Charcoal Kiln Detection from LiDAR-derived Digital Elevation Models
Combining Morphometric Classification and Image Processing Techniques

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Abstract

This paper describes a unique method for the semi-automatic detection of historic charcoal production sites in LiDAR-derived digital elevation models. Intensified iron production in the early 17th century has remarkably influenced ways of how the land in Sweden was managed. Today, the abundance of charcoal kilns embedded in the landscape survives as cultural heritage monuments that testify about the scale forest management for charcoal production has contributed to the uprising iron manufacturing industry. An arbitrary selected study area (54 km²) south west of Gävle city served as an ideal testing ground, which is known to consist of already registered as well as unsurveyed charcoal kiln sites. The proposed approach encompasses combined morphometric classification methods being subjected to analytical image processing, where an image that represents refined terrain morphology was segmented and further followed by Hough Circle transfer function applied in seeking to detect circular shapes that represent charcoal kilns. Sites that have been identified manually and using the proposed method were only verified within an additionally established smaller validation area (6 km²). The resulting outcome accuracy was measured by calculating harmonic mean of precision and recall ($F_1$-Score). Along with indication of previously undiscovered site locations, the proposed method showed relatively high score in recognising already registered sites after post-processing filtering. In spite of required continual fine-tuning, the described method can considerably facilitate mapping and overall management of cultural resources.

Keywords: charcoal kilns, automatic feature extraction, LiDAR, morphometric classification, Hough Circle transfer
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List of Abbreviations

AFE – Automated Feature Extraction
ALS – Airborne Laser Scanning
DEM – Digital Elevation Model
GEOBIA – Geographic object-based image analysis
GIS – Geographic Information Systems
GNSS – Global Positioning Satellite Systems
LiDAR – Light Detection and Ranging
SVF – Sky-View Factor
TO – Topographic Openness
TPI – Topographic Position Index
sv. – in Swedish
1. Introduction

Archaeological knowledge about the past is almost exclusively limited to empirical evidence embedded in the landscape. Understanding processes behind archaeological heritage is subjected to interdisciplinary research concerning diachronic development of human engineered environment. As a rule of thumb, key to assess anthropogenic impact upon past environments rests in the evidence rooted in the very same physical landscapes (Fisher et al., 2016). It is also within the same breadth of exploratory inquiry to invoke judicious approaches in employing appropriate information that describes spatial as well as temporal qualities of the studied landscapes (Chapman, 2006; Gillings, 2012). By accounting these elements, comprehensive effects occur in generating reciprocal knowledge: archaeological landscapes act as objects that are continuously re-established through contextual remapping (Hicks, 2016). Although such epistemological engagement sheds new light on how the past is being analysed and eventually perceived, it also challenges archaeologists to employ far-reaching methods in keeping up with the analytical technologies.

Geographic Information Systems (GIS) together with techniques in Remote Sensing are ubiquitous in archaeological research and comprise of a variety of applications within the discipline and beyond. In studying past landscapes at the present, analysis and interpretation of terrain relies on spatial elements of various scales that require appropriate tools to be investigated. As a result, over the past thirty years GIS applications have tremendously increased within the archaeological research agenda and have become a prerequisite in data analysis routine (Ashmore, 2002; Howard, 2007; Dell'Unto, 2016). Moreover, an important aspect of GIS-based data implementation is data visualisation, which serves well as a tool to present visually interpretable information (Katsianis & Tsipidis, 2005; Nygren et al., 2014). Over the past decade, airborne light detection and ranging, more commonly regarded as LiDAR or ALS (Airborne Laser Scanning), has become a well-established resource utilised to enhance spatial knowledge of the archaeological and cultural landscapes (Johnson & Ouimet, 2014). The current state of art in laser scanning technologies provides below-metre resolution elevation models derived from LiDAR data and grants investigators with availability to interrogate archaeological landscapes using ever developing methods.

This research paper investigates the methodological scope of archaeological feature detection and extraction from LiDAR-derived digital elevation models (DEMs). Based on the premises of GIS analysis and image manipulation techniques, the proposed method intends to present only a conceptual framework which facilitates identification and quantification of charcoal kiln sites with their general characteristics prevailing in central Scandinavia. Nonetheless, this applied approach provides enough room to be modified and adopted to different topographic settings and/or objects of interest other than analysed in the pilot area located in the southern Gävleborg region, Sweden. It is also worth noting that the archaeological context describing charcoal kiln sites only acts as an explanatory background; the analysis and discussion fully focuses on GIS and analytical image processing techniques.
In seeking to address these intentions this paper was subdivided into five logical parts which guide the reader through the course of different research stages. This section further develops background information associated with the current state of art for LiDAR use in archaeological practice as well as delineating motivation and goals to be achieved for this research project. Subsequently, in the second part research materials and methods are underpinned by the rationale of techniques adopted in this study. Obtained results are succinctly presented in the third section, which effectively serves as a starting point in drawing inferential notions. In the fourth part, such ideas are critically examined and discussed on a multi-scale level by additionally providing directions for further research of similar nature. Finally, the closing section draws collective implications of the coalesced ideas and concludes the research paper.

1.1 LiDAR in archaeological practice

Archaeological research revolves around temporal and spatial data; therefore, advancements in either parameter can act as a breakthrough in methodological inquiry. Historically, aerial photography has been the first and the foremost remote sensing technology commonly used for surveying archaeological remains observable on the terrain surface as well as for detecting archaeological arrangements below the ground through the reconnaissance of the so-called "soil" or "crop marks" (Bourgeois & Meganck, 2003). However, for many archaeological applications even modern very high resolution satellite or aerial imagery (including multispectral data) are eminently limited to feature detection in dense vegetation as well as exposing subtle changes in topography, which might be associated with remnants of anthropogenic activity of certain interest. Chase et al. (2012) link advances in LiDAR technology to a paradigm shift in archaeological inquiry that changes ways of surveying and introduces novel means of interpretation of already known sites. Point cloud data acquired over the large areas represent a complex assembly of anthropogenic landscape change that comprises of sites and also the spaces between them (Cherry, 2003). Hence, it generates the presence of ‘big data’, which in studying and understanding the past signifies that archaeology as a discipline has finally entered its own discovery epoch by immersing into a geospatial realm (Fisher et al., 2016). Moreover, it provides unprecedented ways of analysing and preserving archaeological resources that already revolutionise prospects of the broader cultural resource management.

ALS-derived data together with systematic surface surveys can effectively collaborate in drawing a comprehensive picture of the cultural evolution of past landscapes. Both practices already offer significant relationships on aspects of archaeological surveys that have been scarcely analysed in Europe, including the Scandinavian region. In particular, Swedish and Norwegian archaeologists are starting to work in partnership with industries that interfere with cultural resource management policies by employing national LiDAR datasets (Swedish National Heritage Board, 2014). Yet, tendencies suggest that such proceedings have not fully leveraged the collaborative potential of large-scale relationships. When posing questions about any type of archaeological remains, the central issue begs for the definition of its complete spatial distribution across the landscape, what in turn helps to establish coherent relationships to its immediate as well as wider environs. This is the aim of several
collaborative research projects that have been carried out during recent years in Sweden and Norway. Risbøl et al. (2013) provide an in-depth examination of factors that impact identification of archaeological objects observable in LiDAR-derived hill-shaded DEMs over the forested areas of south-eastern Norway. By comparing remotely sensed analysed data with physical terrain survey results, Risbøl et al. (2013) established that LiDAR data resolution and archaeological object size as well as the state of preservation play key roles in successful ALS data interpretation. Another solid example incorporates collaboration between forestry research institute and Dalarna county administrative board in Sweden. Willén & Mohtashami (2017) present an elaborate report by establishing wide-ranging framework of methods in LiDAR data processing and visualisation in seeking to integrate interpreted cultural heritage locations into forestry operational planning to minimise damage during forest logging. The report encompasses case studies by including a variety of different archaeological structures located across the country being analysed involving enhanced morphological elements of the terrain (morphometric variables) that indicate potential site shapes and locations. Although these examples together with many other of similar nature portray a significant and influential move towards integrated task management, there still exists a tremendous methodological gap in exercising massive ALS datasets for factual demands of cultural resource management.

