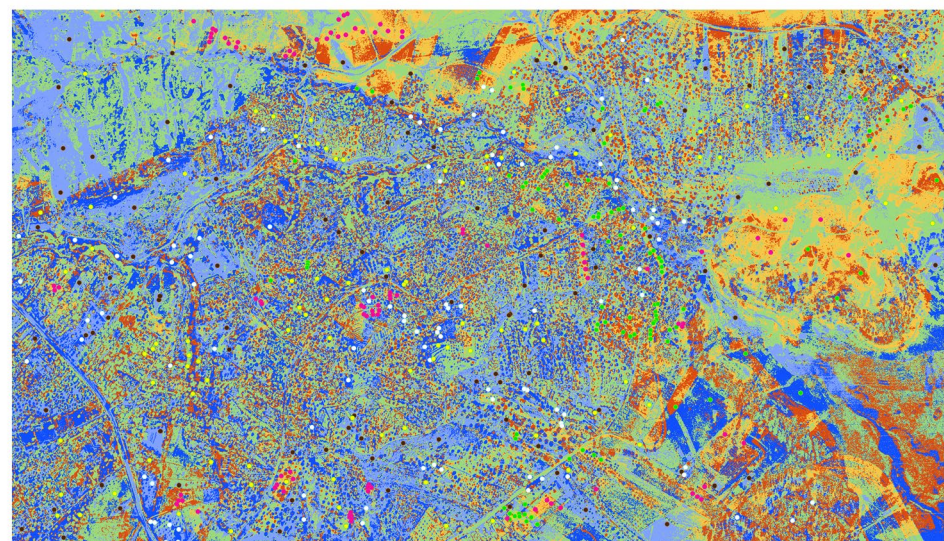
Fig. 6 Raster product (cartographic map) showing the location of the validation points used to assess the accuracy of each class of change/no change detected

Change Detection 1955 - 2005

- -2 vegetation cover (grass, crops) present in 1955, absent in 2005
- -1 vegetation cover (trees, shrubs) present in 1955, absent in 2005
- 0 no change in soil and vegetation cover
- 1 vegetation cover (trees, shrubs) present in 2005, absent in 1955
- 2 vegetation cover (grass, crops) present in 2005, absent in 1955

Accuracy assessment - validation points

- Class -2
- Class -1
- Class 0
- Class 1
- Class 2



0 0.5 km



Classes	C -2	C -1	C 0	C 1	C 2	Total reference point
C -2 Vegetation cover (grass, crops) present in 1955, absent in 2005	78	2	12	3	5	100
C -1 Vegetation cover (trees, shrubs) present in 1955, absent in 2005	1	69	8	22	0	100
C 0 No change in soil and vegetation cover	1	14	65	16	4	100
C 1 Vegetation cover (trees, shrubs) present in 2005, absent in 1955	0	1	1	96	2	100
C 2 Vegetation cover (grass, crops) present in 2005, absent in 1955	0	0	1	0	99	100
	80	86	87	137	110	500
Total correct reference points	407					
Total reference points	500					
Percent accuracy (%)	81.4					

Fig. 7 Error matrix used to calculate and assess the accuracy of the change detection results

has been practised during recent years (allowing regrowth of “old” vegetation) (Fig. 8).

According to our informants, these fruit trees were abandoned, or allowed to die and/or removed because their fruits became inedible or because of the work needed to take care of them. The only trees present in both images (1955 and 2005) were identified as olive trees several centuries old. They have been maintained for both cultural and economic reasons: interviewees reported that it was inconceivable that anyone would remove an old olive tree because they are considered a “productive” heritage, always producing sufficient olives to provide olive oil for household consumption. For open fields and grasslands, our interviewees identified both overgrowth because of land abandonment and more cleared fields caused by the widespread use of tractors and agricultural machines.

By interpreting and integrating the results from change detection with geonarratives, a deeper understanding of landscape changes as an apparent progression from an agricultural system resembling the agroforestry model (or

characterised by polyculture in terms of variety and intercropping of tree species) to a near monoculture of olive trees, marked in some places by overgrowth/successional processes resulting from the abandonment of previously worked areas. According to our informants, the reason for the abandonment of certain types of fruit trees can be explained by market trends, changes in lifestyle, and, above all, by the fact that nobody wants to work the land anymore. The abandonment of the farming practices also accounts for the increase in successional vegetation processes.