1.2 Automated feature extraction

For general use of LiDAR in the archaeological framework, shaded relief digital elevation models are frequently used for object location and delineation. However, in seeking to process ever increasing amounts of spatial datasets by utilising GIS-based analyses, the development and applicability of automated feature extraction (AFE) techniques originating in the field of computer-based image processing are being successfully adopted for archaeological purposes (Hesse, 2010; Luo et al., 2014). Hence, two major trends are showing parallel progress in the current advancement: raster manipulation-based analysis and geo-object-based image analysis (GEOBIA). Prior either analytical procedure, it is important to note that final outcome inevitably relies upon the LiDAR point cloud quality and the way bare ground elevation rasters are compiled. This notion is well scrutinised in the early literature of DEM creation for archaeological purposes using airborne laser scanned data (e.g. Doneus et al., 2008; Chase et al., 2011). The processing routine further includes key DEM pre-building blocks such as vegetation filtering and removal of outliers, which play a significant role in decreasing false positive detections in an ongoing processing (Evans & Hudak, 2007).

Within the scope of raster manipulation-based analytical approaches two techniques are commonly employed. Detection of anthropogenic objects in LiDAR-derived datasets has been majorly subjected to template-matching techniques utilised within image processing and GIS environments. The concept is based on the fact that regular geometric features (straight lines, squares or circles) seldom occur in the natural landscape and thus can be associated to human-built objects. Studies on detecting burial mounds in the Netherlands (De Boer et al., 2008), prehistoric hunting pits it Norway (Trier & Pilø 2012) and charcoal kilns in Germany (Schneider et al., 2015) indicate that manually created templates of desired
objects generally provide adequate amount of true positive matches. Nevertheless, template matching highly depends on the feature size-raster spatial resolution ratio, the state of object preservation and, most importantly, its topographic position; planimetric feature shape changes based on the slope. Moreover, it is often common to investigate features that range in size or contain shape irregularities, what makes template matching algorithmic framework rather complex and inflexible for broader adaptability (Cowley, 2012).

A rather different set of approaches that utilises raster geo-processing techniques encompasses classic geospatial toolsets incorporated in a much more versatile object recognition routine used for archaeological purposes. Riley (2009, 2012) successfully developed a two-step method that combines calculation of terrain morphometric variables from LiDAR-derived DEM to detect archaeological anomalies in terrain represented as conical burial mounds in Iowa and Minnesota states, USA. The established focal range, aspect and slope rasters are combined and areas of interest are ruled out according to a pre-set thresholding algorithm that assesses object fit to a specified collective morphometric range. Another technique explored by Hanus and Evans (2015) effectively exploits the ‘Fill sinks’ hydrological tool found across most of the conventional GIS software packages in seeking to delineate artificial water reservoirs in the ancient Greater Angkor region, Cambodia. Similarly, Freeland et al. (2016) present a study in determining burial mound structures in a complex Tonga archaeological landscape located in the Western Polynesia. The sink filling algorithm was effectively employed for positive feature identification in the landscape by subtracting filled DEM from previously inverted original DEM, which resulted in raster highlighting areas of the earthwork structures.

The very same study (Freeland et al., 2016) chose to compare the results attained from the inverted sink filling algorithm to GEOBIA scheme applied over the same area of interest. In seeking to discern and extract circular mounds, the investigated area was effectively segmented using scale, shape and compactness weighted parameters and a set of rules (GEOBIA features) were subsequently applied. Although inverted sink filling method demonstrated better overall accuracy, GEOBIA provided significantly less false positive returns with the same precision measures. Object-oriented analysis of LiDAR-derived DEMs also proved to be a reliable method in the very recent study carried out by Cerrillo-Cuenca (2016), who applied sophisticated geo-processing and AFE scheme to extract prehistoric circular burial mounds in Extremadura region, Spain. The method includes establishing two morphometric properties from the DEM: unsphericity curvature (Florinsky, 2012) and topographic position index (Weiss, 2001) followed by proceeding of raster image segmentation and Hough circle function (Duda & Hart, 1972), which detects and delineates predicted sites of interest. Again, authors implementing GEOBIA remark that the effectiveness of such rigorous technique directly depends on the DEM spatial resolution and objects' state of preservation; small object size, natural erosion effects or modern alterations of earthworks show significant sensitivity to the analysis.
1.3 Impetus for research

The increasing development of infrastructure and land use more than ever challenges the management of historic heritage objects that today are seen and perceived as part of the landscape. As such, the advancement of transport, housing, forestry and energy industries have particularly raised demands for archaeological resources to carry out necessary inventories and meet the legislative requirements (Cultural Heritage Act, 1988). The legal protection is automatically granted to ancient monuments since the time of discovery, although in most of the cases the official proceedings follow only when the area of interest is under development. As a rule, given such circumstances the scope and diversity of archaeological assessments take considerable amount of time and resources (e.g. Hesse, 2012; Trier & Pilø, 2012).

Limited knowledge about the distribution of cultural heritage sites directly relates to the methods used in archaeological survey. Mapping of cultural remains in forested areas are generally based on manual walk-over surveys by archaeologists. Although such survey technique provides rigorous on-site evaluations, only small areas can be covered in a short time and large areas prove to carry a high price tag. The resulting inefficiency and recognition of the need for more effective approaches have encouraged the archaeological community to seek for wider-scope reconnaissance techniques in the field of remote sensing (Jansson et al., 2009; Doneus & Briese, 2011). Effectively, LiDAR technique serves to be the prime means not only for mapping densely vegetated ground surfaces with high three dimensional accuracy, but also establishing novel approaches to distinguish and analyse desired features across cultural landscapes (Chase et al., 2012; Alexander, 2013a,b). In turn, LiDAR data availability in Swedish territories allows establishing an adopted working framework in seeking to account quantitative methods for mapping cultural remains.

In line with above mentioned aspects of ongoing cultural heritage management practices, historic charcoal production sites constitute as valuable testimony of land use history that pertain to a huge array of unidentified and neglected objects. To date in Sweden, systematic mapping of charcoal kiln site distribution for large areas was hardly attempted and the contextual framework is therefore limited to scattered single sites. Spatial delineation of kiln sites within large areas would, therefore, provide more information and further impetus for contextual reconstruction of historic forest management and land use in general. Hence, the heritage sector requires adopting efficient and cost-effective methods for detecting and monitoring different types of cultural remains.

1.4 Historical and archaeological context

A great number of cultural remains in central Sweden indicates an intensive and wide-ranging human exploitation of forested areas throughout the Iron Age (500 BC—AD 1050), medieval (1050—1550) and historic periods (after 1550) (Rydén & Ågren, 1993; Skogsstyrelsen, 2003). In most cases the remains of altered terrain found within forested landscape are associated to exploitation of the forest biomass as a fuel since the Iron Age
Over centuries, growing demands for charcoal production have had a colossal impact on overall forest management which was directly influenced by increasing manufacturing of iron. Fuel was as important as ore for the iron industry and constant endeavours of its procurement were a global topic of concern (Hammersley, 1973). Until the use of fossil coal became prevalent from the early 19th century onwards, considerable amounts of charcoal were in need to be supplied for the blast furnaces in seeking to achieve sufficiently high temperatures when smelting raw iron (Ågren, 1998). Since ca. early 17th century charcoal production sites in central Scandinavia are generally characterized by circular platforms that were levelled for kilns (sv. kolbottnar efter resmila) constructed out of vertically stacked timber trunks and covered with turf for a controlled charring process of the timber (Fig. 1a) (Samuelsson, 1997; Jensen & Liases, 2003; Risbøl et al., 2013). Among other type of charcoal kiln composition methods, vertical arrangement allowed using smaller diameter trunks, which in effect revolutionised charcoal production management in terms of easier kiln assembly and reduced charring time (for wider discussion refer to: Eriksson, 1996; Bringéus, 2003). After dismantling kilns to collect the produced charcoal, the site geometry formed a distinctive circular earthwork shape varying in outer diameter from 14 to 26 metres and rising from 0.5 to 1 metre above the ground with a pronounced dip in the centre (Fig. 1b). According to documented accounts, small-scale practices of charcoal fabrication using such technique have lasted until the late 1940’s in some parts of Sweden (Hennius et al., 2005).