Discussion

The integration of the results obtained from the change detection analysis with local geonarratives of change provides a picture of the study area as having undergone considerable change between 1955 and 2005 (approx. 29.31% VS 70.70%). When we assess the change dynamics of gain and loss, we see more positive than negative changes (more



Fig. 8 Local disappeared tree species, resprouting again due to prolonged no-tilling by the landowner in a field of the case study area. In order, from the left: *Sorbus domestica* L., *Pyrus pyraster* L. (Burgsd.) young, *Prunus spinosa* L. subsp. *spinosa* young

new grass, crops, and trees/shrub vegetation in 2005 than in 1995, respectively $\sim 37.92\%$ in gains VS $\sim 32.77\%$ in losses). Moreover, the trees and shrubs component of the vegetation cover remains predominant, if compared with grass and crops, for both years: $\sim 20.09\%$ V $\sim 12.68\%$ in 1995, $\sim 22.88\%$ VS $\sim 15.04\%$ in 2005. In the study area, grassland and crops have always been secondary to trees and shrubs.

Local geonarratives helped interpret these figures: the area has always been a place for arboriculture, in the past more variegated, resembling an agroforestry system, which has since been transformed into a monoculture of olive trees. Our informants indicated that farmers “naturally” selected species to keep cultivating and those to abandon, not replaced by other crops. The loss of certain fruit trees has been compensated, in terms of the overall quantity of vegetation cover, by the increased presence of new planted olive trees and the successional regrowth of shrubs (*Rhus coriaria* L., predominantly thorny and deciduous shrublands) in areas no longer cultivated. The increase of woody formations at the expense of agroforestry systems (La Mantia et al., 2008; Rühl et al., 2011) and agricultural areas (Bazan et al., 2019) has been a widespread dynamic in Sicily, connected with agricultural intensification in certain areas and the migration of rural populations after the II World War in other areas of the island. Our study area has a history of feudal exploitation of peasants and terrible working conditions in sulphur mines, which was not reversed by the abolition of the latifundia and the subsequent redistribution of small plots in the 1950s. The simultaneous collapse of the sulphur sector provoked an intense migration flow, which continues today.² Even though there has been a change in the ownership regime (from the “baron” in the latifundia system to the individual peasants owing small plots of land), this has not influenced potential crop concentration dynamics in the study area for two main reasons. Crop concentration dynamics in Sicily have responded to intensive agriculture strategies, pursued in locations of the island with a particular interest in local entrepreneurship. This has not been the case in the study area, which instead experienced significant out-migration from the 1950 of those peasants and mine workers attracted by higher wages and better working conditions in Belgian mines or in German industries that became available after the Second World War (Ferrara, 2005).

In Cozzo del Lampo, tree dynamics have been a primary driver of landscape modification, with certain species of trees maintained (specifically olive), others abandoned (e.g., wild pear, pomegranate, Mediterranean medlar, sorb trees), and regrowth of shrubs and other vegetation after abandonment,

as has been happening elsewhere in Mediterranean Europe (Amici et al., 2015) and worldwide (Khoury et al., 2022). These phenomena can be read through the lens of the progressive reduction and simplification of the agricultural practices, a consequence of partial land abandonment caused by the absence of population and the adoption of heavy tilling practices by those who remained. As such, the progressive loss of local biocultural heritage is linked to the erosion of both the biological heterogeneity of the system and the disappearance of cultural practices connected to the maintenance of such diversity (cf. La Mantia et al., 2011). Other scholars (e.g., Paniagua, 2017) have refocused on what is maintained as a symbol of resistance and adaptation. The cultivation and maintenance of traditional orchards, the continued traditional use and management of forests, and the maintenance of old rural routes, traditional houses, and public spaces of villages, are all examples of everyday resistance in rural depopulated areas and marginal spaces. Here again, a strong component of biocultural heritage is connected to the human choice of what to “save” or what to “hand down” to the next generation. In both narratives, abandonment and resistance, the choice and maintenance dimension is the key, driven by local adaptation strategies made of several different practices and material choices. Our research shows that tree and shrub vegetation dynamics are a primary drivers of landscape modification in the study area. Nevertheless, if we focus on what is maintained (the olive trees), it becomes clearer these dynamics are less dependent on human disturbance but rather are related to the ecological features of the trees themselves. The strong genetic stability and the high variability of locally adapted heterogeneous landraces of olives (*Olea europaea*), further propagated by self-rooting organs and human grafting practices with the wild olive, have ensured their adaptation to different pedoclimatic contexts of the island over the long term (Marchese et al., 2023). An important auto-ecological feature of *Olea europaea* is the high vegetative resilience of its stumps, able to resist and re-sprout even after prolonged disturbances (e.g., fires, human damage, climatic stress), thus maintaining a dynamic link with the natural and endemic vegetation in an area (Blasi et al., 1997; Connor, 2005; Petrocelli et al., 2003; Rühl et al., 2011; Salbitano, 1992). Our case study shows that the specific species kept and maintained (*Olea europaea*) is the most resistant to external ecological disturbances in the area. In addition, the domesticated olive is easier to manage than other species of fruit trees (c.f. Gucci & Caruso, 2011; Tadić et al., 2021). The maintenance of the olive tree as an agricultural system requires little effort and minimum inputs (with the main crucial activity protection from wildfires), above all if compared with the outputs that can be derived in terms of fruits and biomass production (and today carbon storage as well).

While considerations of human disturbance dynamics are essential to understanding the biocultural heritage formation

² As reported by the Fondazione Migrantes in their annual report, the incidence migration rate in 2022 for the town of Villarosa was 151.4% (Ferrara and Lindberg, 2023).

process, our work shows how the autoecological features of certain species are crucial to understanding that what we define as cultural and culturally maintained has instead an ecological solid foundation. If we consider plants as anthropological actors, we can use botanical and ecological perspectives to understand human actions (Shepard & Daly, 2022). At the same time, by engaging local populations in interpreting their own (past-present) practice, they become active agents in the co-production of *ecological* knowledge beyond the simplistic use of local expert knowledge for triangulation (cf. Fazey et al., 2006; Vandermeer & Perfecto, 2013). We used geonarratives as building blocks of geospatial semantics (cf. Norwood & Cumming, 2012), in the sense that we methodologically used first space and then “walking with” interviews with locals to understand interactions of place, people, and the environment (Riley, 2010).

Conclusions

Our research combines mathematical representation of spatial change with oral narratives of land use and landscape transformation to better understand what can be considered as biocultural heritage in a rural area of inner Sicily characterised by the longstanding presence of centuries old olive trees and progressive alarming depopulation trends. Results from spatial analysis with remote-sensed data may facilitate the production of symbolic representations of geographic space (Yuan, 2020a). Most of these representations remain quantitative and thus have clear limitations for the identification and understanding of ongoing dynamics and causality, since they lack context in both time and space. To reach a semantic shift and qualitative interpretations, we included other perspectives provided by geo-narratives, which can allow us to better understand the dynamics underlying georeferenced representations of spatial phenomena. This is particularly important in the case of land use practices, in which spatial patterns of vegetation observable from aerial sensors are the representations of human-nature interactions and human intentionalities in adapting to an environment and crafting agroecosystems in it.

Thanks to this combined methodology, we have been able to identify the relational dynamics between people and place over fifty years, and understand that biocultural heritage is correlated to both social and cultural aspects, as well as ecological components of the local context. Starting from the assumption that spatial patterns are the expression of transformation processes, where the spatial variation of human activities is a significant disturbance element in driving different temporal trajectories of change in a landscape, our research identified and illustrates that what has been locally defined as culturally (thus intentionally) maintained, has instead a strong ecological foundation that is grounded in the genetic and eco-physiology of the key local species, *Olea europaea*.

Even though our work is based on a single case study, we have demonstrated the value of incorporating ecological and botanical

perspectives to facilitate the understanding of past-present human actions. At the same time, the active involvement of local individuals in the narration and interpretation of their own (past-present) practice is key to access new dimensions of ecological knowledge. We recommend that future research in this field be directed to exploring the applicability of our approach and methodology in other geographical contexts of Mediterranean agroecosystems.

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Author Contributions All the authors have equally contributed to the conceptual developed of the manuscript, as well as to data collection. V.F. conducted the spatial analysis, then reviewed by G.S. and T.L. All the figures have been prepared by V.F. All authors reviewed the manuscript.

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Availability of Data and Materials The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request. Data are located in controlled access data storage at Uppsala University.

Declarations

Ethical Approval Data collection through oral interviews was realised within the framework of the ERC project “LICCI. Local Indicator of Climate Change Impacts” (FP7-771056-LICCI) and conducted according to Uppsala University and its Department of Archaeology and Ancient History compliance procedures to the *CODEX Rules and Guidelines for Research* (<http://codex.vr.se/en/omcodex.shtml>), the Swedish Research Council’s (VR) Guidelines for Research Ethics (<https://publikationer.vr.se/produkt/goodresearch-practice/>), the Swedish Research Council’s Guidelines related to the law “Knowing the ethics of research involving humans” (http://www.riksdagen.se/sv/Dokument-Lagar/Lagar/Svenskforfattningssamling/Forordning-20071068-med-ins_sfs-2007-1068/). We collected the free, prior, and informed consent of all participants before starting the survey.

Competing Interests The authors declare no competing interests.

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