Figure 1. a) Profile sketch of charcoal kiln in operation (adapted from http://www.kulturarvostergotland.se), b) photograph of barely noticeable kiln remains in the forested landscape.
Archaeological records of excavated charcoal kilns (sv. *resmilor*) contribute by yielding a range of invaluable information that helps for studying these sites. Although it is seldom that material culture (artefacts) is uncovered in such setting, archaeological recording methods provide insights about structural composition of these earthworks. Figure 2 illustrates an exemplary cross-section model that involves typical stratigraphic arrangement of *resmila*-type kilns (e.g. Hennius *et al.*, 2005; Forenius & Lindberg, 2016). Beyond basic establishment of stratigraphy, samples of charcoal allow investigating and determining the species of timber used in particular kilns as well as radiocarbon $^{14}$C dating (Björck & Ulfhielm, 2011; Hennius *et al.*, 2005). In most cases kilns belong to a wider arrangement of structural remains associated with charcoal production logistics, such as workers’ huts (sv. *kolarkojor*) and transportation trails (Stenbäck Lönnquist & Welinder, 2011; Ulfhielm, 2012). These production areas are occasionally referred in historic maps; however, in order to re-build a complete picture of dynamic forest management in the past, multilevel information inputs are required. Establishing distribution patterns of charcoal kilns is therefore a key element in such process. General observations characterize moderate degradation of the earthworks mainly due to vegetation or forest machinery interference, albeit very little work has been done yet on quantifying the state of charcoal kilns’ preservation (Rösler *et al.*, 2012; Risbøl *et al.*, 2013).

![Figure 2. An example of typical cross-section of *resmila*-type charcoal kiln with its characteristic setting of deposited layers (own work).](image)

**1.5 Study area**

An arbitrary selected study area (54 km$^2$) is located south of E16 highway between Storsjön Lake and national road A56, around 20 km south-west from Gävle city (Fig. 3). Most of the area falls within Gävle municipality extent, yet the western fringes of the area bounds also include territory that belongs to Sandviken’s municipality. The selected area of interest provides diverse terrain setting ranging from densely forested rugged terrain to open marshlands and various sizes of urban spaces. The territory already contains 55 charcoal kiln *resmila*-type sites registered by Länsmuseet Gävleborg archaeologists and can be found in the Swedish National Heritage Board database *Fornsök* (https://fmis.raa.se). It is, however, not all sites that still survive intact or have been entered in the records using
precise positioning systems, such as GNSS. Nevertheless, a number of undiscovered sites can be manually identified from simple slope or hill-shaded digital maps. It is also arguable that the abundance of charcoal kilns in the area may have been associated with Mackmyra ironworks, established in the 16th century and situated few kilometres north of the study area bounds (Andersson, 2000).

1.6 Study aim and objectives

The discourse of this research project is based on the knowledge gaps in the quantitative measures of charcoal kiln spatial distribution and available techniques for those gaps to be filled. As the focal aim of this investigation, this study serves to establish an adopted methodology based on a sequential chain of geo-processing tasks followed by image segmentation and shape recognition techniques in seeking to detect, extract and validate charcoal kiln sites from the LiDAR data. For such multifaceted aim to be achieved, a number of study objectives have been identified. By presenting a series of data processing techniques and examining their utility as well as potential caveats in their application, the first and foremost objective is set to determine best suitable data processing pathways adopted for the studied landscape characteristics. As such, a great amount of different variables and parametric adjustments may certainly influence the course of data processing and indeed the final outcome. For this reason, proven current research approaches are invoked from other
similar studies to shape the project agenda in a selective manner, providing enough of room for analytical and comparative examination of techniques selected for this investigation. This approach directly defines a second challenge to be addressed and adequately overcome. Since multi-level data processing can impact recognition performance of charcoal kilns, an important objective of the proposed method is to determine the success of the used techniques by comparing predicted locations with the ones where archaeological sites have been previously verified. A well-balanced research framework allows building constructive project environment, where officially confirmed charcoal kiln sites would serve as objects for stochastic validation of employed methods to detect predicted charcoal kiln sites. It is also within the interests of this research to identify and account any issues and conceptual drawbacks that emerge along the course of this project.
2. Materials and Methods

The research methodology was explicitly designed in seeking to achieve previously defined goals of this study. In effect, the nature of this research employs inductive reasoning based on the present archaeological evidence, data that characterize physical features in the landscape and analytic geospatial knowledge. These elements altogether serve as meaningful building blocks in the proposed methodology, which involves a number of operational phases. In this section, both the data and its processing steps are respectively described below following procedural order.

2.1 Used materials and software

LiDAR dataset files in LAS 1.2 standard format acquired from geographic data domain administered by the Swedish University for Agricultural Sciences (Geodata Extraction Tool, https://maps.slu.se/get) served as parent dataset forming foundational component of this study. The national LiDAR dataset belongs to the Swedish National Land Survey agency Lantmäteriet and is freely available for research purposes at Swedish universities. The LAS files covering the study area offer high resolution airborne observations of landscape, represented as a 3D point cloud carrying a set of attributes that provide detailed point-level statistics and data acquisition parameters. Over the area of interest, LiDAR data were obtained with Trimble AX60/10 (2015-05-09) and Optech ALTM Gemini/80/61 (2009-05-31) sensors generating point clouds with minimum point density of 0.5 points/m². The LAS files come as geographically adjusted and classified 2.5 x 2.5 km tiles, with minimum of 20% overlap of flight lines. In addition, Geodata Extraction Tool was also used to outsource cadastral vector files of the study area. Data regarding registered archaeological sites were also freely available to download in vector shapefile format from the Swedish National Heritage Board’s interactive database Fornsök (https://fmis.raa.se).

Data processing and visualisation tasks were carried out by employing assorted software suited for required procedures. LiDAR data processing, establishment of DEMs and associated morphometric variables as well as production of maps were accomplished utilising ESRI’s ArcGIS ver. 10.4, Quantum GIS ver. 2.18 and Relief Visualization Toolbox ver. 1.3 (Kokalj et al., 2011) software packages. In parallel, the freeware application CloudCompare ver. 2.8 aided with additional LAS dataset processing operations. Image processing tasks were implemented and achieved within MathWorks’ MATLAB ver. 2016b. All project files were retrieved or re-projected to planar SWEREF99 TM and vertical RH 2000 coordinate reference systems. Specific functions associated with software used in this project are described in detail further in the text.

2.2 Methods

The proposed approach for detecting and extracting charcoal kiln sites incorporates a number of procedural steps in seeking to achieve an outcome corresponding to a semantic association of investigated objects meaningful to archaeologists. In this sense, the established methodological scheme follows an indicative description of charcoal kilns that fulfil the following characteristics:
1. Charcoal kilns are earthworks potentially eroded to some degree, which resemble mathematical annulus shape with inner and outer circular or slightly elliptical bounds;

2. The earthworks appear morphologically homogenous with a fixed range in diameter (14-26 metres) and height (generally lower than 1 metre).

Based on these conditions, the identification of unique charcoal kiln descriptors has been scrutinised to reach best possible results commencing at the very early stages of data processing. The resulting workflow of methodological phases presented below is summarised in the Figure 4.

![Figure 4. Workflow diagram of the proposed methodology.](image)

### 2.2.1 DEM creation from LiDAR

LiDAR point clouds stored in standard published LAS format files hold classification codes assigned to each return of emitted laser pulse, which represent exemplary landscape features. In this study only those returns (points) referring to the bare ground LAS classification (class 2) have been considered. Such LiDAR dataset class filtering was achieved by utilising multifunctional open source toolbox LAStools (Isenburg, 2014), which was executed within ArcGIS working environment. Many future false positive identifications can be avoided by inspecting and filtering outliers of the bare ground point cloud. This is especially relevant in
landscapes with unclear marshland and water delineation where point distribution may introduce unwanted noise in the dataset. The outlying points within the filtered bare ground class were removed by establishing a threshold based on the standard deviation of local distances and processed in CloudCompare software.

A digital elevation model was generated by interpolating filtered ground points and subsequently establishing a geographically referenced raster grid. Although a number of studies (e.g.: Cerrillo-Cuenca, 2016; Freeland et al., 2016) claim spline interpolation method to serve best for terrain representation for archaeological purposes, this study, however, determined its ineffectiveness and instead followed Trier & Pilø (2012) applied scheme based on linear triangulation method. Compared to linear interpolation, spline method completely smoothened out terrain features below metre-level and diminished the likelihood of charcoal kilns to be effectively distinguished. In turn, the triangulated irregular network (TIN) model that represented bare ground was converted to raster grid with 1 metre ground resolution in the x and y coordinates and floating point values for height in metres resulting in study area DEM.

2.2.2 Morphometric DEM properties

Morphometric terrain classification takes form of many different methods and is commonly used in studies that employ analyses of geomorphological ground surface mapping (Kringer, 2010). In most cases the DEM serves as source data that are used to define specific landforms or shapes in topography via parametric statistics-based raster processing (Schneider et al., 2015). These morphometric parameters (or variables) can be effectively used to indicate features with clearly distinct characteristics relative to the neighbouring terrain (Drăguţ & Blaschke, 2006). Methods that establish surface irregularities by means of area convexity in relation to its surroundings have been used in archaeological practice mostly for visualisation and manual exploration purposes (Doneus, 2013). In this study, however, such morphometric maps are effectively employed in automated charcoal kiln site detection. Among many morphometric variables tested, three techniques that describe best studied objects have been selected in this project: local relief, topographic openness and sky-view factor, all outlined in basic details below.

Topographic Position Index (TPI) as promoted by Weiss (2001), or otherwise local relief modelling, compares (by subtraction) elevation values of each DEM raster cell to the mean height values of a defined neighbourhood (Sermin & Jenness, 2008). While positive values of produced TPI raster represent areas that are higher than the average of the specified neighbourhood, negative values accordingly indicate lower positions of original cells than their surroundings (Fig. 5a). In seeking to extract and accentuate charcoal kiln sites, an annulus neighbourhood mask was conveniently utilised to calculate TPI values of the study area DEM within the ArcGIS environment. The established outer radius parameter of the annulus focal mask was corresponding to the largest considered size of the analysed objects (r=13 metres), whereas inner radius proved to show best results set equal to 2 metres. Landform indexing and classification as suggested by Weiss (2001) was not incorporated into this study since TPI raster would have undergone further manipulations of its values later in the image processing phase.
Although TPI generally served well to highlight features of interest, not all objects or their parts were entirely delineated. For this reason topographic openness and sky-view factor variables were effectively utilised in supplementing additional morphometric information when generating a descriptor map of charcoal kilns. Topographic openness (TO) proposed by Yokoyama et al. (2002) serves as a sophisticated terrain visualization technique, which provides the degree of exposure or enclosure of a location within an irregular surface (Doneus, 2013). TO is determined by n-directional profiling within pre-defined radial distance from the considered DEM cell, where largest zenith and nadir angles are established along each profile. Two possible outcomes can be achieved by calculating the mean values of the established angles: the average of all zenith values provides positive openness, while the mean of nadir angles expresses the negative openness (Fig. 5b) (Yokoyama et al., 2002).

Similarly, the Sky-View Factor (SVF) provides an opposite measure to the TO as the algorithm determines relief illumination factor determined via visible portion of the sky’s sphere (for detailed explanation refer to: Zakšek et al., 2011; Štular et al., 2012). Obstructed by surpassing landforms from the visible sky, lower parts of the terrain are assigned to low values and well exposed locations within radial distance from the assessed cell attain higher values in the sky-view factor raster (Fig. 5c). Positive openness and SVF maps were established utilising Relief Visualization Toolbox setting up radial neighbourhood size to \( r=13 \) metres and 16 directions for azimuth, nadir and vertical elevation angular calculations (Kokalj et al., 2011).

\[
\text{TPI} = \text{DEM} - \text{focalmean} \ldots \\
\text{(annulus} [\text{inner}_r, \text{outer}_r])
\]

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<th>Topographic Openness</th>
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<tr>
<td>Single profile determination of zenith and nadir angles:</td>
<td>Single profile determination: Sky-View Factor is characterized as a part of the visible sky (( \Omega )) above observation point (A). The algorithm calculates vertical elevation angle of the horizon ( \gamma ) to the radius equal to 13m.</td>
<td></td>
</tr>
<tr>
<td>( A_1 ) – high value of positive openness, low value of negative openness.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( A_2 ) – low value of positive openness, high value of negative openness.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 5.** Descriptive conceptual examples of morphometric classification methods used in this study: a) Local relief (TPI), b) Topographic Openness, c) Sky-View Factor.
2.2.3 Image segmentation

Normalized and exported to 8-bit geotiff format, individual maps of different morphometric descriptors illustrated in the previous section served as inputs in analytical image processing. At this stage, classified morphometric maps are referred as two-dimensional arrays, where each hold values (0-255) respectively representing a matrix of morphometric arrangement. However, since each descriptor map was not sufficient to fully represent analysed objects, the image processing upon individual rasters indexed into a three-dimensional array was not considered as an effective option. Rather, following the empirical testing, a weighted sum of individual TPI, TO and SVF rasters provided an adequate cumulative descriptor image. Investigated combination of the morphometric maps served best for image segmentation stage where only TPI was assigned to a weight value of 0.8; TO and SVF retained a full weight membership equal to 1 in the sum of all three maps.

Feature detection procedures inherently rely on how well objects of interest are described (Shapiro & Stockman, 2001). In order to delineate charcoal kilns within the image, partitioning techniques (or segmentation) were applied to establish constituent regions in the image based on pre-set threshold values. This study incorporated a two-step image segmentation procedure within the MATLAB environment, firstly converting the greyscale image into a binary two-dimensional array and then exercising morphological opening operations. Although both techniques are considered as elementary within the domain of image processing, they nevertheless provide an effective and well manageable way of segmenting an image (Gonzalez & Woods, 2009; Mitiche & Ayed, 2010). In addition to the entire study area extent, one smaller subset—a validation area of 6 km$^2$—was established for segmentation behaviour testing. The initial image binarization, or contrast split, with percentage threshold of 78% determined where binary division should take place along the greyscale range of the both images. The process involved threshold value establishment through attentive inspection of the known charcoal kiln sites, which in effect estimated delineation of the objects across the entire image represented by bright pixels. Unsuitable regions of bright pixel values were further discriminated by applying the morphology opening operator upon regions that consist smaller or larger number of pixels than those, which are likely to describe charcoal kilns. A simplified example of the entire charcoal kiln delineation process can be appreciated in Figure 6.

2.2.4 Feature extraction

A successive methodological element of feature detection and extraction from the segmented images was further implemented into the MATLAB algorithm (Appendix A) by applying Hough Circle transfer technique found within the MATLAB’s Image Processing Toolbox. Hough transform of curves is a rigorous method widely used across computer vision tasks and compliant to specific shape delineation with available parametric thresholding (Duda & Hart 1972; Davies, 2005). The compiled function that detects circular patterns in segmented images is based on the formula (1) that describes a circle in the two-dimensional array:

\[
r^2 = (x - a)^2 + (y - b)^2
\]  

(1)
Figure 6. Charcoal kiln delineation steps (a–f) shown on a well-preserved site. Note: for visualisation purposes, 40 m x 40 m original data subsets were resampled to cell size = 0.25 m.

where \( r \) is the radius and \((a, b)\) are the corresponding coordinates of the circle centre. Additional parameters of minimum and maximum radii as well as detection and edge gradient sensitivity allow the function to determine whether segmented areas of the image intersect at given \((a, b, r)\) and thus correspond to a circle in the image (Yuen et al., 1990; Atherton & Kerbyson 1999).

Aiming to achieve fine results in charcoal kiln detection, the Hough Circle transfer function was employed to distinguish two circumferences with radii of different metric ranges, which roughly represent the inner and the outer earthwork edges. By setting the circle radii intervals \( r_{\text{outer edge}} = [7, 13] \) and \( r_{\text{inner edge}} = [2, 4] \) (in metres) along with associated function sensitivity and edge thresholds, the output returns an initial list of \( x \) and \( y \) locations for detected circle centres \((x, y)\) and associated radii \( r \). Furthermore, a series of logical conditions that would filter predicted matches were established upon the spatial composition and arrangement of the charcoal kilns inferred from empiric knowledge about the sites and are summarised in the Table 1. Despite effective formulation of circle filtering that match kiln morphological characteristics, the spatial relationship factor between individual entities yielded a rather different approach when considering output presentation of the predicted sites. Since more than one match that satisfies morphological conditions can be identified in the image as overlapping or concentrated in dense clusters and potentially none could hold a

**Table 1.** Filtering conditions established upon Hough Circle transfer. Note: \( \rightarrow \) stands for ‘within’ spatial query.

<table>
<thead>
<tr>
<th>No.</th>
<th>Factual knowledge</th>
<th>Algorithmic condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>The inner edge of the charcoal kiln dyke is always smaller than the outer edge</td>
<td>( r_{\text{inner}} &lt; r_{\text{outer}} )</td>
</tr>
<tr>
<td>2.</td>
<td>The inner edge of the earthwork bank is always within the outer edge</td>
<td>( r_{\text{inner}} \rightarrow r_{\text{outer}} )</td>
</tr>
<tr>
<td>3.</td>
<td>Charcoal kiln sites do not overlap and typically have a buffer area of ca. 50 metres</td>
<td>If ( \text{kiln}_{(a, b)} &gt; 1 \rightarrow 50 \text{ m buffer}, ) identify</td>
</tr>
</tbody>
</table>
true positive match, the only solution outcried identification of such instances presenting them as a different class of predicted locations that requires manual inspection. The output matrix of two classes corresponds to identified locations of charcoal kiln sites.

2.2.5 Accuracy assessment

Standard harmonic mean ($F_1$-Score) of Precision-Recall measure was calculated to quantitatively evaluate charcoal kiln detection method. $F_1$-Score accuracy assessment allows effectively validating binary classification set of predicted sites based on true positive (TP), true negative (TN) and false positive (FP) results (Davis & Goadrich, 2006). The validation area was selected for sampled statistical assessment, which contains fifteen manually identified and ground truth-confirmed charcoal kilns by addressing a variety of terrain visualization techniques previously mentioned in the text (Fig. 7). Ground truth routine of site determination was achieved by visiting pinpointed objects and inspecting them visually as well as examining traces of charcoal abundance under the moss layers. While detected charcoal kilns that coincided with manual observations were defined as true positive detections, the model results that did not match manually identified sites were regarded as false negative detections (omission errors). In studies where absolute number of existing objects is impossible to infer, problematic nature of false positive identifications (commission errors) has been approached in different ways (e.g.: Schneider et al., 2015; Freeland et al., 2016). As undiscovered sites might not hold morphological characteristics identifiable neither by manual visual inspection of maps, nor through field survey, the commission error estimation is usually established upon the available data and resources and therefore inevitably inclines fraction of bias in the final accuracy statistics. In this study manually identified sites serve as a reference set for $F_1$-Score establishment. Nevertheless, additional attention is reserved to investigate potential commission errors by performing ground truth assessment and presenting relational accuracy of manual and automatic detection methods. Altogether, the $F_1$-Score calculation is established through arithmetic expressions (2-4) accounting fraction of detections that are true positives—precision ($p$) and fraction of positive matches that are correctly identified—recall ($r$):

$$p = \frac{TP}{TP + FP} \quad (2)$$

$$r = \frac{TP}{TP + FN} \quad (3)$$

$$F_1 = 2 \cdot \frac{pr}{p + r} \quad (4)$$

The resulting $F_1$-Score values ranging from 0 to 1 (where 1 is a perfect fit) served as an indicator that defines the correctness of the proposed methodology.
**Figure 7.** Validation area (6 km$^2$) within study area extents. Assessed locations of charcoal kilns are shown upon area hillshade map.
3. Charcoal kiln detection results

The mapping of charcoal kilns by employing a combination of three different morphometric classification methods and analytical image processing provided results that exhibit a range of thought-provoking procedural aspects. Details of analysis and its resultant outcome are considered in this section.

Sites detected using methodology proposed in this study and field survey results within the validation area are depicted in the Figure 8 where reference information about individual sites is linked to Table 2. The outcome is based on the extended filtering procedures summarised in Figure 9 as well as latterly established post-processing result refinement explained in detail further in the text.

![Charcoal kiln identifications within validation area.](image)

**Figure 8.** Charcoal kiln identifications within validation area. Additional examples show Hough Circle transfer identifications over the segmented image objects, ©Lantmäteriet [i2017/561].
The $F_1$-Score calculated upon the results retrieved from the charcoal kiln detection algorithm produced adequate results given the available time framework and resources of the research. The resulting $F_1$-Score of 0.54 was determined upon the matches within the validation area of which two thirds of automatically detected sites coincided with visually identified kilns (Table 3). Further investigation of false negative and false positive returns took place since both came in relatively great numbers. Based on the number and locations of identified sites, physical investigations in the field maintained reliable ways of assessing the manual and automatic approaches in detecting charcoal kilns. The information collected during the ground truth assessment yielded invaluable insights about how morphometric arrangements visible in the map and feature detection returns appear as physical landscape features (Table 2).

Table 2. List of identified sites using automatic and manual visual map inspection. The table summarises which sites coincide with real sites providing short comment from field inspection.

<table>
<thead>
<tr>
<th>Site No.</th>
<th>Site Id</th>
<th>Detection Method</th>
<th>Kiln match</th>
<th>Ground truth observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Valbo 1112</td>
<td>Automatic/Manual</td>
<td>Yes</td>
<td>Good preservation, cleared vegetation</td>
</tr>
<tr>
<td>2.</td>
<td>Valbo 1113</td>
<td>Automatic/Manual</td>
<td>Yes</td>
<td>Good preservation, cleared vegetation</td>
</tr>
<tr>
<td>3.</td>
<td>Valbo 1115</td>
<td>Automatic/Manual</td>
<td>Yes</td>
<td>Good preservation</td>
</tr>
<tr>
<td>4.</td>
<td>Valbo 1116</td>
<td>Automatic/Manual</td>
<td>Yes</td>
<td>Good preservation</td>
</tr>
<tr>
<td>5.</td>
<td>Not registered</td>
<td>Automatic/Manual</td>
<td>Yes</td>
<td>Good preservation, cleared vegetation</td>
</tr>
<tr>
<td>6.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Good preservation</td>
</tr>
<tr>
<td>7.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Good preservation</td>
</tr>
<tr>
<td>8.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Good preservation</td>
</tr>
<tr>
<td>9.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Adequate preservation</td>
</tr>
<tr>
<td>10.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Adequate preservation</td>
</tr>
<tr>
<td>11.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Path intersects the platform</td>
</tr>
<tr>
<td>12.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Incomplete, but conspicuous</td>
</tr>
<tr>
<td>13.</td>
<td>Automatic</td>
<td>Yes</td>
<td></td>
<td>Damaged</td>
</tr>
<tr>
<td>14.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against property boundary</td>
</tr>
<tr>
<td>15.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against property boundary</td>
</tr>
<tr>
<td>16.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against property boundary</td>
</tr>
<tr>
<td>17.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Boulder formation after forest clearing</td>
</tr>
<tr>
<td>18.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against the road</td>
</tr>
<tr>
<td>19.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against the road</td>
</tr>
<tr>
<td>20.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against drainage ditch</td>
</tr>
<tr>
<td>21.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against property boundary</td>
</tr>
<tr>
<td>22.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against the quarry edge</td>
</tr>
<tr>
<td>23.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against the road</td>
</tr>
<tr>
<td>24.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Boulder formation after forest clearing</td>
</tr>
<tr>
<td>25.</td>
<td>Automatic</td>
<td>No</td>
<td>FP</td>
<td>Border effect against the road</td>
</tr>
<tr>
<td>26.</td>
<td>Manual</td>
<td>No</td>
<td></td>
<td>Good preservation, small diameter</td>
</tr>
<tr>
<td>27.</td>
<td>Manual</td>
<td>No</td>
<td></td>
<td>Damaged</td>
</tr>
<tr>
<td>28.</td>
<td>Manual</td>
<td>No</td>
<td></td>
<td>Damaged</td>
</tr>
<tr>
<td>29.</td>
<td>Manual</td>
<td>No</td>
<td></td>
<td>Damaged</td>
</tr>
<tr>
<td>30.</td>
<td>Manual</td>
<td>No</td>
<td></td>
<td>Good preservation, no central depression</td>
</tr>
</tbody>
</table>
### Table 3. Charcoal kiln extraction validation results.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Kilns detected</th>
<th>Reference (manual)</th>
<th>TP</th>
<th>FP</th>
<th>FN</th>
<th>New sites</th>
<th>(p)</th>
<th>(r)</th>
<th>F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>No filtering</td>
<td>25</td>
<td>15</td>
<td>10</td>
<td>5</td>
<td>3</td>
<td>0.45</td>
<td>0.67</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td>After border effect filtering</td>
<td>3</td>
<td>0.77</td>
<td>0.71</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Omission errors (FN) among manually identified sites occurred mainly due to disrupted morphology of the studied objects, i.e. poor preservation or unusual shapes. Such appearances, however, would have been able to distinguish by setting lower sensitivity thresholds, which would have increased numbers in false positive returns. In any case, the number of commission errors (FP) appeared to present two major aspects that further drew investigative attention. Firstly, three previously unnoticed sites were detected during the field assessment of the FP locations. These particular sites could not be easily distinguished through visual inspection neither in shaded relief, nor different morphometric classification maps. Secondly, two thirds of FP detections were recognised to be located along linear terrain features, which created sufficient conditions for Hough transform to establish circular objects along them (Figures 8 and 9). Such systematic pattern was regarded as a border effect, which was eliminated by executing spatial query filtering where all returns were intersected with buffered (10 metres) linear vector data that represent boundaries of cadastral, road and water body features. As expected, only identified FP returns with border effect were eliminated, which accordingly reflected in an increase of the \(F_1\)-Score by 17% (Table 3).

![Figure 9](image_url)  
**Figure 9.** Examples of Hough Circle transfer filtering results based on pre-set conditions (Table 1): a) inner circle is smaller and inside the outer circle, b) inner circle is smaller, but cross the outer circle, c) two identified locations are closer than 50 m. Note: case c) of two nearby matches was only used in visual inspection; it is not indicated in other maps to avoid cluttering.
In terms of larger assessment area, which extends to the interest bounds of this study, 314 potential matches were investigated (Fig. 10). Although such number of rendered predicted locations could not be objectively examined by physical site assessment, it nevertheless provided significant insights about the performance of the proposed method. After filtering invalid locations with border effect, 97 sites were visually confirmed from shaded relief and combined morphometric classification maps, of which 26 sites are officially registered at the *Fornsök* database. At the same time, however, 29 registered sites did not have a corresponding match, where main causes of such overlook could be referred to as damaged, imprecisely located or invisible sites for the used DEM resolution (Appendix B). The remaining 118 predicted locations could not be recognized as charcoal kilns using visual assessment, yet, as it could be seen in the validation area, some number of sites would almost certainly emerge as real ones after physical verification in the field.

![Figure 10](image.png)

**Figure 10.** Charcoal kiln matches within study area extent. Additional examples illustrate correct and filtered matches, ©Lantmäteriet [i2017/561].
4. Discussion

“The Information Age offers much to mankind, and I would like to think that we will rise to the challenges it presents. But it is vital to remember that information – in the sense of raw data – is not knowledge, that knowledge is not wisdom, and that wisdom is not foresight. But information is the first essential step to all of these”  

Arthur C. Clarke  
in Nalaka (2003)

The proposed methodology for detecting charcoal kiln remnants resulted in a reasonable proportion of accurately identified locations, which effectively serves as a semi-automatic approach in seeking to find and examine spatial distribution of such archaeological sites. An important remark is assigned to the achieved methodological workflow which was effectively established upon conceptually longstanding techniques and recent data that allowed analytical assessment of such character. Since not all aspects of the proposed scheme could be reflected only as methods and results, a series of coherent elements can be further considered when juxtaposed in a wider contextual discourse.

4.1 Aspects of data processing outcome

Throughout the comparative testing on morphometric weighs it determined that combining different rasters that represent distinct morphological elements of the terrain play one of the key roles that affect the final result. In respect to the established weights, such combination seemed to work in the assessed terrain setting, albeit the use of such parameters has not been tested on highly variable terrain. It also required a considerable amount of processing time in order to accomplish best possible result under analytical conditions. As a result, within short time framework established morphometric configuration allowed to handle image segmentation steps only with an adequate level of control.

Although during the first image segmentation phase the same image binarization threshold value of 78% served well within both validation area and the whole study extent in defining charcoal kiln shapes, morphological opening procedure maintained rather different shape size estimation. In the very essence of image clean-up process, where unsuitable regions are removed based only on the consisting pixel number, the operation can be erosive eliminating potential shape matches. Larger processing extents, therefore, introduce diversity in shape sizes, which consequently increase chances of either lower overall true positive score or higher number of false positive detections. Based on these premises, the validation area had a narrower range of segmented objects to be retained within the image, while the wider study area inevitably contained broader range of object sizes. Such area size-dependent arrangement had a decisive influence on feature detection procedure.

The behaviour of Hough Circle transfer function heavily relied on the preceding data processing steps. In such relational task, the prior knowledge of manually identified charcoal kiln sites with ground truth confirmation within the validation area aided with much easier sensitivity and edge threshold establishment. These measures also played an influential role
for determining final outcome, especially being constrained by filtering conditions (Table 1 and Figure 9). Altogether, filtering procedure disclosed up to 40% of invalid initial coincidences where outer circles did not fully contain the inner circles. It was observed that the percentage of eliminated false matches is somewhat inversely proportional to Hough transform function parameters; lower detection sensitivity contributed to a larger number of circle detections, which correspondingly increased a proportion of excluded invalid coincidences.

4.2 Methodological implications

In the very nature of any AFE technique a fundamental trade-off between precision and recall is prevalent; a case provided in this study is by no means an exception. Difficult ways of calibrating series of threshold values without a fixed number of existing charcoal kiln reference locations inevitably initiated a level of uncertainty within commission and omission errors. It was also clear that the ground truth assessment could correctly adjust both manual and automatic ways of object identification. In line with such observations, the bias that predicates any type of error can also not be ignored on the assumption that some charcoal kilns were unidentified. Despite aforementioned uncertainty, the evaluation of individual sites within validation area and registered sites across study area bounds allowed drawing a set of potential caveats which may have been associated with the used materials and methods.

Although LiDAR data generally provide sufficient means for AFE techniques to be implemented upon DEMs interpolated from filtered ground points, it nevertheless raise considerations whether a higher density than 0.5 points/m² would improve the process of detecting and extracting charcoal kilns. Highly dense small forest stands obstruct laser pulses of reaching the bare ground level, which consequently respond to a poor terrain representation after interpolation of sparsely distributed points (Fig. 11). Such issue directly calls for attention not only in terms of object hindrance, but object visibility as an integral entity. One of the primary reasons why the proposed algorithm failed to identify existing charcoal kilns was the altered morphology of the objects. Most of the assessed sites that were not identified using the proposed method had suffered from a various degree of disturbance. Although it was able to visually distinguish a part of these sites, contrast split segmentation corresponding to morphometric classification raster values disintegrated damaged features into smaller fragments which eventually disappeared after morphology opening phase. Since the proposed algorithm returned what it should have based on the established charcoal kiln description (generally integral objects), the loss of insufficiently described or confused morphological information has its direct repercussions reflected in the choice of segmentation, which is a common problem in the image processing routine (Gonzalez & Woods 2009). An instance of such consolidation is illustrated in Figure 12, where the charcoal kiln site (No. 27 in Table 3) has suffered from a large vehicle interruption and such effect can be clearly recognised in the data employed for the analysis.
Figure 11. Profile view of LiDAR point cloud over a) charcoal kiln covered by high vegetation and b) over low and dense vegetation.

In the extended AFE study, Trier & Pilø (2012) have implemented LiDAR datasets of different resolution (0.007-7.277 points/m²) in order to assess detection rates of prehistoric hunting pits slightly smaller and less pronounced than charcoal kilns. The implied results showed a surprising increase of detection rate from 54% to 81% only by increasing point density from 0.5 to 2.0 points/m², whereas higher point density than 2.0 points/m² did not show such a dramatic shift in recognised sites. The example from Norway provides an obvious justification how higher quality data could help to overcome poorly represented areas of terrain or even damaged sites. Moreover, higher LiDAR point density would instantly allow establishing AFE solutions upon DEMs of higher than 1 metre resolution, which is a key aspect in the performance of the Hough Circle transfer, where amount of pixels determines pattern recognition. Hence it can be deduced that data itself might be responsible for a fraction of dismissed sites, thus charcoal kiln visibility would come along with further ALS data improvements.

In spite of hypothetical conjectures, a range of already implemented techniques require further fine tuning in seeking to reach an even finer set of results from the proposed methodology. In this attempt border effect filtering was applied as a post-processing procedure, which included supplementary vector data and potentially might not work in various different environments. As a solution, additional image segmentation operation based on morphological shape delineation would serve as an effective filtering factor within the core of the method. Segmented regions along linear landscape features tend to occur in
oblong shapes, which could be eliminated with some effort in setting specialized parameters for assessing a ratio between semi-major and semi-minor axes of image segments. Such improvement would also dispose many more unwanted regions which cannot satisfy the initial inquiry of shape morphology. Furthermore, study area, as seen in the results, plays a meaningful role in how the segmentation is set up. Manual adjustments based on the known charcoal kiln locations take a significant amount of time and effort; therefore, smaller areas are more likely to be processed quicker with finer results and less false positive returns. Over and above, assessing judiciously chosen area size would also provide more manageable ways of evaluating the processed outcome in the field.

4.3 Implications for cultural resource management

This study has meaningful implications for cultural resource management prospection employing remote sensing data and GIS. Recent tendencies of archaeologists working hand in hand with geospatial data seem to stimulate the discourse of applying (semi)automatic feature extraction methods of uniform cultural relics that are now a part of the landscape (Lou et al., 2014; Cerrillo-Cuenca, 2016). For this reason it is important to keep generating applied conceptual schemes of AFE in order to exhaust the available data as well as techniques and share them by improving current ways of managing cultural resources.

The proposed method of charcoal kiln extraction from LiDAR-derived DEMs, with some further improvements, may be implemented into already existing heritage management programs where systematic ground truth assessments could take place as part of archaeological inventory routines. Such application can help to narrow down the focus of fieldwork evaluations, where additional on-site observations would include information about the settings of recognised sites. It would be also interesting to utilise the technique by cross-referencing with historic records of iron production places and analyse the extent of
charcoal supply relying on the spatial distribution of identified charcoal kilns. Based on such investigations, past land management practices could be easier delineated with spatial and temporal attributes. At the same time, delineating charcoal kilns can ease up management in large development areas, whether it is forestry, energy or transportation projects, which interfere with previously unsurveyed territories.

4.4 Future prospects

Further work on this topic has two main orientations: current method improvement and development of the method implementation. The introduced sequence of geo-processing and image processing tasks may be revised by assessing selected methodological elements based on different terrain settings and/or using higher resolution ALS data. It would also be of interest to test more morphometric classification methods, which could delineate charcoal kilns in reasonable terms. In line with additional techniques, satellite or orthophoto high resolution spectral image classification could also potentially serve as a supplementary weight if charcoal kiln locations provide enough of solid and meaningful properties to discriminate them.

In terms of current methodological solution proposed in this paper, a comparative study using advanced GEOBIA software would allow drawing analytic inferences based on the difference of the outcomes. This would also put into perspective how the same methodology could be achieved by using several different techniques. In parallel, the approach of detecting charcoal kiln sites requires knowledge of both the technical and archaeological aspects as well as constant supervision along the entire workflow. In order to improve the method towards fully automatic process, the main focus should be concentrated upon modelling threshold determination algorithms for image segmentation and Hough Circle transfer functions based on given geomorphology. On one hand, such tasks are rather advanced for GIS specialists (not to say archaeologists), on the other—for computer science and machine learning domain such assignments are within a relatively easy reach. Therefore, as mentioned at the very onset of this paper, interdisciplinary inquiry is a key for further development of the tools that help understanding our past.

Last but by no means least, the integrity and accessibility of the method counts as a future prospect. This study has utilised a range of commercial and open source software, which might not be easily attainable or available in seeking to carry out the method (or parts of it) described in this paper. A feasible solution would be implementing the entire workflow into an open-source line of procedures. Such task could be achieved by using Python programming language since it embraces an extended list of scientific libraries that cover the range of processes that were used in this study (e.g.: GDAL, Numpy, Scipy and scikit-image). Furthermore, introduction of user interface and ability to recognise series of user-defined shapes would ultimately harness the potential of the prototypical method investigated in this study.
5. Conclusion

Throughout the course of this research paper, a pipeline of methodological steps in order to detect historic charcoal production sites was investigated. Bare ground DEM extracted from LiDAR datasets effectively served as a main data source to establish three different morphometric classification maps. The combined maps functioned as an input for image processing phase, which comprised of image segmentation and Hough Circle transfer function. Thereafter, a set of logical rules were applied to the circle detection algorithm in seeking to delineate charcoal kiln sites. The initial $F_1$-Score equal to 0.54 was established upon sample area, which contained 30 sites that have been identified manually and using the proposed method. The primary means of false positive identifications were recognised as border effect and after additional post-processing the $F_1$-Score increased to 0.71. The analysis of extended study area identified 97 charcoal kiln sites, which were confirmed by visual assessment. Problematic matters and associated drawbacks observed during the work were critically examined and discussed in the wider context of potential applicability of the obtained result.

Processed remotely sensed data cannot explicitly yield contextual information that archaeological sites on the ground may contain. However, it can provide archaeologists with a focused direction towards more efficient and cost-effective ways of pin-pointing sites that correspond to their user-defined characteristics. The developed method of detecting remnants of charcoal kilns by utilising GIS, remote sensing and image processing techniques has demonstrated that archaeological phenomena of such size can be extracted and scrutinized at the current resolution of the Swedish national LiDAR dataset. This tested prototypical conception is a significantly valuable contribution towards a better management of cultural resources.
References


Appendices

Appendix A

A complete MATLAB code for circular feature extraction from a morphometric map (own work). Text in green specifies comments about functions used in the calculations. User-specified parameters are indicated in red colour.

tic
clc
clear all
format longg

% Import morphometric map and adjust the contrast
[A, R, d] = geotiffread('morphometric_map.tif');
info = geotiffinfo(A);
con_adjust = imadjust (A); % Contrast stretch

% Image segmentation
binary_split = im2bw(con_adjust, 0.78); % Binarize with a set threshold value

% Set segmented object size variables
LB = 40; %lower limit
UB = 220; %upper limit

morphology_open = xor (bwareaopen(binary_split,LB), bwareaopen(binary_split,UB));

% Display the result
figure,
imshowpair (con_adjust, morphology_open , 'blend'), impixelinfo;

% Set variables for outer and inner circle radii range
Rb_min = 7;
Rb_max = 13;
Rm_min = 2;
Rm_max = 4;

% Hough Circle transform for bright and dark circles
[centersBright, radiiBright] = imfindcircles(morphology_open,[Rb_min Rb_max],...
    'ObjectPolarity','bright', 'Method', 'TwoStage', 'Sensitivity', 0.87,...
    'EdgeThreshold', 0.65);
[centersDark, radiiDark] = imfindcircles(morphology_open,[Rm_min Rm_max],...
    'ObjectPolarity','dark', 'Method', 'TwoStage', 'Sensitivity', 0.88,...
    'EdgeThreshold', 0.6);

% Drawing circles on the paired segmented image
outer = viscircles(centersBright, radiiBright, 'Color','b');
inner = viscircles(centersDark, radiiDark, 'Color','r');

% Condition 1.
% Setting and storing coordinates in array variables
xSm=centersDark(:,1);
ySm=centersDark(:,2);
xBig=centersBright(:,1);
yBig=centersBright(:,2);
counter=0;
for i=1:length(xBig)
    for j=1:length(xSm)
        if (xSm(j) - xBig(i)).^2 + (ySm(j) - yBig(i)).^2 < radiiBright(i).^2;
            counter=counter+1; %counts amount of circles inside the big circles
            xyS(counter,:)=xSm(j),ySm(j)]; %stores the coordinates in x and y
            rB(counter,:)=radiiBright(i)];
            rS(counter,:)=radiiDark(j); %stores the coordinates in x and y
        end
    end
end

% Transforms x and y to lon/lat
[latRS, lonRS] = pix2latlon(R,xyS(:,2), xyS(:,1));
[latRB, lonRB] = pix2latlon(R,xyB(:,2), xyB(:,1));

%Condition 2
% Setting the array size of A
[m, n] = size(A);

% Creates "small circles" binary image by calculating a distance to the center
% of big circle from each pixel and compare this distance to radius
wS=zeros(m,n);
    for h = 1 : length(xyS)
        for i = 1 : m
            for j = 1 : n
                if ((i - xyS(h,2)).^2 + (j - xyS(h,1)).^2) < rS(h).^2
                    wS(i, j) = 1;
            end
        end
    end

% Displaying the result
figure,
imshow (wS), impixelinfo;

% Creates "big circles" binary image by calculating a distance to the center
% of big circle from each pixel and compare this distance to radius
wB=zeros(m,n);
    for h = 1 : length(xyB)
        for i = 1 : m
            for j = 1 : n
                if ((i - xyB(h,2)).^2 + (j - xyB(h,1)).^2) < rB(h).^2
                    wB(i, j) = 1;
            end
        end
    end

% Displaying the result
figure,
imsho wpair (A,wB, 'blend'), impixelinfo;

% Finds only those circles that are fully inside the big circles by
% firstly subtracting and filling circles that contain a closed hole,
% then extracts hole segments, which represent centers of coinciding circles.
only_minus = imsubtract(wB, wS);
only_fill = imfill(only_minus);
only_gand = only_fill==1&wS==1;
only_gandd = only_gand*1;
only_subt = imsubtract(wB, only_gandd);
only_pand = only_subt==0&wS==1;
colc = im2bw (only_pand); % makes sure it is binary
only_clean = bwareaopen (colc, 25);

% Displaying the result
figure,
imshowpair(A, only_subt, 'blend'), impixelinfo;

% Hough Circle transfer finding the extracted circles
[F_centers, F_radii] = imfindcircles(only_clean, [2 4],
   'ObjectPolarity', 'bright', 'Method', 'TwoStage',
   'Sensitivity', 0.91, 'EdgeThreshold', 0.55);

% Counts the number of identified circles
F_counter = numel(F_centers)/2;

% Drawing circles on the image of filtered circles
figure,
imshowpair (A, only_clean, 'blend'), impixelinfo;
viscircles(F_centers, F_radii, 'EdgeColor', 'b');

% Transforms identified circle centers to lat/lon
[latAnd, lonAnd] = pix2latlon(R, F_centers(:, 2), F_centers(:, 1));

% Condition 3
% Distance measuring by buffer masking and alerting.
% Create a mask with circles (r=50px) over the known filtered locations

% Setting the variable for the mask
radius = 50;
xy_circles = [F_centers(:, 1), F_centers(:, 2)];

wmask = zeros (m, n);
for k = 1 : length (xy_circles)
   for e = 1 : m
      for d = 1 : n
         if (e - F_centers(k, 2)).^2 + (d - F_centers(k, 1)).^2 <= radius.^2;
            wmask(e, d) = 1;
         end
      end
   end
end

% Find and extract areas which exceed the amount of pixels
% contained within one circle and returns result with viscircles().
cmask = im2bw (wmask);
area = bwareafilt(cmask, [7870 200000]); % Extracts circles with 1 circle r=50<pxs

% Finds overlapping circles
[A_centers, A_radii] = imfindcircles(area, [49 51],
   'ObjectPolarity', 'bright', 'Method', 'TwoStage',
   'Sensitivity', 0.92, 'EdgeThreshold', 0.75);

% Counts the number of overlapping circles
A_counter = numel (A_centers)/2;
% Transforms x and y of circle centers to lat/lon
[latA, lonA] = pix2latlon(R, A_centers(:,2), A_centers(:,1));

% Writes the identified circle center coordinates to a text file
dlmwrite(t_coordinates.txt, [lonAnd latAnd], 'newline', 'pc');

% Display the results
figure;
axis image
mapshow(A, R), impixelinfo;
hold on
plot(lonA, latA, 'Marker', 'o', 'MarkerFaceColor', 'green', 'MarkerSize', 8, 'LineStyle', 'none');
hold on
plot(lonRB, latRB, 'Marker', 'o', 'MarkerFaceColor', 'blue', 'MarkerSize', 5, 'LineStyle', 'none');
hold on
plot(lonRS, latRS, 'Marker', 'o', 'MarkerFaceColor', 'red', 'MarkerSize', 5, 'LineStyle', 'none');
hold on
plot(lonAnd, latAnd, 'Marker', 'o', 'MarkerFaceColor', 'yellow', 'MarkerSize', 6, 'LineStyle', 'none');
hold on
toc

Appendix B

Summary table of assessed charcoal kiln sites already registered in Fornsök database.

<table>
<thead>
<tr>
<th>No.</th>
<th>Site Id</th>
<th>Recorded state of preservation</th>
<th>Automatically Detected</th>
<th>Potential causes of omission</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Valbo 739</td>
<td>Good</td>
<td>No</td>
<td>Disturbed. Intersected by a road</td>
</tr>
<tr>
<td>2</td>
<td>Valbo 743</td>
<td>Good</td>
<td>No</td>
<td>Border effect</td>
</tr>
<tr>
<td>3</td>
<td>Valbo 864</td>
<td>Damaged</td>
<td>No</td>
<td>Unidentifiable in the map</td>
</tr>
<tr>
<td>4</td>
<td>Valbo 867</td>
<td>Damaged</td>
<td>No</td>
<td>Unidentifiable in the map</td>
</tr>
<tr>
<td>5</td>
<td>Valbo 871</td>
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<td>No</td>
<td>Unidentifiable in the map</td>
</tr>
<tr>
<td>6</td>
<td>Valbo 875</td>
<td>Damaged</td>
<td>No</td>
<td>Disintegrated into small parts</td>
</tr>
<tr>
<td>7</td>
<td>Valbo 879</td>
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</tr>
<tr>
<td>8</td>
<td>Valbo 880</td>
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</tr>
<tr>
<td>9</td>
<td>Valbo 881</td>
<td>Good</td>
<td>No</td>
<td>Complex topography</td>
</tr>
<tr>
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<td>No</td>
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</tr>
<tr>
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<td>Valbo 886</td>
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<td>Poor preservation</td>
</tr>
<tr>
<td>12</td>
<td>Valbo 890</td>
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<td>No</td>
<td>Disturbed, small in size (r=5 m)</td>
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<tr>
<td>13</td>
<td>Valbo 895</td>
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<td>Small in size (r=6 m)</td>
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<tr>
<td>16</td>
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<td>No</td>
<td>Disintegrated into small parts</td>
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<tr>
<td>17</td>
<td>Valbo 928</td>
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<td>No</td>
<td>Located on the slope.</td>
</tr>
<tr>
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<td>Valbo 945</td>
<td>Good</td>
<td>No</td>
<td>Unidentifiable in the map</td>
</tr>
<tr>
<td>No.</td>
<td>Site Id</td>
<td>Recorded state of preservation</td>
<td>Automatically Detected</td>
<td>Potential causes of omission</td>
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<td>------------------------</td>
<td>-----------------------------------------------</td>
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<td>Unidentifiable in the map</td>
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<td>Border effect</td>
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</tr>
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<td>Poor preservation and border effect</td>
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